Employee Skill Development in Manufacturing: Consequences of Learning and Forgetting on Production Planning and Task Scheduling

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Zusammenfassung

Der Druck auf produzierende Unternehmen nimmt stetig zu. Während globale Märkte für mehr Konkurrenz sorgen, verändern der technische Fortschritt und die Digitalisierung bestehende Produktionsprozesse. Endverbraucher neigen dazu Konsumgüter schneller zu ersetzen und fordern mehr Möglichkeiten, um neue Produkte individuell an ihre Bedürfnisse anzupassen. Diese Trends zwingen Unternehmen dazu in die Entwicklung neuer Produkte zu investieren und diese in immer kürzerer Zeit auf den Markt zu bringen. Das wiederum hat zur Folge, dass die Einführung neuer Produktionslinien und damit verbundene Produktionsanläufe häufiger auftreten und vermehrt in den Fokus der Unternehmen rücken. Hierbei bietet ein aktives und effizientes Anlaufmanagement potentielle Wettbewerbsvorteile. Diese sogenannte Ramp-Up Phase der Produktion zeichnet sich auf der einen Seite durch Unsicherheiten, nicht zuletzt der Nachfrage, sowie ein geringes Produktionsvolumen aus. Auf der anderen Seite stehen hohe Verkaufspreise, die bei der Markteinführung erzielt werden können, dem gegenüber. Die Einführung neuer Produktionsprozesse, aber auch die Veränderung bestehender Arbeitsabläufe durch die Digitalisierung von Prozessen oder den Einsatz neuer Fertigungsmaschinen, haben insbesondere einen Einfluss auf die Mitarbeiterkompetenzen. Die Mitarbeiter benötigen Zeit, um sich auf neue Tätigkeiten einzustellen damit sie diese effizient durchführen können. Daher ist es essentiell, dass Firmen die Entwicklung ihrer Mitarbeiter durch ein zielgerichtetes Kompetenzmanagement unterstützen.

Die vorliegende Dissertation analysiert den Einfluss von Kompetenzmanagement auf produzierende Unternehmen. In diesem Zusammenhang stellen Forschungspublikationen und Methoden aus dem Bereich Operational Research und Management Science den Hauptfokus dieser Arbeit dar. Eingeleitet wird die Doktorarbeit durch eine Darstellung der übergreifenden Forschungsfrage sowie des zugrundeliegenden Forschungsmodels. Zudem werden die Treiber und Motivation hinter den vier einzelnen Forschungspapieren gemeinsam mit den wesentlichen Resultaten und Limitationen herausgearbeitet.

Im Rahmen einer strukturierten Literaturanalyse vermitteln die ersten beiden Forschungsartikel einen Überblick über den Stand der Forschung. Die in der Analyse enthaltenen Publikationen sind in unterschiedliche Themenbereiche gegliedert. Zum einen werden die Ergebnisse empirischer Studien sowie deren Umsetzung in mathematischen Modellen von Lern- und Vergessenskurven dargestellt. Zum anderen werden verschiedene Stadien der Produktionsplanung, die von Mitarbeiterkompetenzen beeinflusst werden, aufgezeigt. Diese umfassen die Schaffung neuen Wissens, das Produktdesign, die Planung von Produktionsstätten sowie Einstellungs- und Trainingsentscheidungen in Bezug auf Mitarbeiter. Während der erste Artikel eine ganzheitliche Betrachtung verschiedener Produktionsszenarien anstrebt, liegt der Fokus des zweiten Artikels auf dem Bereich Machine Scheduling.

Motiviert durch die Vielzahl an Forschungsbeiträgen, die Lerneffekte mit Machine Scheduling Problemen in Verbindung bringen, zielt der dritte Artikel auf eine Forschungslücke ab, die im Rahmen der Literaturanalyse aufgedeckt wurde. Zu diesem Zweck wird ein Lerneffekt präsentiert, der ebenfalls den Verlust von Wissen und Kompetenzen durch Vergessen berücksichtigt. Passend zu Trends der Mass Customization- also zunehmender Produktdiversität - werden unterschiedliche Produktkategorien auf einer gemeinsamen Produktionslinie gefertigt. Während Lerneffekte beim

Fertigen ähnlicher Produkte auftreten, führen Unterbrechungen, bzw. der Wechsel zwischen Kategorien, zu Vergessenseffekten. Zusätzlich zum Lern- und Vergessensmodel werden in dem Forschungspapier Lösungsmethoden für die Zielfunktionen makespan und total completion time präsentiert. In einer Simulationsstudie wird die Performance der vorgestellten Lösungsvarianten gegen herkömmliche Methoden, die zur Optimierung von Lerneffekten genutzt werden, gebenchmarkt. Die Ergebnisse dieser Vergleichsstudie zeigen, wie wichtig es ist, nicht nur Lerneffekte, sondern auch den Einfluss von Vergessen in der Produktionsplanung zu berücksichtigen.

Der gezielte Einsatz von Mitarbeitertrainings erlaubt es, eine flexible Belegschaft zu schaffen, die auf neue Kundenwünsche und Nachfrageschwankungen dynamisch reagieren kann. Zudem kann durch den Einsatz unterschiedlicher Aufgabenfelder Ermüdungserscheinungen von Mitarbeitern entgegengewirkt und somit Vergessenseffekte reduziert werden. Da neben Lern- und Vergessenseffekten auch Training ein Haupttreiber für die Entwicklung von Mitarbeiterfähigkeiten und -kompetenzen ist, betrachtet der letzte Artikel alle drei Effekte gemeinsam. Dabei stehen die Auswirkungen von budgetierten Trainingsmöglichkeiten im Vergleich zu einer flexiblen Verfügbarkeit im Fokus. Passend zur Ramp-Up Phase werden verschiedene Produktionsszenarien mit Nachfrageschwankungen sowie unterschiedlichen Mitarbeiterkapazitäten und -fähigkeiten betrachtet. Die Ergebnisse der Studie zeigen, dass ein flexibler Einsatz von Trainingsmethoden sowohl in Bezug auf die zeitliche als auch die mengenmäße Verfügbarkeit Vergessenseffekten entgegenwirken kann. Außerdem ist es möglich, mit weniger Trainingseinheiten vergleichbare Kompetenzlevel von Mitarbeitern zu erreichen, sofern diese flexibel und passgenau eingesetzt werden können. Diese Effekte werden durch Nachfrageschwankungen und geringe Produktionskapazitäten verstärkt.

Zusammengefasst liefert diese Dissertation einen Überblick über die Einflüsse von Kompetenzmanagement in der Produktion. Dabei wird ein besonderer Fokus auf Lern- und Vergessenseffekte für Machine Scheduling Probleme gelegt. Schließlich wird der gemeinsame Einfluss von Lernen, Vergessen und Training auf die Kompetenzentwicklung von Mitarbeitern im Produktionsanlauf analysiert.

Summary

The pressure on manufacturing companies is increasing with global competition, technical advances in production technology, and increasingly changing individual customer wishes. Product life cycles are decreasing, forcing companies to invest in new product developments, which results in production ramp-ups. Actively and efficiently managing the ramp-up phase of production with its inherent uncertainties may yield a competitive advantage for companies. High demand variation, high prices paid for newly introduced products, and a workforce that needs to get accustomed to the new production processes characterize this phase of low capacity utilization. Especially during the ramp-up phase, managing employees' competence development is of utmost importance. In addition, the digitization and the automation of production are changing the competencies required for production as well as the responsibilities placed on employees. Therefore, the adjusting and the maintaining of the worker's skill portfolios have become crucial factors of success.

This dissertation analyzes the impact of human competence management on manufacturing production. In this context publications and methods from the fields of operational research and management science are the main focus. For this purpose, four individual research papers analyze different aspects of competence management in production. These research articles, which form the second part of the dissertation, are guided by a first introductory part. This introduction connects the articles in an overarching research model and question to provide a larger picture. In this vein, the drivers motivating this dissertation as well as the methods utilized to address the research questions and the article's key findings, together with their implications and limitations, are described.

First, an overview of the extent to which competence management is already covered by the literature is presented in order to guide researchers and practitioners alike. Therefore, structured literature reviews are conducted in Research Paper 1 and Research Paper 2. The publications are clustered to make the state of research in the different areas easily accessible. One stream of literature focuses on empirical results and their manifestation in mathematical models as well as learning and forgetting curves. The underlying dynamics further impact different stages of organizational planning and therefore form the base for different optimization and planning models. Human competencies and their target-oriented development influence strategic as well as operational shop floor decisions. For organizational decisions, the influence of competencies accompanies production decisions from creating new knowledge and product designs to planning the production plant, timing implementing changes, and selecting as well as training the workforce. On an operational level, individual production environments are affected differently by aspects of competence management. Therefore, for the areas of assembly line balancing, cellular manufacturing, economic order quantity, machine scheduling, and worker assignment, the differences are elaborated together with gaps in the existing research.

Motivated by the variety of literature on machine scheduling, which presents several different learning effects while mostly neglecting forgetting effects and training approaches, the results from this field are analyzed more closely. On the one hand, a survey article Research Paper 2 is presented that moreover introduces a unified notation. On the other hand, a new processing time effect incorporating learning and forgetting into single machine scheduling is introduced in Research Paper

3. This effect addresses a research gap identified in the second article by including an interruption-based forgetting effect in processing times. This effect further accounts for mass customization developments and shared production lines by assessing different product categories. Hereby, the paper aims to address a second gap in research that concerns ramp-up management for small batch production. Solution methods addressing two relevant objective functions, the makespan and the total completion time, allow the inclusion of forgetting effects in scheduling problems. A computational study benchmarks the results of a combination of different heuristics against the standard solution method utilized when learning effects are considered. The results emphasize the importance of including forgetting effects in production planning.

Different studies highlight the importance of training measures: for example, to gain a flexible workforce, to react to demand volatility and altering customer wishes, or to reduce employees' boredom and to counter forgetting. Since training, besides learning and forgetting, is a main driver of employee development, Research Paper 4 sheds light on the interplay of these concepts. Precisely, the effect of budgeting the available training measures on employee's skill development is analyzed in a production environment with variable employee capacities, different levels of demand volatility, as well as task and worker heterogeneity. Results indicate that flexible training concepts, characterized by an all-time availability of training measures to employees, foster the skill development of employees. In particular, the total amount of training measures necessary to achieve a comparable level of skills at the end of the planning horizon is higher if training measures are budgeted. In the same manner, the amount of knowledge forgotten increases when budgeting is employed. These negative effects on the workforce's skills are amplified by demand volatility and limited employee capacity.

In a nutshell, the dissertation initially provides a holistic overview of competence management in production. It later focuses on machine scheduling by introducing and evaluating a forgetting effect, and it closes by analyzing the mediating effect of training on learning and forgetting effects summarized in employees' skill development.

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Contents

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List of Abbreviations

agg aggregable conditions / constraints for machine scheduling

ALB Assembly Line Balancing

ALGO algorithm

ASGMT assignment problem

B&B Branch and Bound

BS Batch Sizing

BSPT Batchwise-Shortest-Processing-Time-First

C$_{\max}$ makespan

CM Competence Management

DDA due date assignment problem

DDA(CON) common due date for all jobs with regard to the due date assignment problem

DDA(CONW) common due date for all jobs in a given time window with regard to the due date assignment problem

DDA(DIF) individual (different) due dates for all jobs with regard to the due date assignment problem

DDA(SLK) due dates for the due date assignment problem satisfy a slack condition ($d_j := p_j + q$)

DLB Dynamic Load Balancing

DPLFM dual phase learn-forget model

DPLM dual phase learning model

DSPT Dynamic-Shortest-Processing-Time-First

$\mathbf{E}_j := \max\{0, d_j - C_j\}$ earliness

e.g. exempli gratia, lat. (eng. for example)

EDD Earliest-Due-Date-First

EOQ Economic Order Quantity

Eur. J. Oper. Res. European Journal of Operational Research

FiFo First-in-First-out

GAP deviation from the optimal solution

GEE Generalized Estimating Equations

GLFCM generalized learn-forget curve model

GT Group Technology or Cellular Manufacturing

HE heuristic

HFS hybrid flow-shop problem

i.e. id est, lat. (eng. that is)

Int. J. Prod. Econ. International Journal of Production Economics

Int. J. Prod. Res. International Journal of Production Research

J. Oper. Manag. Journal of Operation Management

JIT Just-In-Time

$\mathbf{L}_j := \{C_j - d_j\}$ lateness

$\mathbf{L}_{\max} := \max\{L_j\}$ maximum lateness

LFCM learn-forget curve model

LGR Largest-Growth-Rate-First

Manag. Sci. Management Science

Manuf. Serv. Oper. Manag Manufacturing & Service Operational Research

$\mathbf{MF}_{s,m}$ multi-stage flow-shop problem with s stages and m machines

MILP Mixed Integer Linear Program

MIP Mixed Integer Program

MS Management Science

NP Non-Deterministic polynomial time

OMEGA The International Journal of Management Science

Oper. Res. Operations Research

OPT Optimal Solution

OR Operational Research

ord ordered processing times

p. page

P$_m$ parallel machine scheduling with m identical machines

PLC Plateau Learning Curve

prmu permutation

Prod. Oper. Manag. Production and Operations Management

Q$_m$ parallel machine scheduling with m related machines (speed of machines of different machines is proportional)

QLC Quality Learning Curve

R$_m$ parallel machine scheduling with m unrelated machines

RP Research Paper

RP1 Research Paper 1

RP2 Research Paper 2

RP3 Research Paper 3

RP4 Research Paper 4

RQ Research Question

S Machine Scheduling

SALBP Simple Assembly Line Load Balancing Problem

SLR Structured Literature Review

SPT Shortest-Processing-Time-First

$\mathbf{T}_j := \max\{0, C_j - d_j\} = \{0, L_j\}$ tardiness

$\mathbf{T}_{\max} := \max\{T_j\}$ maximum tardiness

TC Total Completion Time

VRVF Variable Regression Variable Forgetting model

WA Worker Assignment

WDSPT Weighted-Discounted-Shortest-Processing-Time-First

WIP Work in Progress

WLC Wright Learning Curve

WSPT Weighted-Shortest-Processing-Time-First

WTC Weighted Total Completion Times

Foreword

The dissertation at hand considers the impact of different factors of employee competencies on manufacturing production. Hereby a comprehensive overview depicts to which extent competence management, utilized as an umbrella term unifying different facets, is incorporated into problems of operational research. In detail, the way in which learning and forgetting of knowledge acquired affect production planning and scheduling is analyzed. Particularly the impact of forgetting on production time and the mitigating effects of training are considered. Associated research questions are analyzed in four separate research papers. These, taken together, form the main part of the cumulative dissertation.

Before turning to the individual research papers, an introductory part first guides the reader by explaining the affiliated interrelations. Section 1 briefly describes the relationships that motivated this research and emphasizes the relevance of the considered research questions. Moreover, the connecting research model, the individual research questions, as well as an overarching research question are presented. In Section 2 definitions for the terms related to competence management as well as problems from the field of operational research, relevant for production, are introduced. Further, the state of research on the interface of these fields is presented. The methodologies utilized to answer the research questions and the key findings are provided in Section 3 and 4 respectively. Section 5 concludes by summarizing the theoretical contributions and implications for practitioners alongside limitations and avenues for future research.

The second part of this dissertation contains the following articles:

Research Paper 1 (RP1):
Competence Management in Operational Research - A Structured Literature Review
Authors: Patricia Heuser, Prof. Dr. Peter Letmathe, Prof. Dr. Thomas Vossen

Research Paper 2 (RP2):
Skill Development in the Field of Scheduling - A Structured Literature Review
Authors: Patricia Heuser, Prof. Dr. Peter Letmathe, Prof. Dr. Thomas Vossen

Research Paper 3 (RP3):
Single Machine Scheduling with Learning and Forgetting Effects
Authors: Patricia Heuser, Björn Tauer

Research Paper 4 (RP4):

The Consequences of Budgeted Training Measures on Worker Forgetting in Production Planning

Authors: Patricia Heuser, Peter Letmathe, Matthias Schinner

Part I

Comprehensive Overview of the Dissertation

Comprehensive Overview of the Dissertation

1 Introduction

1.1 Motivation

Global competition, digitization, and changing customer wishes are increasing the pressure on manufacturing companies (Wisner, 1996; Surbier et al., 2014; Neumann et al., 2021). In order to be able to adapt to changes, companies need to attain a high level of flexibility (Qin et al., 2015). Shrinking product life cycles are giving rise to an increasing number of new product introductions (Otto and Otto, 2014). These, in turn, demand renewed production processes and effective management of the ramp-up phase (Glock and Grosse, 2015), which is connected to high complexity and prone to uncertainties (Surbier et al., 2014). This stage of production is characterized by great potentials for learning, low production capacity (Terwiesch and Bohn, 2001), interruptions and defects (Glock and Grosse, 2015), companies must invest in fast ramp-ups (Hansen and Grunow, 2015). Mass customization utilizes technological advances to fulfill individual desires while keeping production costs at a constant level (Neumann et al., 2021). For this purpose, smaller batches are produced which require frequent switching between processes connected with different levels of task complexity (Anzanello et al., 2014).

These developments do not only impact the production process but also the workplaces in manufacturing environments. Automation, on the one hand, leads to a number of novel challenges and interactions for employees (Neumann et al., 2021), which require more complex skills and competencies (Beier et al., 2020). Production ramp-ups and mass customization, on the other hand, increase the number of changes in production processes. Thus, workers will have to adapt to new tasks more frequently (Anzanello et al., 2014). The ramp-up phase, in particular, is featured by a trade-off between investing time in production, satisfying the high demand in the early phase, or training of employees to increase throughput (Schultz et al., 2003).

Since the requirements of workplaces and, at the same time, responsibilities increase (Autor, 2015; Davies et al., 2017; Neumann et al., 2021), active management of firms' and employees' competencies is crucial if firms are to successfully compete on the global market (Surbier et al., 2014; Qin et al., 2015). To this end, either staffing decisions can be based on hiring employees holding the required competencies (Arlotto et al., 2014; De Bruecker et al., 2015) or skills of employees can be developed over time (Dutton and Thomas, 1984; Li et al., 2000). Additionally to hiring and training policies, strategies for worker retention (Anderson, 2001; Arlotto et al., 2014; Azadeh et al., 2016), as well as maintenance of competence levels, need to be considered (Heimerl and Kolisch, 2010). Existing competencies might lose value due to technological changes Vits et al. (2006); Pan and Li (2016) or decrease as a consequence of forgetting effects(Jaber et al., 2003). Further issues encompass defining the required competencies necessary for production (Franchini et al., 2001; Siskos et al., 2007), as well as managing organizational knowledge creation (Argote and Hora, 2017). Succinctly defining, adjusting, and maintaining employee skills and competencies corresponds to a variety of challenges for companies (North et al., 2013; Neumann et al., 2021). In this regard, the dissertation at hand aims to shed light on the necessity and benefits of considering aspects of human competencies and the development of employees' skills in manufacturing production. More precisely, problems addressed in methods of operational research and management science are the focus of this work.

1.2 Research Model and Associated Research Questions

This cumulative dissertation consists of four individual Research Papers RP analyzing different aspects of competence management and their impact on production.

Table 1: Overview: Individual Research Papers

	Titel	Authors	Publication Status
RP1	Competence Management in Operational Research - A Structured Literature Review	P. Heuser, P. Letmathe, T. Vossen	to be submitted
RP2	Skill Development in the Field of Scheduling - A Structured Literature Review	P. Heuser, P. Letmathe, T. Vossen	invited review submitted to: European Journal of Operational Research
RP3	Single-Machine Scheduling with Learning and Forgetting Effects	P. Heuser, B. Tauer	revised and resubmitted to: The International Journal of Management Science
RP4	Budgeted Training and Demand Volatility in Production Systems and Workforce Planning	P. Heuser, P. Letmathe, M. Schinner	published in: Journal of Business Economics

Table 1 lists the articles included as well as the publication status (date: July 19, 2022). In this section, the scope and focus of these papers, the research questions, and the overarching research model depicting the inter-dependencies of the single works are described. In order to guide the research presented, the following overarching Research Questions (RQ) were formulated:

1. *In which way are aspects of competence management currently embedded in models of operational research addressing manufacturing production?*

2. *How can the understanding of the relevance of competence management in operation research*

improve existing models of scheduling and production planning?

Throughout this dissertation, the term ‘competence management’ is utilized as an umbrella term uniting different aspects associated with the factor of human labor. These encompass not only the qualification of employees in terms of skills and competencies but moreover the processes of worker learning and forgetting, which can be fostered or mitigated due to training. Mere qualifications and learning processes of employees are combined with hiring, retaining, and termination decisions that play a crucial role for companies to acquire the competencies needed.
The research model depicted in Figures 1 to 4 visualizes the interplay of the four research papers. To guide the reader, the aspects of the interface of the fields of Operational Research and Competence Management addressed by the individual research articles are highlighted separately.

Research Paper 1 In order to provide a comprehensive overview of the research conducted in the mentioned fields and to identify research gaps that hint at avenues for future research, Research Paper 1 (RP1) focuses on the research question:

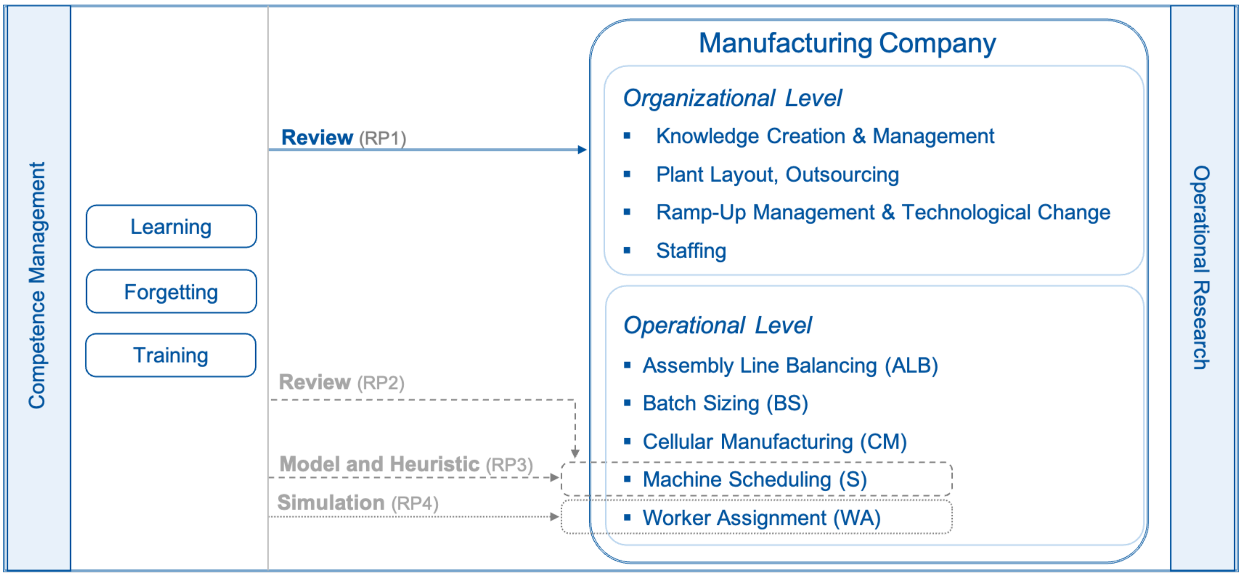

Figure 1: Research Model - Focus of Research Paper 1

RQ1: *To what extent are different aspects of Competence Management (competencies, skills, experience, learning, forgetting, training and hiring) embedded in the field of Operational Research?*

For this purpose, a Structured Literature Review (SLR) was chosen to assess the state of research while complying with the four quality criteria of literature reviews by Fink (2014): systematic, explicit, comprehensive, and reproducible. The underlying method that entails the time horizon, the search terms, databases, and journals is described in detail in Section 3.1.

Figure 1 provides a brief overview of the different areas of production research that account for competence-related aspects that arose from the survey. These can be divided into two dimensions. First, organizational decisions, which concern the strategical level. These encompass the creation and management of knowledge, the configuration of the plant layout, outsourcing and staffing decisions, as well as timing production ramp-ups and introducing technological changes. Second, the operational level and production planning, which in turn can be categorized according to different production scenarios or problem settings, i.e. Assembly Line Balancing (ALB), Batch Sizing (BS), Competence Management (CM), Machine Scheduling (S), Worker Assignment (WA). The distinction made between the organizational and operative production level is of certain importance as these come with individual requirements and problem sets. The same applies to the different shop floor production environments, whereas results and theories on employee learning and forgetting, depicted on the left side, affect all mentioned areas. A more detailed overview of the results from the survey is presented in Section 4.1 or RP1 (Part II, Chapter 1).

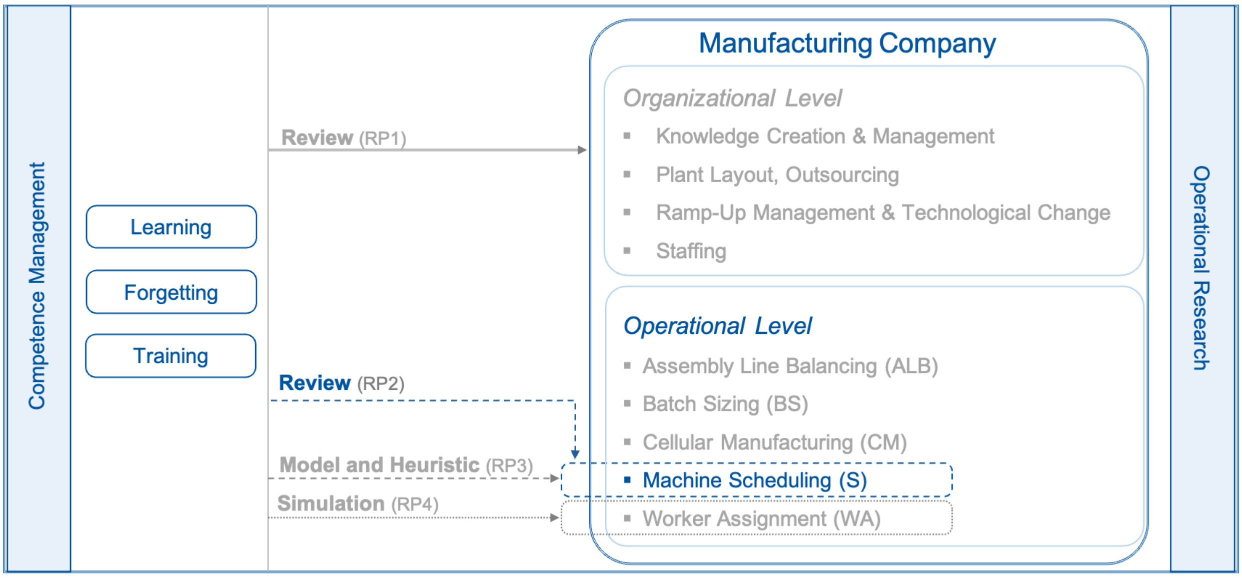

Figure 2: Research Model - Focus of Research Paper 2

Research Paper 2 Building on the results of RP1, the focus of Research Paper 2 (RP2) is set on analyzing the influence of competence management on publications from the field of machine scheduling in more detail, compare Figure 2. The focus on machine scheduling is based on the following arguments. First, it enables us to cope with the diversity and complexity of the models provided. Second, although various publications deal with the subject area, there is no uniform terminology. For this purpose, a unified notation, as well as a holistic overview of learning processes in machine scheduling, was introduced. Lastly, this area, in particular, presents avenues for further research. In this context, the research question was formulated as follows:

RQ2: *Which concepts of competence management have been considered in machine scheduling models?*

To answer this question, the publications focusing on machine scheduling problems, retrieved in the structured search from RP1, were analyzed in more depth and supplemented by further publications explicitly addressing the identified research gaps. The results and contribution from RP2 are provided in Section 4.2 and Chapter 2 in Part II.

Research Paper 3 Since the results of the survey articles presented avenues for further research in the area of machine scheduling, the research idea for RP3 stemmed from the results of RP2. Particularly models for single-machine problems lack a consideration of interruption-based forgetting, which is the most prominent learning effect considered in the literature on learning curves (Nembhard and Osothsilp, 2001; Jaber et al., 2003). Since these models form the basis for other, more complex, multi-machine production environments, heuristics and solution methods can either be transferred to more sophisticated problems or used to solve sub-problems (Pinedo, 2012). For example, bottlenecks in a complex production system might be dealt with as a single-machine problem (Pinedo, 2012). Based on these insights, a model addressing this research gap for single-machine problems has been developed and evaluated in RP3. The model introduced considers different families of products manufactured on a single production line, complying with mass customization theory (Anzanello et al., 2014). For the given scenario the learning, as well as interruption-based forgetting effect presented in Section 3.1 was developed.

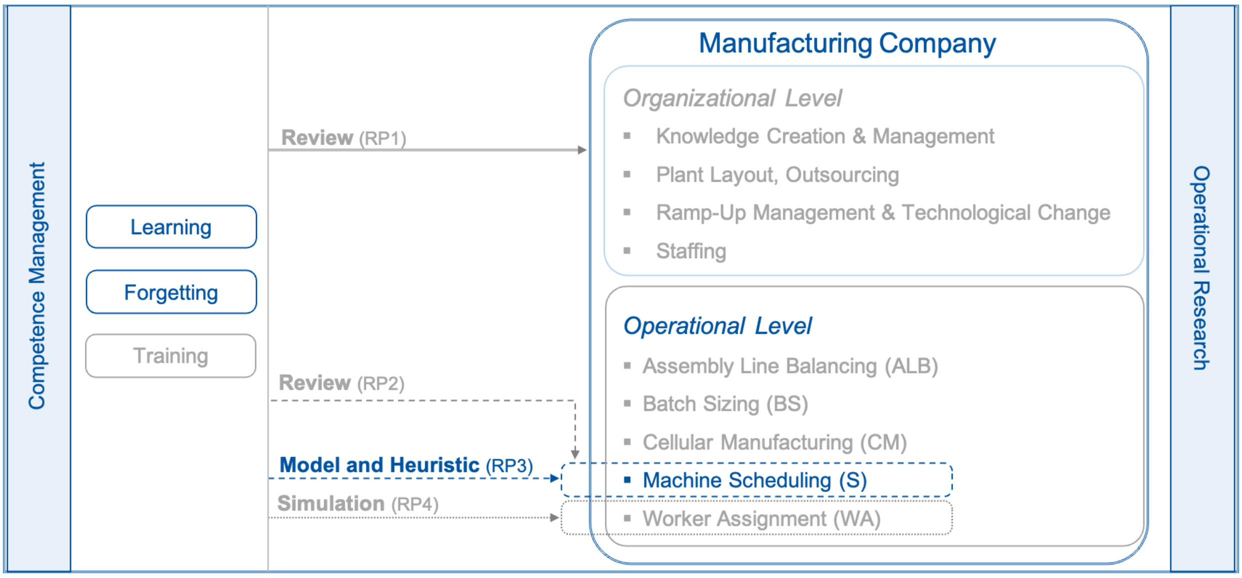

Figure 3: Research Model - Focus of Research Paper 3

Figure 3 illustrates the two aspects from employee skill development considered in RP3, namely learning and forgetting. Moreover, cross-learning or spillover effects between jobs can be reflected in the model. In Section 4.3, solution methods for minimizing the objective functions makespan and total completion time are presented. These solution methods either solve the presented problems to optimality or provide near-optimal solutions. The performance of the heuristic approaches was evaluated in a computational study. For this purpose, the gaps to the optimal solutions were calculated for small problem sizes, whereas larger problem sizes were benchmarked to the results obtained by the standard solution method applied to related problems with a learning effect. The definition of the learning and forgetting effects, the solution methods, as well as the theoretical results and computational study, are presented in Section 4.3 and in RP3 in Chapter 3 from Part II.

Research Paper 4 The dissertation closes with an evaluation of the effects of demand volatility on employees' learning and forgetting in combination with either flexible or limited training measures in Research Paper 4 (RP4). Figure 4 emphasizes the three aspects of learning, forgetting, and training and their influence on multi-period production planning.

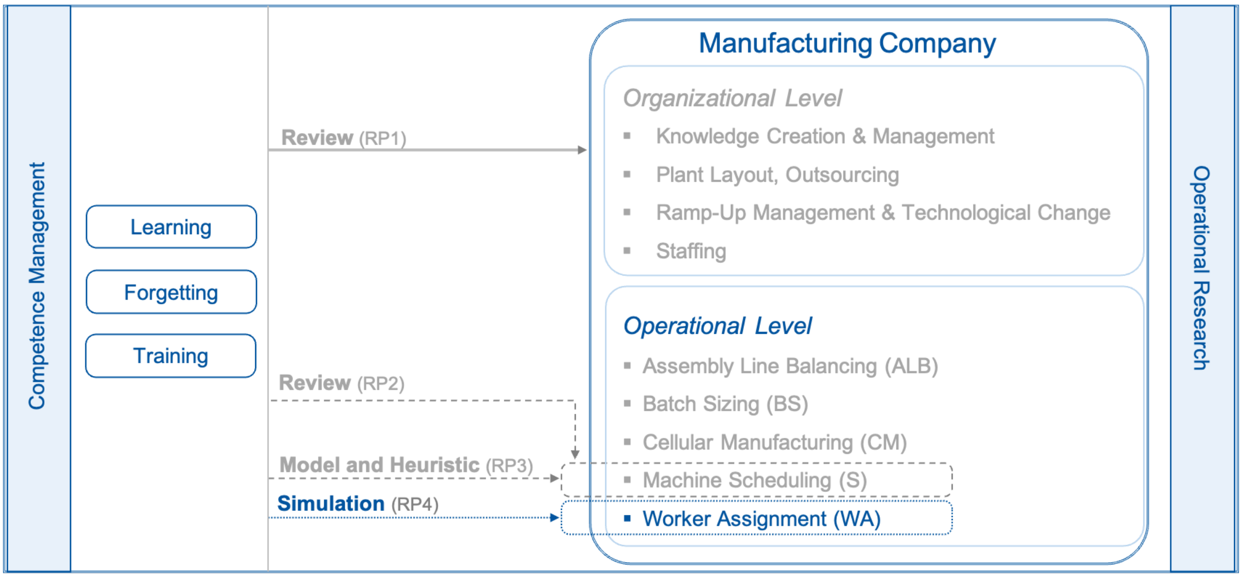

Figure 4: Research Model - Focus of Research Paper 4

In order to assess to what extent training measures mediate the effects of learning and forgetting in production environments over time, a simulation study was conducted, aiming at analyzing the following research question:

RQ4: *What impact do demand volatility and the application of budgeted training measures have on the learning and training outcomes of employees in production systems?*

The term 'budgeting' describes a limitation of the availability of training sessions during the ramp-up phase of a production line. For this purpose, training is limited in two ways: first, training measures are only available in the first periods of the production ramp-up, which relates to classical training approaches. Second, only a limited number of training sessions per period are provided for the whole workforce. These in turn can be allocated to a heterogeneous, multi-skilled workforce. Each worker is enabled to perform different production tasks and equipped with a fixed time capacity per period. In addition to efficiency gains from training sessions also learning-by-doing is considered. Consequently, categorical and hierarchical skills in combination with autonomous and induced learning, as well as forgetting, are considered workforce-wise. The introduced Mixed Integer Linear Program (MILP) seeks a cost-efficient assignment of training sessions and tasks to employees over multiple periods while satisfying a volatile demand. For this purpose, shortage costs for not satisfying demand, costs for production, and training costs were included. Note that employees undertaking training sessions are connected with twofold costs. On the one hand, direct costs arise and on the other hand, opportunity costs arise because the time spent on training cannot be used for production.

Section 3.3 describes the characteristics and parameters of the simulation study as well as the hypothesis derived. Section 4.4 summarizes the results from the simulation study. A holistic overview of the research conducted can be found in Research Paper 4 (RP4) in Chapter 4 from

Part II.

The remainder of this work is structured as follows: Section 2 gives an overview of the theory and concepts of competence management that laid the basis for this dissertation. However, in order to avoid redundancies, the reader is referred to Chapters 1 and 2 in Part II for a more holistic presentation in RP1 and RP2. Section 3 presents the methodologies utilized in the individual research papers. For this purpose, a subsection is devoted to each approach used. Section 4 presents the results and findings from the research conducted. To conclude, a brief overall summary, implications for researchers and practitioners alike, as well as limitations and avenues for further research, are presented in Section 5.

2 Theoretical Background

Human labor is a key factor in production that will gain even more importance in the future, as job profiles become more complex and tasks increasingly interconnected (Neumann et al., 2021). This in turn influences the requirements of jobs and thus of competencies held by employees. This section aims to provide a brief overview of definitions and theories related to human competencies, their development, and competence management.

2.1 Competencies and Competence Management

Reinhardt and North define competencies as '*relation between requirements placed on a person/group or self-created requirements and these persons' skills and potentials to be able to meet these requirements*' (Reinhardt and North (2003), p.1374). Competencies '*can [further] be described as self-organization dispositions*' (Erpenbeck and Michel (2006), p.128), which '*are concretized at the moment knowledge is applied and [thus] become measurable in the achieved result of the actions.*' (Reinhardt and North (2003), p. 1374).

Particularly the second part of this definition emphasizes the difference between competencies and qualifications. While qualifications, which in turn can be defined as dispositions of knowledge and skills Erpenbeck (2007), can be assessed in exams (Erpenbeck and Michel, 2006), competencies in contrast also relate to problem-solving abilities and the desired work outcome. Consequently, competencies unite a person's knowledge, skills, experience, as well as personality-related characteristics, and become measurable by the result of an action (Erpenbeck, 2007). As a result of the competencies' tacit nature, the actual skill endowment of employees can only be estimated over time (Ortega, 2001). Therefore, hiring employees with the required competencies is connected to uncertainties regarding their true qualifications (Arlotto et al., 2014). Regardless of these uncertainties, employees' competencies can be developed over time due to experience gains (Meyer et al., 2015). The adoption, improvement, and maintenance of competencies, however, present a number of challenges that span a variety of facets (North et al., 2013). Nevertheless, actively managing competence portfolios and evaluating which skills are relevant now and in the future can yield a competitive advantage (Meyer et al., 2015). Organizational knowledge and competencies are embedded in the tools, tasks, and members of a company (Argote and Hora, 2017). In this regard, the information structure, processes, and technologies utilized in a firm must be taken into account when considering decisions related to competence management North et al. (2013). The economy of scale effects, characteristics of industries and firms, technological changes, and human learning were identified as the main drivers of improvement in firms (Dutton and Thomas, 1984). However, potentials for improvement were found to be higher in human-labor-paced compared to machine-based production environments (Hirsch, 1956; Biskup, 2008).

2.2 Skill Development and Knowledge Transfer

Learning and Training In the literature two concepts of improvement processes influencing employees' skills are distinguished: *autonomous* and *induced* learning (Dutton and Thomas, 1984). Autonomous learning is a natural experience-based improvement process that happens due to task repetition (Wright, 1936; De Bruecker et al., 2015), in terms of learning-by-doing, or as spillover learning from similar tasks, i.e. cross-learning (Pratsini and Marks, 2001). These learning effects are accompanied by gaining procedural or operational knowledge, i.e. know-how (Lapré and Van Wassenhove, 2001), and tacit knowledge, which is hard to articulate, intuition-based, and embodied in the employees themselves (Argote and Hora, 2017; Letmathe and Rößler, 2019).

Induced learning in turn is an explicit and intended form of knowledge transfer, also referred to as training, which allows providing procedural knowledge (know-how) and conceptual knowledge (know-why) (Letmathe et al., 2012). Training measures are a managerial opportunity to stimulate learning processes, accelerate the learning curve of employees (Lapré and Van Wassenhove, 2001), and manage for example production ramp-ups (Terwiesch and Bohn, 2001; Vits et al., 2006). Training measures can again be differentiated into *endogenous* training, on the shop floor during production, and *exogenous* training, apart from the production process (Vits and Gelders, 2002). While these concepts allow transferring procedural and conceptual knowledge, which can be explicitly formulated, tacit knowledge can in general not be transferred by means of training. Still, it is possible to transfer such knowledge, for example via spillover effects from the observation of coworkers (Letmathe and Rößler, 2019).

The impact of learning or training can either broaden or deepen the employees' set of skills (Campbell, 1999). For this purpose a distinction between *categorical* and *hierarchical* skills is made (De Bruecker et al., 2015). Individual skills that enable employees to pursue different tasks are referred to as categorical skills (De Bruecker et al., 2015). In this vein, a multi-skilled, heterogeneous workforce can be achieved through cross-training employees (Qin et al., 2015; Nembhard and Bentefouet, 2012). Hierarchical skills, in contrast, increase the workers' efficiency concerning one production task, which is also referred to as an increase in the skill levels.

Implications from learning processes are manifold. One major effect considered in the literature is a decrease in unit production time caused by task repetition. In this regard, the first learning effect in production was described by Wright (1936), who discovered that unit processing times decrease at a uniform rate - the learning rate - as production output doubles. Regardless of its simplicity the Wright Learning Curve (WLC) is capable of properly describing learning effects in production (Yelle, 1979; Globerson, 1987; Globerson and Gold, 1997; Dar-El et al., 1995; Hansen and Grunow, 2015). Additionally, the rate of items that need to be reworked (Ittner et al., 2001) and the waste production (Lapré et al., 2000) decrease while product (De Bruecker et al., 2015) and rework (Giri and Glock, 2017) quality was found to increase with higher skill levels. Overall, improvements in employee skills result in cost reductions and efficiency gains (Yelle, 1979; Lapré et al., 2000; Chen et al., 2010).

Forgetting Despite progress developments, production efficiency is further impacted by disruptive effects decreasing organizational knowledge. These effects are summarized by the term *forgetting*.

Employees holding competencies required for production might leave the company due to expected or unexpected turnover (Arlotto et al., 2014), as well as temporary absenteeism (Inman et al., 2004; Olivella and Nembhard, 2016). Likewise, technological changes and new production processes lead to altering skill requirements (Demeester and Qi, 2005; Neumann et al., 2021). Thus, existing competencies decrease in value and employees need to adapt to new production requirements (Terwiesch and Bohn, 2001; Biskup, 2008).

In addition, forgetting effects may also occur during production. Disruptions of the production process or breaks in production which lead to employees interrupting their processes might decrease their stock of knowledge and thus efficiency (Jaber et al., 2003). This effect can be caused by an interplay of short-term effects, i.e. a break in work rhythm (Schultz et al., 2003) or a loss of knowledge from the immediate memory (Delasay et al., 2019), and a general decrease of knowledge (Jaber et al., 2003). In this regard, the effect size of forgetting is contingent on the number and length of interruptions, as well as the learning rate and knowledge acquired priorly (Bailey, 1989; Globerson et al., 1989; Dar-El et al., 1995; Jaber et al., 2003).

Apart from these effects, forgetting may at the same time be caused by monotonous production. For example, due to continuous repetition of recurring movements boredom (Azizi et al., 2010), a lack of motivation (Anzanello et al., 2014) or fatigue (Digiesi et al., 2009; Dode et al., 2016) may arise, which can decrease efficiency. Routine tasks are further prone to causing work-related injuries (Azizi et al., 2010) and ergonomic problems (Anzanello et al., 2014). As a result, monotonous production can lead to dissatisfaction, which in turn can foster employee turnover and absenteeism (Azizi et al., 2010).

2.3 Factors Influencing Skill Development

In line with the uncertainty regarding employee competencies, learning effects are similarly prone to uncertainties and influenced by different factors. According to empirical research, learning curves in production vary between 60% and 90%, however, 80% is by far the most common learning rate observed in practice (De Jong, 1957). These rates vary between different industries, companies, or plants but also different production lines from one company utilizing the same equipment (Yelle, 1979; Argote and Epple, 1990; Wiersma, 2007; Argote, 2013). Consequently, it is of key importance to consider worker heterogeneity, in terms of individual learning curves, prior experience, and steady-state productivity in production settings (Shafer et al., 2001; Howick and Eden, 2007; Nembhard and Shafer, 2008). Moreover, aspects characterizing a working environment that fosters learning processes have been validated empirically. Providing workers with slack time for individual learning (Haas, 2006) or with monetary incentives (Vits and Gelders, 2002) can have a positive impact. Further, team learning (Reagans et al., 2005) combined with a heterogeneous workforce in terms of a mix of temporal and permanent workers (Wiersma, 2007) contributes to individual learning. In this regard, social skills are a key requirement for employees to cooperate in teams (Chakravorty and Hales, 2008; Norman and Needy, 2010). Lastly, the nature of the tasks themselves promotes skill development. Product heterogeneity has the potential to increase learning rates (Haas, 2006), particularly when small variations of similar products are considered (Schilling et al., 2003). In this vein, accounting for the complexity and the associated cognitive abilities of the underlying production task impacts learning potentials (Shafiei-Monfared and Jenab, 2011). Here, a distinction between cognitive and motor tasks has proven helpful (Dar-El et al., 1995).

The benefits of cross-training and job rotation are diverse. Multi-skilled workers can support bottlenecks in production (Hopp et al., 2004; McCreery et al., 2004; Sennott et al., 2006), reduce idle times of machines, as well as holding costs by decreasing work in progress (Hopp et al., 2004; Bokhorst, 2011) and thus increasing production efficiency. Job rotation further contributes to employees' satisfaction by reducing boredom and the likelihood of ergonomic problems, which, in turn, increases employee motivation (Azizi et al., 2010; Nembhard, 2007). A cross-trained workforce is, further, able to mitigate effects of absenteeism and employee turnover (Inman et al., 2004; Olivella and Nembhard, 2016) and allows workers to adapt rapidly to demand variations (Campbell, 1999; McCreery et al., 2004; Nembhard, 2007). On the other hand, negative effects arise, i.e. when employees switch between different production tasks, forgetting effects are triggered. Moreover, environments with high employee turnover rates cannot cope with cross-training, since these depend on quick learning processes (Kher et al., 1999).

Additionally, negative effects fostering forgetting arise due to changes in production processes (Dutton and Thomas, 1984; Vits et al., 2006). These changes can be a consequence of new product designs, the implementation of new production processes or updated technologies, as well as new product generations (Jaber et al., 2003; Carrillo and Gaimon, 2004; Vits et al., 2006; Howick and Eden, 2007). Similarly, unplanned disruptions of the production processes (Howick and Eden, 2007), caused by machine breakdowns (Marmier et al., 2009) or supply shortages, cause interruptions (Wang et al., 2013). Overall, environments that are subject to changes and uncertainties, i.e. demand variation, on a regular basis are prone to forgetting effects (Dutton and Thomas, 1984; Jaber et al., 2003; Vits et al., 2006).

2.4 Learning and Forgetting Curves

The first learning curve was introduced by Wright (1936). He formulated his famous log-linear model, based on observations in the airplane manufacturing industry. According to this model production costs decrease at a uniformed learning rate l as production output doubles. Given the processing time T_1 for the first job pursued, costs for the nth job T_n are defined by

$$T_n := T_1 \cdot r^a.$$

Hereby, the learning coefficient a is defined as $a := -\log_2(l)$. Building on his results studies did not only analyze the underlying dynamics, drivers, and interdependencies provided above but further developed different learning and forgetting models to describe learning processes more precisely (Yelle, 1979; Dutton and Thomas, 1984). One strain of literature focused on providing alternative formulations. These entail, for example, hyperbolic or exponential learning curves (Anzanello and Fogliatto, 2011; Grosse et al., 2015), continuous models that are not based on unit production (Smunt, 1987), or an S-shaped model that includes a slow startup-phase of production (Carr, 1946; Baloff, 1971). Other publications set their focus on incorporating additional aspects of competencies into learning curves. In this vein, plateau effects which prevent processing times from decreasing arbitrarily to zero were introduced by either splitting the processing times into a fixed part and a variable part that is subject to learning effects (De Jong, 1957) or by defining a steady-state processing time for the production system (Baloff, 1971). Further extensions account for the prior experience of employees, such as the Stanford-B curve of Asher (1956), split the learning process into cognitive and motor tasks to represent different speeds of learning such as the dual phase learning model (DPLM) of Dar-El et al. (1995), or distinguish between cognitive ability and task complexity when describing learning behavior (Shafiei-Monfared and Jenab, 2011). Moreover, the already mentioned influence on product quality is considered in the Quality Learning Curve (QLC) by Jaber and Guiffrida (2004, 2008); Jaber and Khan (2010).

Jaber et al. (2003) summarized results from different empirical studies that analyzed forgetting effects, e.g. by Globerson et al. (1989); Bailey (1989); Dar-El et al. (1995) and Schultz et al. (2003). These results indicate several properties. In addition to the already mentioned characteristics, forgetting rates and relearning rates equal the learning rate considered. Consequently, the learning and forgetting curves are mirror images, while the forgetting effect can be described appropriately by a power-based formulation (Jaber et al., 2003). Similar to the literature on learning curves, different models describing forgetting effects have been introduced. Carlson and Rowe (1976) based their forgetting curve, the Variable Regression Variable Forgetting model (VRVF), on the WLC with a fixed forgetting rate f but an variable time T_1 to describe prior experience. Jaber and Bonney (1996), in contrast, modeled the forgetting rate as a function depending on the learning rate in their learn-forget curve model (LFCM). In terms of extensions, a multi-product forgetting curve was introduced by Mazzola et al. (1998). Alamri and Balkhi (2007) introduced a forgetting curve that accounts for deteriorating items in storage, and Jaber and Kher (2002) extended the DPLM to comprise also forgetting effects in the dual phase learn-forget model (DPLFM). Unlike the above-mentioned, a forgetting effect which is not based on production interruption but on deterioration was introduced by Kim and Seo (2009).

Both learning and forgetting curves were considered in comparative studies that evaluate the different effects developed as well as in methodological articles introducing effects that include more production or competence aspects. Regardless of the refinements and alternate formulations for learning effects presented, different empirical studies found the WLC to be appropriate for describing learning effects in production (Yelle, 1979; Globerson, 1987; Globerson and Gold, 1997; Dar-El et al., 1995; Grosse et al., 2015). Survey articles on learning curves are presented by Yelle (1979); Hackett (1983); Badiru (1992); Nembhard and Uzumeri (2000); Anzanello and Fogliatto (2011) or

Grosse et al. (2015), while forgetting effects are considered by Nembhard and Osothsilp (2001); Jaber et al. (2003) and Jaber and Guiffrida (2004).

Evidently, competence management comprises a number of challenges. As presented above, skill development does not only depend on the individual employees as well as their skills, qualifications, and abilities but is influenced by several external factors. In this regard, it is crucial to consider the work environment, products, processes, tasks, and technologies involved in the production process. To this end, the interconnection between the separate aspects must be accounted for. Hereby trade-offs between, for example, efficiency gains due to specialization and worker satisfaction, cross-training and forgetting effects, workforce flexibility, and staffing costs must be carefully weighed. RP1 and RP2 analyze to what extent the described concepts are embodied in models and methods of operational research and management science. RP3 aims to contribute to the interface of the mentioned field by providing a model machine scheduling model with forgetting effects and addressing a research gap. RP4 provides insight on the interplay of different competence-related and production-related aspects, comprising forgetting, training, demand variation, and budgeting approaches. The methods utilized are explained in the next section.

3 Methodology

This section provides an overview of the utilized methods in the individual research papers or presents relevant notation and definitions. Section 3.1 outlines the structured literature review process followed in RP1 and RP2. Section 3.2 describes the basic notations and objectives relevant for RP2 and RP3 as well as the learning and forgetting effects introduced. The hypothesis and statistical evaluation methods applied in the simulation study conducted in RP4 are briefly described in Section 3.3

3.1 Structured Literature Review

In order to provide a state-of-the-art overview of the aspects of competence management covered in operational research, a Structured Literature Review (SLR) was conducted. This method was chosen based on its systematic, explicit, comprehensive, and reproducible character (Fink, 2014). To comply with these properties an approach from Okoli and Schabram (2010), comprising the four phases *planning, selection, extraction, and execution*, shown in Section 3.1, is followed. The individual phases are outlined hereafter.

Figure 5: phases of the structured literature review by Okoli and Schabram (2010)

Planning Phase The planning phase defines the purpose of the survey article and hence the framework of the search. Hereto, the taxonomy for literature reviews by Cooper (1988) is utilized. In this context, the *focus, goal, perspective, coverage, organization, and audience*, shown in Table 2, were defined.

Table 2: Taxonomy of Literature Review Cooper (1988)

Focus	research outcomes	**research methods**	**theories**	practices or applications
Goal	**integration**	criticism	identification of central issues	
Perspective	**neutral representation**	exposal of position		
Coverage	exhaustive	**exhaustive with selective citation**	representative	central or pivotal
Organization	historical	**conceptual**	methodological	
Target	**specialized scholars**	**general scholars**	practitioners or policy makers	general public

A comprehensive and *conceptual* review with *neutral* and *integrated representation* of *theories* as well as utilized *research methods* was aimed at. The *exhaustive overview (with selective citation)* on the research conducted at the interface of Competence Management and Operations Research as well as Management Science is dedicated to *general and specialized scholars.* The screening criteria derived from the hereby defined purpose entail *the time horizon, journals, databases, and keywords.*

Consistent with the goal and focus, keywords were restricted to competence-related terms. In this context, Competence Management (CM) was used as an umbrella term to integrate keywords relating to learning theory, means of training, and employee skill development. From these keywords seven search terms covering the 15 keywords, displayed in brackets, were derived:

learning: learning curve, autonomous learning, learning-by-doing, absorptive learning,

training: cross-training,

forgetting,

competence/ies: competence management, competence development,

skill/s: employee skills,

experience,

hiring.

Further, nine major journals from the fields of OR and MS were chosen. Table 3 lists the journals and databases that were utilized to screen *Title, Abstract, or Author-Specified Keywords* for the search terms.

Table 3: Journals considered in the literature reviews

Database	Journals
EbscoHost	International Journal of Production Research (Int. J. Prod. Res.), Management Science (Manag. Sci.) Operations Research (Oper. Res.) Production and Operations Management (Prod. Oper. Manag.) Manufacturing & Service Operational Research (Manuf. Serv. Oper. Manag)
ScienceDirect (Elsevier advanced search)	European Journal of Operational Research (Eur. J. Oper. Res.), International Journal of Production Economics (Int. J. Prod. Econ.), Journal of Operation Management (J. Oper. Manag.) The International Journal of Management Science (OMEGA)

The time horizon was set to the last two decades. Consistently, publications between the 1st of January in 1998 and the 31st of January in 2019, which was the actual date of the search, were included.

Selection Phase During the selection phase, articles for a possible consideration are retrieved. Concerning EbscoHost the search query *JN '[journal]' AND (DE '[keyword]' OR TI '[keyword]' OR AB '[keyword]')* was used. The advanced search of Elsevier provided search fields for the title, abstract, and author's keywords separately. For each search query, a bib.tex file which included the information on the articles retrieved was exported and labeled with the search term. The individual files were further combined in one excel file, containing 2448 entries. In this vein, duplicates were merged and labeled with corresponding search terms. Consequently, several publications were labeled with more than one term. Lastly, the remaining 2398 records were checked for completeness and missing details were added.

Extraction Phase For the purpose of extracting publications relevant to the survey article, two screening phases were established.

In the first pre-screening process, the abstracts of all publications were read to exclude articles that do not correspond to our research question. To this end, the entries were processed according to the following order:

1. keywords [in alphabetical order]
2. journals [number of articles from a journal]
3. year [chronological order]

Note that the screening procedure was adapted for articles that were only labeled with the keyword *experience*. This category was not fully screened; exclusively the European Journal of Operational Research was covered extensively. This decision is based on the fact that the majority of the publications solely included the term *computational experience*. In this context, only articles that include the term *experience* independent from *computational* or the expressions *employee,* *workforce, worker, or work* were considered. Articles not complying with the aforementioned conditions were excluded. The remaining abstracts were thoroughly screened, resulting in 216 publications.

In the second screening step, an in-depth assessment of the underlying research was conducted. In this regard, the articles were retrieved online, again labeled with corresponding keywords, and imported into a reference manager. The publications were fully read, a short description covering the contribution of each article and keywords indicating the method utilized were summarized in a table. Hereby, publications were clustered according to different problem settings or fields of research. Again, some publications were excluded.

Execution Phase In total, 201 articles have been found suitable for describing the current state of research. These were supplemented by relevant findings from previous years or related research from other journals when appropriate. The execution phase encompasses the actual writing process of the survey articles which can be found in Part II. For the comprehensive survey article covering different strains of research of Operational Research and Management Science, refer to RP1 in Chapter 1. A detailed overview of the coverage of employee skill development in machine scheduling research is presented in RP2 in Chapter 2.

3.2 Single-Machine Scheduling

RP3 introduces a new learning and forgetting effect for processing times in machine scheduling problems. Scheduling problems are a decision-making process that allocates resources to tasks over a given time horizon while aiming to optimize considered objectives (Pinedo, 2012). In particular, the focus of RP3 is set on single-machine problems, seeking an optimal order of jobs with respect to a single machine or worker.

This choice can be justified in a twofold way. Single-machine scheduling problems form the basis for different more complex scheduling problems. Therefore, the proposed effects can be extended to fit parallel multi-machine environments, multi-stage, or hybrid scheduling problems as well. In contrast, effects from multi-machine environments might become redundant when reducing them to a single-machine problem. Based on the results from the survey presented in RP2, this is the case for all interruption-based forgetting effects introduced so far. These effects depend on the translation of jobs between two different machines or production stages. The resulting break is considered to be an interruption of the production process. Moreover, machine scheduling problems assume that each machine represents a worker. Since this article focuses on learning effects triggered by human skill development, it is reasonable to consider single-machine problems when including forgetting effects based on production interruption. A forgetting effect based on the break between two machines would moreover assume implicitly that jobs carry the learning and forgetting behavior independently of operators.

An additional rationale for focusing on single-machine environments is based on the complexity. While single-machine problems are oftentimes efficiently solvable for a number of objective functions (Pinedo, 2012), this does not generally apply for multi-machine problems, e.g. flow-shop problems are *NP-complete* in case more than two machines are considered (Garey and Johnson, 1979). These can oftentimes only be solved efficiently when assuming additional conditions and restrictions to the parameter. Moreover, the majority of the proposed learning curves are non-linear, i.e. the log-linear model by Wright (1936) as well as numerous hyperbolic or exponential curves (Anzanello and Fogliatto, 2011; Grosse et al., 2015) introduced. Including these learning and forgetting effects leads to increased computational complexity for the considered scheduling models. As a consequence, several scheduling problems with straightforward solution methods become computationally intractable. Some examples, identified in RP2, are the weighted total completion time, the maximum lateness, and the number of tardy jobs.

Building on these findings from RP2, the model presented in RP3 aims to contribute to the literature of machine scheduling by addressing the research gap identified which concerns forgetting effects. Based on the above rationale, a focus on single-machine problems is set. However, the model introduced can be extended to fit multi-machine problems. Moreover, practitioners might apply the model for production planning. To this end, objective functions that remain efficiently solvable when including learning effects are considered within RP3. Namely, the total completion time and the makespan were identified in RP2 to fit these requirements for the majority of learning and forgetting effects introduced.

Variables, Notation, and Objective functions Typically, scheduling problems are expressed in the three-field notation $\alpha|\beta|\gamma$, introduced by Graham et al. (1979). It provides information on the machine environment α, the constraints β, and the objective function γ. A brief overview of the notation and objective functions relevant in the later chapters will be provided in this section. Definitions and more detailed explanations can be found e.g. in Pinedo (2012) or RP2.

A schedule is defined as a permutation $\pi_i(J)$ of a given set $J = \{1, ..., n\}$ of n jobs on a set $I = 1, ..., m$ of m machines is. Each job $j \in J$ considered is equipped with a standard processing time $p_{i,j}$ on machine i and a schedule dependent completion time $C_{i,j}$. Either common or job-dependent due dates d and d_j account for time restrictions, while job-dependent weights w_j emphasize the importance of different jobs.

RP2 summarizes results on learning processes in machine scheduling problems combined with a variety of different objective functions. These objectives can be divided into completion time-related objectives and due date-related objectives. The main objective functions relevant for the key results in RP2 are displayed in Table 4.

The literature distinguishes two types of learning effects for machine scheduling, a position-based and a time-based approach. Both relate to the WLC and affect the processing times of jobs with respect to the underlying schedule. While position-based effects reduce the processing times, based on the jobs' position in the schedule, time-based effects further take the duration of the jobs processed previously into account. In the same way as Wright (1936), both effects consider a learning coefficient $a := -log(l)$ based on the learning rate l observable in production. Table 5 provides the mathematical definitions for these main effects.

Table 4: Objective Functions Analyzed with Regard to Skill Development

Completion Time Related	
Makespan	$C_{\max} := \max\{C_1, ..., C_j\}$
Total Completion Time	$TC := \sum_{j=1}^{n} C_j$
Total Weighted Completion Time	
Due Date Related	
Earliness	$E_j := \max_{j \in J}\{0, d_j - C_j\}$
Lateness	$L_j := \{C_n - d_j\}$
Tardiness	$T_j := \max_{j \in J}\{0, C_j - d_j\}$
Maximum Lateness	$L_{\max} := \max_{j \in J}\{L_j\}$
Maximum tardiness	$T_{\max} := \max_{j \in J}\{T_j\}$
Number of Tardy Jobs	$\sum_{j \in J} U_j$ (with $U_j = 1$ if $C_j > d_j$ and $U_j = 0$ otherwise)

Table 5: Learning Effects Single-Machine Scheduling

Position-based (Biskup, 1999)	Time-based (Kuo and Yang, 2006)
$p_{j,r} := p_j \cdot r^a$	$p_{j,r} := p_j \cdot \left(1 + \sum_{k=1}^{r-1} p_{[k]}\right)^a$

A rationale for the distinction between the effects is the underlying production environment as well as the nature of the considered production tasks. The position-based effect assumes learning based on unit production. Here, jobs consist of several different operations. The time-based effect, in contrast, considers monotonous production tasks. Thus, each job consists of a number of similar operations. This allows learning effects for each incremental production step. Consequently, the whole processing time of a job affects the learning results.

3.2.1 Proposed Scheduling model

The model introduced in RP3 uses a position-based effect. Different categories of similar yet not identical jobs are processed on a single machine. Learning effects between jobs from one category are assumed as well as forgetting effects when switching between different categories. For this purpose, the following variables and parameters are considered:

The position-dependent processing times introduced by Biskup (1999) are modified to only account for the number of identically categorized jobs that were previously processed. Therefore, the counter function $r_{c_j}^{a_c} := \sum_{c \in \mathcal{C}} (\chi(c_j, c) \cdot r_c^{a_c})$ describes the number of jobs of category c processed before job r in the schedule π. Using this counter function the position-based category-dependent learning effect is defined as follows:

$$p_{j,r} := p_j \cdot r_{c_j}^{a_c}.$$

Next, the learning effect has been extended to incorporate forgetting based on the interruption of the consecutive production of jobs from one category. For this purpose, the counter function r_c

$J := \{1, \dots, n\}$	finite set of jobs j
$\mathcal{C} := \{1, \dots, k\}$	finite set of categories c
$c_j = c \in \mathcal{C}$	category $c \in \mathcal{C}$ of job j
$p_j \in \mathbb{R}^+$	standard processing time of job j
$l \in [0.5, 1)$	learning rate
$a := -\log_2(l)$	learning coefficient $a \in [-1, 0)$
$a_c := -\log_2(l)$	learning coefficient $a_{\in}[-1, 0)$ for category c
$r \in J$	position of a job in the schedule π
$x_{i,j} \in \{0, 1\}$	decision variable indicating whether job j is processed on position i in the schedule.
$\chi(c_j, c) = \begin{cases} 1, & \text{if } c_j = c \\ 0, & \text{otherwise} \end{cases}$	characteristic function indicating category of job
$\delta \in \mathbb{R}^+$	generalized forgetting parameter
γ_c	category-dependent counter
$\hat{\gamma}_{r,c}$	recursive formulation of the category-dependent counter

formulated above is reformulated as a recursive function for all $c \in \mathcal{C}$ as follows:

$$\begin{aligned} &\hat{\gamma}_{i,c} := \hat{\gamma}_{i-1,c} + \sum_{j \in J} \chi(c_j, c) \cdot x_{j,i}, && \forall i \in \{1, \dots, r\}, \\ &\hat{\gamma}_{0,c} := 1. \end{aligned}$$

The term $\sum_{i-1,c} \chi(c_j, c) \cdot x_{j,i}$ increases the counter by 1 if the job on position i belongs to category c. Next, the forgetting parameter $\delta > 0$ was introduced to account for interruptions and to moderate the relation between learning and forgetting:

$$\gamma_{r,c}(\delta) := \max \left\{ 1, \gamma_{r-1,c} - \delta + 2 \cdot \sum_{j \in J} \left(\chi(c_j, c) \cdot x_{j,r} \right) \right\}.$$

Here, the term $-\delta + 2 \cdot \sum_{j \in J} \left(\chi(c_j, c) \cdot x_{j,r} \right)$ decreases the counter by δ for each interruption or increases the counter by $2 - \delta$ for consecutively produced jobs from one category. Finally, the actual processing times with position-based learning and forgetting effects and different product categories are

$$p_{j,r} := p_j \cdot \gamma_{r,c_j}^{a_c}.$$

Note that choosing $\delta = 1$ complies with different empirical forgetting properties, e.g. learning and forgetting curves are mirror images of each other, and the relearning rate equals the learning rate.

The algorithms introduced to solve the proposed learning effect as well as the learning and forgetting effect will be dealt with in Section 4.3 together with a performance evaluation. For the performance evaluation focusing on computationally intractable cases, a computational study was conducted. The heuristics introduced were implemented in Python and used to solve random instances. For small problems, the results are benchmarked against the optimal solutions to the problems. Results for larger problem sizes ($n > 9$) are compared to commonly used rules to solve machine-scheduling problems with learning effects for the considered objective functions.

In order to avoid redundancy, only variables, parameters, and objective functions that are relevant for this introductory part of the dissertation were covered in this section. For a more comprehensive overview, please consider RP2 and RP3.

3.3 Simulation Study

To account for digital advances in training measures and knowledge transfer (Letmathe and Rößler, 2021), which allow for more flexible deployment of training, RP4 focuses on comparing traditional with flexible training approaches during the ramp-up phase of new production. In order to assess the influence of training measures on the skill development of employees in terms of learning-by-doing and forgetting, a simulation experiment based on a MILP was conducted. Mathematical models from the field of operational research and management science are appropriate for modeling changes in a production system to predict their influence on a real production system (Dooley, 2005). Hereby, alternate models can be compared based on deliberate changes in the underlying input variables (Carson and Maria, 1997). Especially in production systems that involve human labor, simulations studies eliminate treatment biases and congestion effects (Dooley, 2005).

In the study from RP4 the ramp-up phase of production was chosen since it offers high potentials for learning and vice versa for forgetting, as employees are on the steep part of their learning curve while getting accustomed to new production processes (Terwiesch and Bohn, 2001; Surbier et al., 2014; Hansen and Grunow, 2015). This phase is characterized by a trade-off between investments in employee skill development in terms of training and meeting a given high demand (Schultz et al., 2003). The mentioned trade-off is amplified by a low capacity utilization (Terwiesch and Bohn, 2001), unknown demand for products (Surbier et al., 2014), and customers that pay premium prices for products (Terwiesch and Bohn, 2001). Thus, high shortage costs arise while employee capacities are limited (Terwiesch and Bohn, 2001). Complying with the assumptions made in RP3 and current developments like mass customization, a multi-product environment with individual learning curves for different products is considered (Anzanello et al., 2014; Neumann et al., 2021). Further, a heterogeneous workforce with categorical and hierarchical skills (De Bruecker et al., 2015) is assessed as well as an overall skill target at the end of the ramp-up phase to broaden the company's skill portfolio (Heimerl and Kolisch, 2010).

In order to compare different training environments, budgeting of training measures is employed. To this end, training measures are limited in two ways, first, only a limited number of training measures per period are available to the whole workforce. Second, training measures are only available in the first periods of the ramp-up phase of a new production line production. This setting corresponds to traditional training approaches that provide knowledge at the beginning of a new production line or employment in a condensed period only (Ally, 2009).

Simulation Characteristics Based on the impact factors motivated above, RP4 focuses on a budgeting of training measures in a volatile production environment and the joint impact on employees' skill development. To be able to address different influencing factors in detail, four theoretically motivated hypotheses were derived. These define the purpose of the simulation study in accordance with RQ4. For a detailed motivation and rationale for the hypotheses, refer to Chapter 4 in Part II.

H1: The budgeting of training measures has a negative impact on skill development.
H2: Demand volatility has a negative impact on skill development.
H3: Employees' skill development is affected positively by the interaction effect of budgeting and employee capacity.
H4: Employees' skill development is affected negatively by the interaction effect of budgeting and demand volatility.

The structure of the simulation study, explained hereinafter, was chosen based on related literature in the field as well as results from a former study by Letmathe and Schinner (2022). Moreover, parameters and variables are defined in accordance with the considered production environment, the research question, and the hypotheses.

A heterogeneous production setting includes a workforce of four employees that produce three different products simultaneously. Workers are cross-trained in three categorical skills to be able to produce different products over multiple periods. Therefore, they gain experience in the production task by either learning-by-doing or explicit training measures. Note that training measures are connected to direct costs and indirect costs in terms of time consumption which could otherwise be utilized for production. A discretized log-linear learning effect for the production time is considered to represent the experience gained. The discretization was chosen to reduce the computational complexity of the model. Further learning effects on the productions costs are incorporated which combine human effects, e.g. waste production and material handling, with effects from re-engineering processes. Lastly, employees' skills decrease in terms of skill units lost if a certain production task does not reach a given threshold in one period. This forgetting effect is again based on the number as well as the length of interruptions and the relearning rate equals the learning rate.

Throughout the study, the following variables were manipulated to assess their impact on the learning, forgetting, and training behavior:

Demand volatility: 100 different levels of demand volatility are assessed. A level of 0 is considered as an environment without demand variation, while a level of 100 allows for high demand fluctuations between consecutive periods. The level describes to what extent the demand can deviate from a set average demand per period.

Employee capacity: Three distinct scenarios of employee capacity in terms of time units available for training or production are considered, i.e. a low, medium, and high capacity scenario. In the low capacity, scenario employees are not able to meet the given average demand per period, while the medium scenario allows meeting the given average demand exactly and the high capacity further provides excess time units that can be utilized for training.

Budgeting: Training measures are budgeted as motivated above: a limited amount of training measures per period are available for training in the first 5 of 18 periods.

For the given production setting, the total costs were minimized over 18 periods. These entail shortage costs, unit production costs, and costs for training measures undertaken by employees. The MILP, which is described in detail within RP4, was implemented in GAMS and minimized by utilizing a Gurobi 7.5.2. solver. The resulting 600 scenarios and 10,800 data points were analyzed by using linear Generalized Estimating Equations (GEE), which were implemented in *R* (Version 3.6.1) and the package *geepaack* (Halekoh et al., 2006). To this end, an *identitylink* was used and a *gaussian* family was employed based on the normal distribution of the variables (Ballinger, 2004). In general, GEE are appropriate for conducting regression analysis on longitudinal data. To further account for the time-dependent nature of our variables, an AR(1) structure was chosen (Ballinger, 2004).

4 Findings

This section provides an overview of the findings from the different research papers. It is structured as follows: Section 4.1 and Section 4.2 present an overview of the insights from the survey articles. The solution methods and performance evaluations of the introduced scheduling effect with learning and forgetting are described in Section 4.3. The section closes by providing empirical results on the interplay of learning and forgetting mediated by different training approaches derived from the simulation study in Section 4.4.

4.1 Key Findings of Research Paper 1

RP1 provides an overview of the state of research of competence management in the fields of operational research, management science, and operation management. In this regard, the focus of the survey conducted was set on publications dealing with manufacturing production while providing an extensive but not exhaustive overview of the literature. In this context, the survey did not aim to present all models and results in detail but to describe the breadth of the fields impacted by human labor and competencies, in contrast to other surveys that primarily focus on specific problem sets. The results from the literature review can be divided into three interconnected areas briefly introduced within this subsection.

First, empirical results on learning and forgetting processes as well as the influence of training measures, different concepts of employee training, and training policies are considered in the literature. In terms of training, especially cross-training approaches and their successful implementation play a crucial role. Building on these empirical results a variety of learning and forgetting curves have been introduced, refined, and extended. Nevertheless, different publications found the WLC appropriate for capturing learning behavior in production. Moreover, the learning rate observable in production can be used to utilize this curve for production planning. Therefore, some publications focus on estimating the learning rate and employing error terms in the WLC for more accurate results. In order to avoid redundancy, please consider Section 2 for a brief but more detailed outline of the concepts and factors, as well as learning and forgetting curves discussed in the literature. A more detailed overview is presented in RP1 Chapter 1 in Part II.

The second area concerns strategic and organizational aspects. Section 4.1 provides a brief overview of different areas covered, i.e. organizational knowledge creation, production decisions, change management, and staffing, which includes determining required competencies and deciding about upfront training.

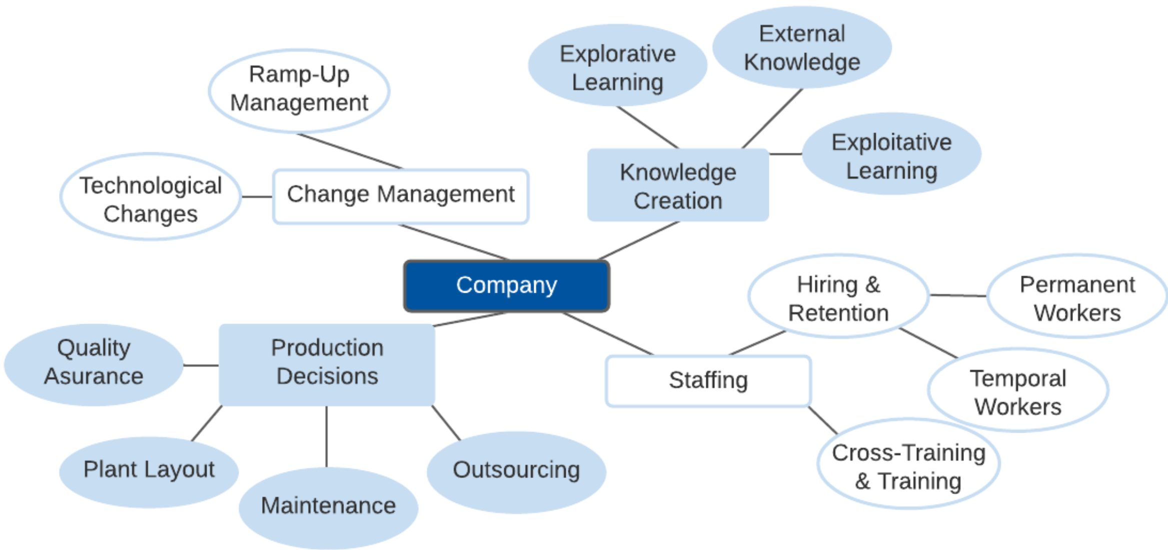

Figure 6: Overview of organizational factors influences by employee competence management

Several aspects are rarely considered in research, for example, plant layout decisions, maintenance scheduling, outsourcing decisions, or external knowledge transfer. However, the literature on other aspects is quite rich. Since changes in production due to production ramp-ups, technological or procedural changes, as well as newly hired employees, give rise to learning effects, a variety of publications incorporated learning and forgetting effects when dealing with these topics. While the aspects covered are of a different nature some common factors could be identified. First companies need to assess the skills required for production and analyze the production activities. Taking the tasks' complexity into account influences not only the learning rates and learning potentials but also the amount of cross-training that contributes to production efficiency. In general, a moderate amount of cross-training provides already a major part of the achievable efficiency gains and flexibility while yielding moderate cost. The importance of cross-training is further underpinned by the results of the third class of publications which focuses on operative shop-floor and production planning optimization.

In particular, results for different production environments are presented, i.e. Assembly Line Balancing (ALB), Competence Management (CM), Economic Order Quantity (EOQ), Group Technology or Cellular Manufacturing (GT), Worker Assignment (WA), and Machine Scheduling (S). The main objectives of these fields are henceforth listed. Moreover, the impact that competencies have concerning these environments, as well as the aspects of competence management already considered in the literature are presented.

ALB Avoiding blockage or starvation of the system due to worker absenteeism, turnover, and worker or task heterogeneity as well as reducing work in progress and inventory costs.
Considered aspects of competence management:
Learning, forgetting, worker heterogeneity.

GT Cell formation based on parts families and workers' skills as well as character traits and soft skills. Estimation of an optimal deployment level, defined as the worker machine ratio, based on cross-training decisions.
Considered aspects of competence management:
social skills, cross-training, cross-learning effects, and worker heterogeneity.

EOQ Determining the batch size based on employees learning behavior and forgetting effects during interruptions between batches. Considering the influence of workers' skills on production quality in terms of the rate of defect items and re-manufacturing.
Considered aspects of competence management:
Learning and forgetting.

S Defining a permutation for a given set of jobs on a given set of machines optimizing given objectives under processing times that are subject to learning and forgetting effects.
Considered aspects of competence management:
Learning and forgetting.

WA Assignment of workers to tasks, or workers to machines and tasks to machines with regard to employees' skills. Finding cross-training policies that allow the mitigation of forgetting effects stemming from absenteeism of workers and comply with demand volatility and task complexity.
Considered aspects of competence management:
Cross-training and worker heterogeneity.

The individual areas outlined above present different avenues for future research, which will be considered jointly in Section 5.3.

4.2 Key Findings of Research Paper 2

RP2 reviewed the publications on machine scheduling with a focus on competence management in more depth. The contributions of this article encompass evaluating and providing an overview of learning and forgetting models considered in machine scheduling, introducing a unified notation for the underlying problems, and providing avenues for future research.

The individual effects covered by the literature are presented in Figure 7. As explained in Section 3.2, the processing time learning effects in machine scheduling research can be divided into position- and time-based approaches. Position-based forgetting effects cover a variety of different aspects. For example, plateau effects, induced learning, controllable processing times, or the deterioration of processing times (independent of forgetting) have been incorporated into models, as

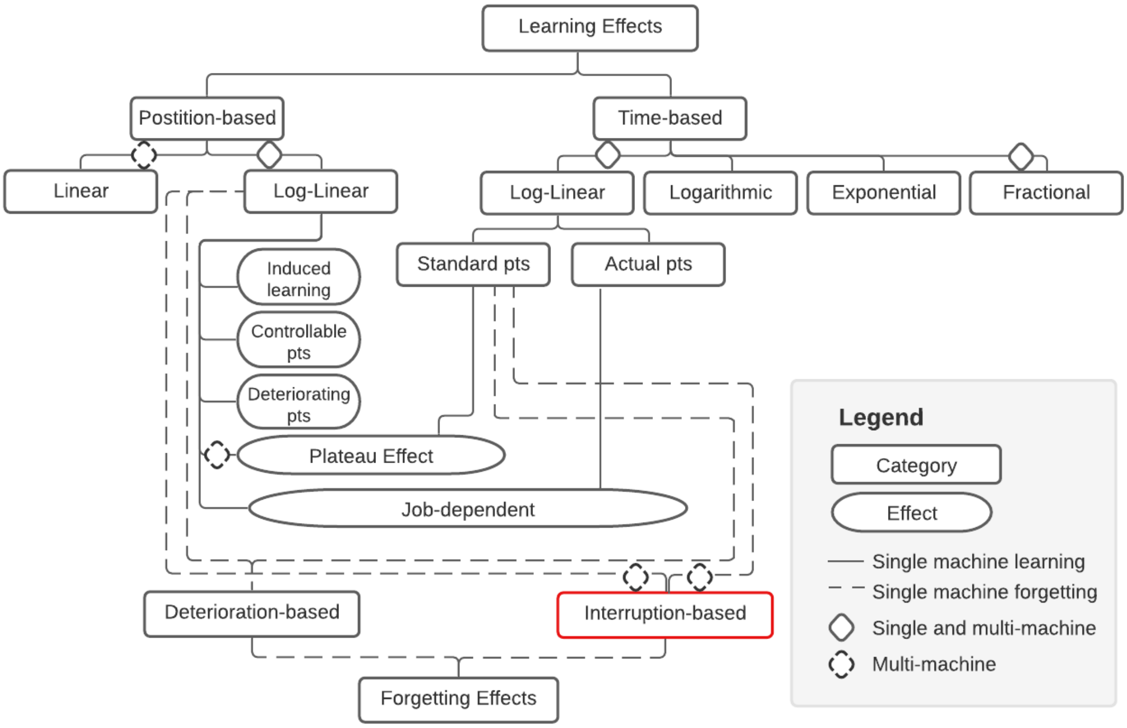

Figure 7: Overview of Scheduling Models (RP2 Figure 1)

well as the inherently different nature of jobs by introducing job-dependence learning rates. For the time-based effect, in contrast, model alternatives have been introduced. These capture learning based on the total time spent in production in log-linear, logarithmic, exponential, or fractions functions while focusing either on the standard processing times or the actual processing times of jobs with respect to their position in the schedule and a given learning effect. Therefore, only a few extensions have been considered, i.e. solely a plateau effect, or job-dependence. In a nutshell, position-based effects have been covered in more depth whereas publications introducing time-based effects span a broader field.

Forgetting effects can in general be distinguished by the underlying drivers; deterioration and interruption (see Section 2). Deterioration considers processing times to increase after a certain amount of time spent in production based on decreases in motivation or fatigue effects, boredom, and ergonomic factors. Although this effect is rarely considered in empirical research and learning curves compared to the interruption-based effect, which is based on breaks in the production processes, it is the only forgetting effect considered for single-machine scheduling. A few exclusive publications which moreover focus on very specific and detailed multi-machine environments included interruption-based forgetting effects.

Despite the number of publications that introduced a variety of extensions and alternate formulations, no unified notation for these effects has been introduced so far. RP2 addresses this shortcoming by introducing a notation that allows learning effects to be classified. Moreover learning effects can be included in the three-field notation Graham et al. (1979) as condition γ. In line with the existing body of literature, learning effects are denoted by LE (Biskup, 1999). Further, forgetting effects are denoted by F. The effects can be extended in twofold ways. Indices provide information on the learning and forgetting effect considered, e.g. position-based learning LE_p or time-based learning LE_t, as well as extensions considered. A combined learning and interruption-based forgetting effect may thus be denoted by $LE_p + F_i$. Table 6 provides an overview of the indices introduced. However, this list can easily be extended to include future learning effects. The notations moreover allow an indication of the underlying production environment. The effect LEF, for example, denotes a learning effect for a flow-shop environment Fm.

Table 6: Denotation for Machine Scheduling Problems with Learning Effects (RP2 Table 1)

LE	Learning Effects	F	Forgetting Effects
g	general effects	g	general effects
t	time-based	i	interruption-based
p	position-based	d	deterioration-based
pl	linear position-based		
exp	exponential		
log	logarithmic		
$plat$	plateau learning		
j	job-dependent		
A	actual processing time dependent		
det	deterioration processing times		
con	controllable processing times		

An overview of the learning effects presented in Figure 7 considered in single-machine scheduling and the objective functions addressed is provided in Table 7. The results in Table 7 indicate that introducing learning effects leads to increased computational complexity for the majority of problems. While the total weighted completion time, the maximum lateness, the maximum tardiness, and the number of tardy jobs can only be solved when including additional conditions, the makespan and total completion time stay efficiently solvable in the majority of cases. Note that the total tardiness is known to be computationally intractable even without learning effects (Garey and Johnson, 1979). For a holistic overview of the learning effects already introduced as well as their formal definitions, please consider the overview provided by RP2 in Part II.

Building on the survey's results RP3 addresses a gap in the literature by providing an interruption-based forgetting effect. Table 7 further emphasizes the choice of the objective functions makespan and total completion time. The results are presented in the next section.

4.3 Key Findings of Research Paper 3

RP3 extended the position-based learning effect LE_p to account for different product categories as outlined in Section 3.2. For this purpose, the list of indices in Table 6 introduced in RP2 is extended by the subscript $_{cat}$. Thus the effects presented in RP3 and Section 3.2 are denoted by $L_{p,cat}$, as well as $L_{p,cat} + F_{I,cat}$ for the learning effect with interruption-based forgetting.

To find minimal solutions to the presented effects for the total completion time and the makespan,

Table 7: Single-Machine Problems and Learning Effects

	Make-span	Total Completion Time	Total Weighted Completion Time	Maximum Lateness	Maximum Tardiness	Total Tardiness	Number of Tardy Jobs
	$C_{\max}$	$\sum C_j$	$\sum w_j \cdot C_j$	$L_{\max}$	$T_{\max}$	$\sum T_j$	$\sum U_j$
LE_p	✓	✓	(✓)	(✓)	(✓)	(✓)	(✓)
$LE_{p,j}$	✓	✓					(✓)
$LE_{p,plat}$							
$LE_{p,det}$	✓	✓	(✓)				
LE_t	✓	✓	(✓)	(✓)	(✓)	(✓)	(✓)
$LE_{t,A}$	✓	✓	(✓)	(✓)			
$LE_{t,A,j}$	*NP*		*NP*	*SNP*			
$LE_{t,exp}$	✓	✓	(✓)	(✓)	(✓)	(✓)	
$LEC_{t,frac}$	✓	✓	(✓)	(✓)	(✓)	(✓)	
$LE_{t,log}$	✓	✓	(✓)	(✓)	(✓)	(✓)	
$LE+F_{p,sum,g}$	✓	✓	(✓)	(✓)	(✓)	(✓)	
$LE+F_{p,int,g}$	✓	✓	(✓)	(✓)	(✓)	(✓)	
$LE+F_{t,int,g}$	✓	✓	(✓)			(✓)	

✓polynomial time solution for the problem exists; (✓) approximation algorithms have been introduced or polynomial time solutions exist only if including further constraints; *SNP / NP* problem is *(strongly) NP-Complete* (RP2). Table 5.

two sorting algorithms were introduced. The Batchwise-Shortest-Processing-Time-First (BSPT)- and the Dynamic-Shortest-Processing-Time-First (DSPT)-rule. Both heuristics are based on the Shortest-Processing-Time-First (SPT)-rule, which is utilized to derive minimal solutions for the position-based learning effect LE_p and the time-based learning effect LE_t. Moreover, the majority of learning effects introduced is efficiently solved using the SPT-rule (see RP2 in Part II). The DSPT-rule schedules jobs according to the smallest actual processing time. Thereby, it accounts for processing times already being discounted by the learning effect. Via the DSPT-rule, a minimal schedule for the total completion time with position-based learning can be obtained. The BSPT-rule, on the other hand, schedules jobs from one category in one consecutive batch and further calculates the batch size based on an average processing time. It yields a makespan minimal schedule for the learning effects, as well as the learning and forgetting effect. Formal descriptions of the algorithms are provided in RP2. Table 8 summarizes the results for the efficiently solvable problem cases considered and provides complexity results.

Table 8: Overview of problems and solution methods from RP3

	Problem	Algorithm	Complexity
learning	$1\|LE_{p,cat}\|C_{\max}$	SPT	$O(n \cdot \log(n))$
	$1\|LE_{p,cat}\|C_{\max}$	BSPT	$O(\|\mathcal{C}\| \cdot \log(\|\mathcal{C}\|) \cdot \sum_{c\in\mathcal{C}} n_c \cdot \log(n_c))$
	$1\|LE_{p,cat}\|\sum_{j\in J} C_j$	DSPT	$O(n^2)$
learning and forgetting	$1\|LE_{p,cat}+F_{i,cat}\|C_{\max}$	BSPT	$O(\|\mathcal{C}\| \cdot \log(\|\mathcal{C}\|) \cdot \sum_{c\in\mathcal{C}} n_c \cdot \log(n_c))$

For the total completion time, in contrast, no optimal solution can be calculated by the heuristics when considering learning and forgetting. RP3 presents counterexamples as well as a computational

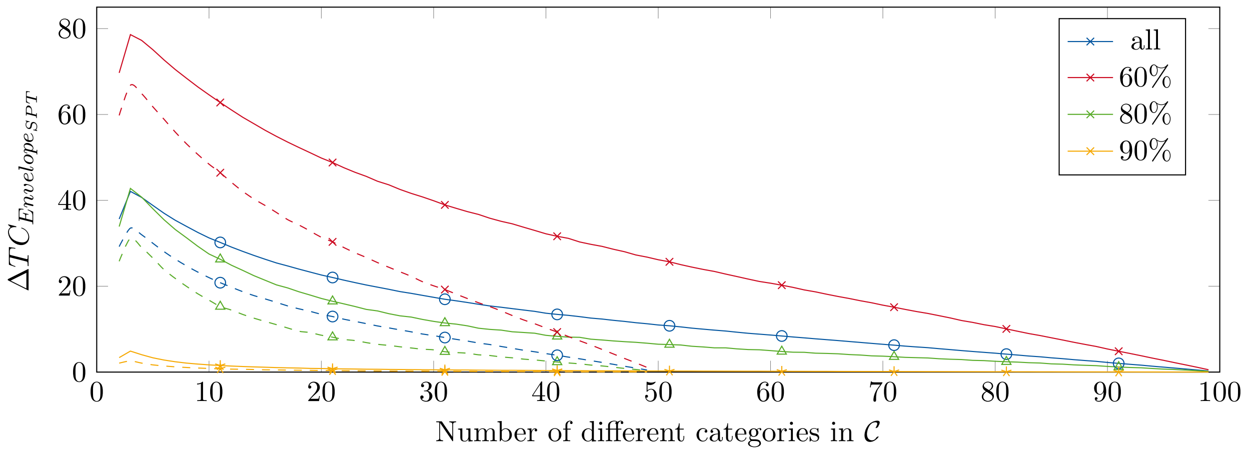

Figure 8: Improvements of the performance of the upper envelope compared to the SPT-rule for 50 (dashed) and 100 jobs and different number of categories (RP3 Figure 9)

study to provide insights on the performance of the upper envelope of the three heuristics SPT-, DSPT-, and BSPT-rule when benchmarked against the SPT-rule. For small problem instances of up to nine jobs, optimal solutions were calculated. These indicate that the performance of the SPT-rule decreases with an increasing number of jobs. This effect is particularly strong when considering two to three different categories. Moreover, all optimal solutions are merges of jobs sequences while the jobs within a category are ordered according to the SPT-rule. This gives rise to the proposition that an optimal solution might be given by an SPT-merge of jobs from different categories. Nevertheless, Figure 8 shows that for high (60%) and medium (80%) learning rates, cost and time savings of 40%-80% can be realized on average if two or three different product categories are considered and 100 jobs are scheduled. Note that 80% is also the most common learning rate observed in production environments (Dutton and Thomas, 1984). Thus, not only the performance of the SPT-rule, as standard solution method, is hence evaluated but also the effect of including interruption-based forgetting effects. The results in turn indicate that neglecting forgetting effects in calculations while they are present in production can lead to major deviations from the optimal solution.

Table 9: Evaluation of the hypothesis of RP4

	$H1$ ✓ $Budget$	$H2$ ✓ $Volatility$	$H3$ (✓) $Budget*$ $Capacity$	$H4$ ✓ $Volatility*$ $Budget$
Training	−	+	+	−
Learning-by-doing	+	−		
Learning-outcome	−	−	+	−
Forgetting	+	+	+	
Total Skill Development	−	−		−
Achieved Skill Units		−	+	−

4.4 Key Findings of Research Paper 4

RP3 emphasized the importance of including forgetting effects in production planning. Building on this result, the simulation study in RP4 focuses on the joint effect of learning and forgetting on skill development and the way training measures mediate this relationship. Specifically, the influence of limiting training measures (*Budget*), demand variation ($Volatility$), the interplay between limited training measures and increasing available employee capacity (*Budget* $*$ *Capacity*), as well as the interplay between budgeted training and increasing demand volatility ($Budget{*}Volatility$) are analyzed statistically. To observe the effects on employees' skill development and the effects of the different influential factors different variables are introduced: $Training$ and *Learning-by-doing* measure the skill units gained. These are combined in *Learning Output* $=$ $Training$ $-$ *Learning-By-Doing*. $Forgetting$ describes the decrease in skill units, while the variable $Total$ *Skill Development* $=$ *Learning Output* $-$ $Forgetting$ describes the combined effect of training, learning, and forgetting. *Achieved Skill Units* describe the skill units at the end of the planning horizon. Table 9 provides the results of the GEE regression. Here, the row which contains the main and interaction effects on the variable $Total$ *Skill Development*, and thus the hypothesis, is highlighted. Further, the inverse effects on $Training$ and $Forgetting$ that lead to an only partial support of $H3$ are emphasized.

$H1$: Budgeting training measures has a significant negative influence on employees' skill development (Table 9, column 1, $Total$ *Skill Development*). The *Learning Output* is influenced significantly negatively while a significant positive (increasing) effect on forgetting can be observed. Nevertheless, the *Achieved Skill Levels* are not affected significantly.

$H2$: Demand Volatility has a significant negative influence on employees' skill development (Table 9, column 2, *Total Skill Development*). The *Learning Output* is influenced significantly negatively while a significant positive (increasing) effect on $Forgetting$ can be observed.

$H3$: The interaction effect of budgeting training measures and increasing employee capacity endowment does not influence employees' $Total$ *Skill Development*. However, a significant positive effect on the *Achieved Skill Units* is present (Table 9, column 3). These two observations might be driven by a significant positive effect on training measures undertaken when employees have a sufficient capacity endow at their disposal combined with the significant positive (increased) effect on forgetting. Figure 9 depicts the amount of forgetting (dashed lines) as well as the training measures undertaken (solid lines) over time. In the first periods, especially in periods three, four, and five, employees undergo more training measures in the budgeted scenario compared to the flexible scenario without budgeting. During that time the average amount of forgetting is lower in the budgeted scenario. This relationship is reverted from period six on. Employees in the budgeted scenario undergo a higher decrease in skill units due to forgetting. Thus, the positive effect of excess training sessions (undertaken in the first periods) and the contrary positive effect on forgetting (in the later periods) offset each other. This results in no significant effect on the $Total$ *Skill Development* of employees. As a result, hypothesis H3 is at most partially supported. The observable effect on *Achieved Skill Levels* must be considered with caution.

*H*4 : The interaction effect of budgeting training measures and demand volatility has a significant negative effect on employees' skill development (Table 9, column 4, *Total Skill Development*). This effect is driven by a significant negative effect on *Training*, which results in negative effects on *Learning-Outcome*, *Total Skill Development*, and *Achieved Skill Units*.

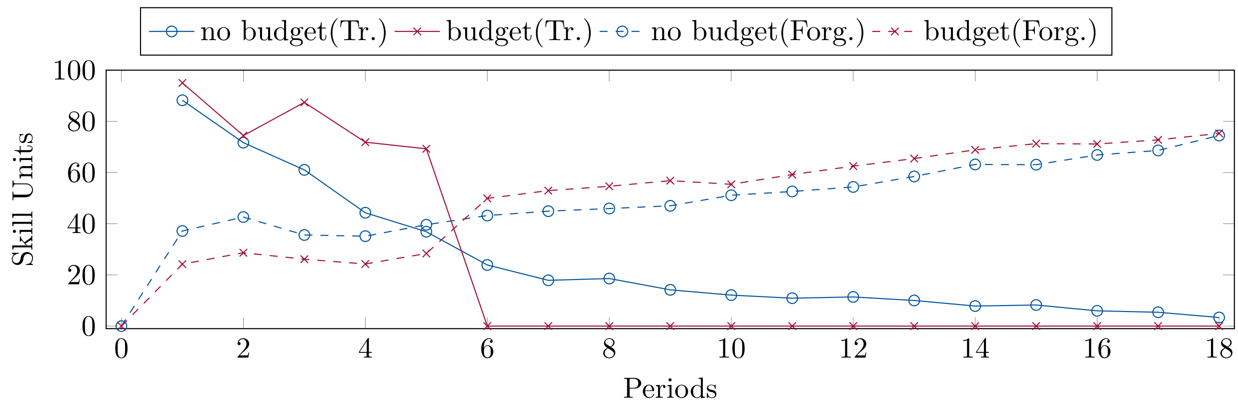

Figure 9: Average Training per Period (RP4 Figure 1 and Figure 2)

A detailed analysis of all effects observed is presented in RP4 in Part II. These effects provide additional rationales for the main effects considered in the hypothesis. In particular, the non-linear effect of the different employee capacities endowments is evaluated carefully concerning results for the individual scenarios.

5 Conclusion

This section highlights theoretical contributions and implications for practitioners. Moreover, the limitations connected with the methods utilized are presented alongside avenues for future research. The main contributions and findings provided thus far are summarized in Table 10 and addressed in the following.

5.1 Implications for Theory

The results form this dissertation contribute to the literature from different fields of research. These encompass on the one hand operational research, management science, and operational management, on the other competence management in terms of human resource development. For the latter a focus is set on learning and forgetting effects in production combined with the mitigating effects of training approaches. For this purpose, the first article, RP1 sheds light on empirical and theoretical results on the underlying dynamics of skill development as well as models form operational research that incorporate aspects of competence management. In this context not only a specific field is reviewed exhaustively but the breadth of application areas is analyzed. These areas range from knowledge creation in the early stage of product development to introducing changes as well as staffing decisions. Moreover, different production environments with their specific problems, such as assembly line balancing, worker assignment or machine scheduling, are covered. Thus, a holistic overview guides researchers through the whole production process while hinting

Table 10: Overview: Individual Research Papers

Research Paper	Key Findings
RP1	1. A holistic overview of theoretical results on competence or skill development due to learning, forgetting, and training. 2. Organizational, i.e. strategic and operational, decisions impacted by competence management. 3. Aspects important of different areas and avenues for future research / research gaps.
RP2	1. Exhaustive overview on the models presented for machine scheduling research. 2. Unified notation to describe learning and forgetting effects for single-machine scheduling. 3. Overview of objective functions covered and effects of learning and forgetting on the problems' complexity. 4. Gaps in literature and avenues for further research.
RP3	1. Two models for single-machine position-based learning as well as position-based learning and interruption-based forgetting effects based on product categories. 2. Two variations of the Shortest-Processing-Time-First-rule are introduced, addressing the minimization of the makespan or the total completion time. 3. A computational study shows the performance of the upper envelope of the proposed heuristics. For small problems, the optimal solution was calculated: for problem sizes $n \geq 10$, the performance is benchmarked against the SPT-rule.
RP4	1. Insights into the negative effect of budgeting training measures on employees' skill development in production ramp-ups. 2. Insights into the amplifying effects of demand variation and scarce employee capacity. 3. Simulation model for analyzing the interplay between learning, forgetting, and training in production, considering task and workforce heterogeneity, employee capacity levels, demand variation, and a skill target.

at aspects that may be included in future models to gain more precise production plannings. Important results are highlighted together with gaps in the existing literature which present avenues for further research. In contrast, RP2 provides an exhaustive overview of theoretical results on machine scheduling. For this purpose various processing time learning and forgetting models are analyzed. The individual effects are classified to allow researchers to access results form the field straightforwardly, identify relevant models as well as important aspects that have not been covered thus far. The article also evaluates the influence of including these learning or forgetting effects into machine scheduling on the computational complexity concerning different objective functions. Further, a unified notation is introduced to cluster the body of learning and forgetting models already developed. Utilizing this notation allows us to easily assess the dynamics behind the considered learning effect in the three-field notation of Graham et al. (1979). The nature of the notation allows to capture new learning effects developed in the future.

To address research gaps identified in RP2, two new effects for single-machine scheduling are presented in RP3. To be precise, a position-based learning as well as a combined position-based learning and interruption-based forgetting effect are presented. Both effects account for different product types manufactured on a single machine or production line, which complies with mass customization theory. On the one hand, a gap in machine scheduling literature identified in RP2 is addressed by providing an interruption-based forgetting effect. On the other hand, a gap in the ramp-up literature identified by (Surbier et al., 2014) is addressed by focusing on small batch production. In this sense, also complexity levels of different product categories are considered by allowing for individual learning rates per category. Similarities between product families can be included in the model by manipulating the forgetting parameter introduced. In addition, seven of the empirically validated properties summarized by Jaber et al. (2003) are satisfied by the forgetting effect. In order to minimize the makespan or the total completion time, two variations of the SPT-rule are introduced. Their performance is further evaluated in a computational study and benchmarked against existing solution methods typically utilized to address the considered problem types.

The dissertation closes with an analysis of the joint impact of learning and forgetting together with training approaches in RP4. The results imply that it is worthwhile to align training measures to the employees' needs for a target oriented and efficient skill development. Instead of including a limited number of training sessions, optimizations and planning models might benefit from employing flexible approaches especially in volatile production settings. Moreover, the study provides evidence for employee capacity sensitivity effects. Hence, future simulation studies might want to include different capacity scenarios in their research on skill development. In addition to the theoretical implications, the model presented in the article can be used for simulation studies that focus on the interplay of learning, forgetting, and training measures in combinations with exogenous and endogenous factors, e.g. demand variation, employees' capacity, as well as task and worker heterogeneity.

5.2 Implications for Practitioners

In this dissertation practitioners and companies find guidance to identify aspects of human competence development relevant for their production and ramp-up management. Various strategic and operational decisions of an organization that are influenced by competencies are highlighted throughout the dissertation.

The results of the thorough analysis of the existing body of literature underlines the importance of considering learning effects in practice not only in operational shop floor optimization. Quiet the opposite, one major take-away for practitioners is including considerations of competencies and their influence already at the time when new product ideas are developed, which is also true when deciding on the introduction of changes to an operating production. Thus, it is worthwhile to choose a holistic approach that covers the whole production process. This includes the early stages of knowledge creation and new product development as well as the upfront decisions on the layout of the production plant. Here parallel or serial production lines offer, for example, different potentials for human learning and thus for long term productivity. Nevertheless, these decisions depend on the nature of the underlying tasks. Important factors such as the complexity of the task or a distinction between motor and cognitive tasks should be examined upfront. Generally, also external factors, i.e. demand variations and supplier dependencies, should be assessed because they influence, for example, the ways different training approaches contribute to the productivity of the system. Such changes might concern the product itself when reengineering the design or replacing technical equipment as well as adapting existing processes. Here the timing, with regard to the learning rate, the knowledge acquired and the demand for a product are important influence factors. The workforce itself and related staffing decisions are levers for managers to realize efficiency gains. Defining the required competencies upfront, assessing the experience of employees of an often heterogeneous workforce, and deciding on training approaches are crucial for a target-oriented development of the employees' skills. Training approaches encompass on the one hand deciding on the way and amount cross-training should be implemented. Here, even a little cross-training implemented in a reasonable way that fits the production environment often provides results comparable to a fully cross-trained workforce but comes with lower costs for training and employment. On the other hand, results from RP4 hint that it is likewise important to consider investing in more flexible ways to provide training sessions to employees, compared to approaches which train employees in the early phase of production to a desired skill level. This can be especially beneficial in times of low demand or when production disruptions occur due to supplier bottlenecks. A now very prominent example is the break down in the semi-conductor industry which leads to tremendous problems in many different industries, such as the automobile, home appliance and computer sector, to name a few examples only. Periods that do not demand for high employee capacity could then be used to train employees in order to reach higher productivity levels or counter forgetting due to interruption. Considering forgetting effects is not only important when the production system is disrupted due to external factors. Interruptions in batch production as well as fatigue effects as a consequence of boredom or ergonomic factors should be considered in operational production planning. In terms of operational shop floor optimization results on assembly line balancing, cellular manufacturing, economic order quantity, machine scheduling, and worker assignment are analyzed and aspects important for consideration by practitioners are highlighted. A special case considered in RP3 of this dissertation is the influence of forgetting effects on production efficiency in shared production lines. Results suggest that especially production lines that switch between a small amount of different product types might realize high cost savings. These might be realized by taking the differences or similarities between tasks and products into account when creating production schedules. Prominent examples are small batch production of mass customized products.

The analysis of existing concepts presented in the survey articles in RP1 and RP2 does not only hint to aspects that should be considered in practice but also evaluates the presented concepts concerning their applicability for companies. Although several different learning curves have been considered in research, individual studies still encourage practitioners to utilize the WLC for production planning. Independent of its simplicity, different empirical and computational results show that the WLC is appropriate for capturing learning effects in production. Moreover, in comparison to other models the WLC requires the estimation of a single parameter only, i.e. the learning rate, which can be derived from shop floor observations straightforwardly. For this purpose, different studies provide support for estimating the learning rate and including error terms to increase the accuracy of the resulting production planning.

In summary, practitioners find insights on how to implement competence management in their production processes. For this purpose, the whole process of developing new products, designing production systems, selecting and staffing projects and finally operational shop floor optimizations are considered.

5.3 Avenues for Future Research and Limitations

Alongside the findings and the resulting implications, this work is subject to limitations, which present avenues for future research.

The structured literature reviews in RP1 and RP2 mainly include articles published within the last two decades in nine major journals in the field of operational research and management science. Although the surveys build on relevant publications and review articles, the scope of this research might be extended by incorporating more journals or extending the time horizon. Similarly, the search terms, which already cover several important keywords and facets of competence management, could be extended to incorporate other aspects as well. Of course, the survey articles themselves hint at directions for further research by presenting gaps in the existing literature. These range from including empirical and theoretical results on learning, forgetting, and training into models of operational production planning to consider aspects that have been neglected in the literature thus far. Here, for example, the cognitive load of employees, spillover effects, and social aspects are only a few concepts existing models could benefit from. A more technical point of attack concerns the development of efficient solution procedures. While more detailed models lead to increased computational complexity, little is being done about the practical applicability of these concepts. Especially for machine scheduling, special production settings are considered while a number of classical solution methods become computationally intractable when including even simple learning effects.

Turning to machine scheduling, the results presented in RP3 entail further limitations. First, the complexity of the learning and forgetting effect when minimizing the total completion time remains open. Together with assessing the prevailing assumption that the presented problem is NP-complete, also the existence of an FPT-Algorithm consisting of arbitrary merges of SPT-sequences should be addressed. Moreover, worst-case bounds for the solution methods evaluated in the computational study might be derived. For the computational study, several random instances were generated. This performance evaluation of the solution methods could further be validated using company data.

One major limitation of the simulation study in RP4 is the choice of parameters. Although these as well as the learning curves are derived from empirical results, the production environment in the study is not based on real company data. An extension of this study could again validate the results by using production data. However, simulation studies are models that aim to predict the influence of changes in the production system Dooley (2005). Therefore, the results need to be seen as theoretical and not empirical evidence. Thus they are not directly transferable and do not claim general applicability. Moreover, the study considers a cross-trained workforce with hierarchical skills. Another study could evaluate whether the results persist if a workforce of specialized workers or a cross-trained workforce with categorical skills is considered. Lastly, effect aspect that could be included is teamwork, which demands social skills while allowing for cross-learning or spillover learning effects.

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Part II

Individual Research Papers

Research Paper 1: Competence Management in Operational Research - A Structured Literature Review

Authors: Patricia Heuser, Peter Letmathe, Thomas Vossen

Publication Status: to be submitted

Abstract Digitalization, globalization and demographic changes reshape the way we work today. Current developments are characterized by an aging workforce, while production processes become increasingly interconnected and automated. As a consequence, required employee skills are changing and traditional competencies are losing value. This situation presents a variety of new challenges that are compelling organizations to effectively account for employee skill and firm competencies in their strategic and operational management initiatives if they are to stay competitive. We aim to address this need by providing a state-of-the-art overview of research on Competence Management (CM) in the field of Operational Research (OR) and by exploring avenues for further research. Therefore, the term 'competence management' is used as an umbrella term to integrate different approaches that encompass a broad set of concepts, ranging from learning, forgetting, and training over to skill portfolios. The structured literature review includes articles published between 1998 and 2019 in nine renowned Operational Research and Management Science (MS) journals. From 2398 articles, relevant research papers are extracted and clustered according to topic and methods. Further, publications and survey articles were added, resulting in 254 publications considered.

1 Introduction

Scholars disagree about whether automation and digitization of processes will lead to a reduction in the number of workplaces or whether this will change the nature of work routines (Autor, 2015; Beier et al., 2020). They agree, however, that these developments will increase requirements and responsibilities in those workplaces that remain (Autor, 2015; Davies et al., 2017; Neumann et al., 2021). For firms to stay competitive, effective management of employee and firm competencies will therefore become an even more crucial factor (Qin et al., 2015; Beier et al., 2020).

The adoption, improvement, and maintenance of competencies is related to a number of challenges that span a variety of facets (North et al., 2013; Beier et al., 2020; Neumann et al., 2021). While competencies can be acquired by hiring employees with prerequisite qualifications and experience, more often competencies are developed over time when employees work in defined processes or environments (Arlotto et al., 2014). For example, employees repeatedly operating in the same processes may improve their competencies through autonomous learning (Dutton and Thomas, 1984; Yelle, 1979). More sophisticated approaches toward Competence Management (CM) include the training of employees - explicit knowledge transfer - (Dutton and Thomas, 1984), the interaction with experienced colleagues who oftentimes cannot express their know-how - tacit knowledge transfer - (Letmathe et al., 2012; Letmathe and Rößler, 2019), or the conscious testing of alternatives to find optimal solutions - experimental learning (Lapré and Van Wassenhove, 2001; Terwiesch and Bohn, 2001). Other challenges for CM arise when firms lose important competencies. This may occur through forgetting (Jaber et al., 2003), expected or unexpected turnover of employees (Arlotto et al., 2014), or when technology changes reduce the value of existing competencies (Vits et al., 2006).

Due to technological changes and market dynamics, the measurement and proactive management of competencies has gained tremendous importance (Surbier et al., 2014; Neumann et al., 2021). Whereas in the past it was often sufficient to hire employees with the required qualifications, firms now have to continuously adjust individual competencies and organizational competence portfolios to align them with changing technological and production requirements (Qin and Nembhard, 2010; Qin et al., 2015). In fact, many management scholars mention acquiring, developing, and maintaining competencies as some of the most important factors that impact firm success (Terwiesch and Bohn, 2001; Surbier et al., 2014; Glock and Grosse, 2015; Qin et al., 2015; Beier et al., 2020). Terms such as ‘lifelong learning’, ‘the war for talent’, and ‘the competence-based view of the firm’ reflect this development.

In recent years, the number of publications that target different aspects of competence management in the field of operations management related to manufacturing and production have increased substantially. Therefore, this review aims to provide an overview of the recent state of research in this field. We use the term ‘competence management’ as an umbrella term that integrates different concepts, ranging from competencies and learning to skill portfolios and workforce planning. Generally speaking, we believe that this field is under-researched and has substantial potential for more integrated optimization models that combine aspects of competence management which have thus far been analyzed separately. We present such potential avenues for future research in a separate section.

The remainder of this paper is structured as follows. Section 2 describes the review process and provides a descriptive analysis of the selected publications. Section 3 focuses on insights and theories related to learning, forgetting, and training. Section 4 describes the influence of competence management on the strategic and tactical decisions of companies, while Section 5 considers the operational production decisions. We consider competence management-related issues in Economic Order Quantity (EOQ), worker assignment, assembly line balancing, cellular manufacturing, and machine scheduling problems. In Section 6, we conclude and provide avenues for further research.

2 Methodology and Review Process

We follow the approach of Okoli and Schabram (2010) to provide a systematic, explicit, comprehensive, and reproducible (Fink, 2014) state of the art Structured Literature Review (SLR). This involves four phases: *planning, selection, extraction, and execution.*

2.1 Planning Phase

The purpose of the search is determined by utilizing the taxonomy for literature reviews by Cooper Cooper (1988). Therefore, we first defined the *focus, goal, perspective, coverage, organization, and audience* of the review. This conceptual review focuses on a neutral and integrated representation of theories and utilized research methods, and it addresses general and specialized scholars who may benefit from an exhaustive overview (with selective citations) on research conducted in the field of operations management and management science on competence management. Given this purpose, the following screening criteria were employed. The search queries were limited to the years 1998 to 2019. Articles published in 2019 were only included up until the actual date of the search, January 31st, 2019. To provide a comprehensive overview, we chose the most relevant journals from the field of operational research and management science: *European Journal of Operational Research (Eur. J. Oper. Res.), International Journal of Production Research (Int. J. Prod. Res.), International Journal of Production Economics (Int. J. Prod. Econ.), Management Science (Manag. Sci.), Operations Research (Oper. Res.), The International Journal of Management Science (OMEGA), Journal of Operation Management (J. Oper. Manag.), Production and Operations Management (Prod. Oper. Manag.), Manufacturing & Service Operational Research (Manuf. Serv. Oper. Manag).* Consistent with the goal and focus, the keywords were restricted to competence-related terms. In this regard, the term ‘competence management’ is used to integrate 15 keywords relating to learning theory, means of training, and employee competencies. From these keywords, seven search terms were selected: *learning [learning curve, absorptive learning], training [cross-training], forgetting, competence/ies [competence management, competence development], skill/s [employee skills], experience, hiring.* The title, abstract, and authors’ keywords were respectively screened for the above search terms. In addition to the retrieved articles, the most relevant publications related to either competence management or operational research / management science were also included.

2.2 Selection

Two databases were considered in order to obtain journal articles. The advanced search of *Elsevier* was used to identify articles from the *Eur. J. Oper. Res., Int. J. Prod. Econ., J. Oper. Manag. and OMEGA*. The selected search terms were entered individually into the search to screen *Title, Abstract or Author-Specified Keywords*. Further, the database *Ebsco Host* was used to search the remaining journals. The results (2448 articles) from both databases were exported as individual bib.tex files for each journal and keyword, labeled with the corresponding keywords, and merged to eliminate duplicates.

2.3 Extraction

The pre-screening of the remaining 2398 articles was based on both the keyword combinations and the journals. Regarding the keyword *experience*, a complete screening was conducted for the abstracts from the Eur. J. Oper. Res.. Since the majority of the publications solely included the term *computational experience*, the screening procedure was adapted for all journals, and only articles that either included the term *experience* independent from *computational experience* or, in addition, at least one of the expressions *employee, workforce, worker, or work* were considered in order to cover all articles related to human labor. Articles that do not match this condition were excluded. All remaining abstracts were screened by one of the reviewers. Articles that did not consider employee skills or competencies as well as those that are not related to production processes and decisions were excluded. Following the pre-screening 216 journal articles were selected for an in-depth screening process, after which 200 articles remained. These publications were thoroughly read, summarized, and categorized.

2.3.1 Journal and Keyword Distribution

The majority of the 201 papers had been published in the Int. J. Prod. Res. (32%) and the Eur. J. Oper. Res. (30%), closely followed by the Int. J. Prod. Econ. (22 %). The remaining journals each represented 1 to 7 % of the total results; for a detailed distribution, see Figure 1.

Figure 2 depicts the percentage of articles that were labeled with a keyword, and the share of the totally assigned keywords, as articles may have had more than one label. Both ratios indicate that learning was by far the most frequent keyword considered. In 73.13 % of the articles, human learning processes had been considered in the underlying research. Of these, 40.30% of the publications were solely labeled as *learning*. In total, learning accounted for 46.82 % of all keywords. While the impact of employee learning was considered by many researchers, training (21.89%) and forgetting (19.40%) effects seem to have been assessed less frequently. Experience (17.91%) and skill (15.92%) were considered in 15-20% of the articles, which corresponds to roughly 10-15% of the total number of keywords. Competencies and hiring were only considered in 3.98 % of the articles. Overall, after adding relevant survey or research articles, 254 publications have been included in this review.

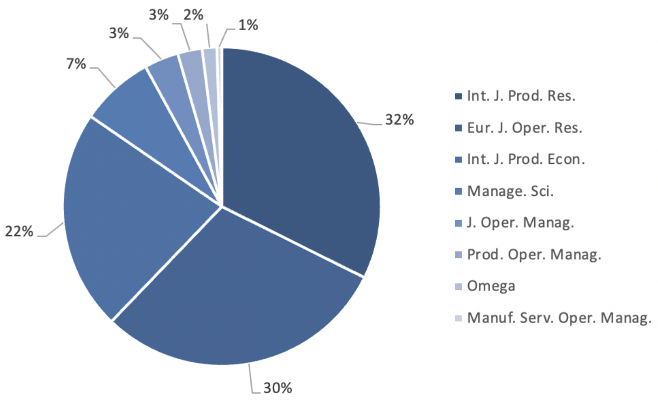

Figure 1: Average Forgetting per Capacity

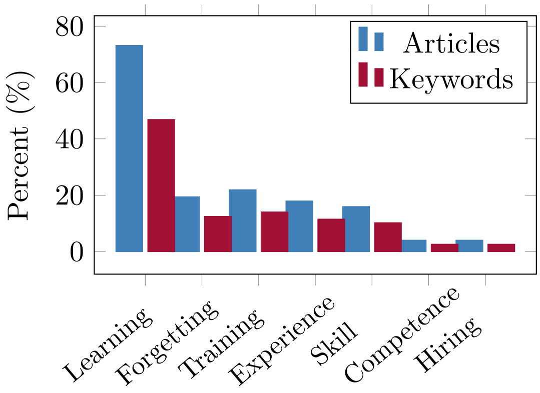

Figure 2: Percentage of articles that contain the keyword (based on 201 articles) and percentage of keywords assigned in total (based on 314 Keywords)

3 Skill development

This section focuses on different aspects of employee skill development and their interconnections. A brief overview of the concepts is displayed in Figure 3. A workforce can either be modeled as a homogeneous pool of workers or consisting of employees holding distinct categorical or hierarchical skills and competencies at different skill levels. The nature of the skills required (for example, technical or social skills) is determined by the production environment. These competencies can be developed over time. Sections 3.1 and 3.2 describe the drivers behind learning and forgetting processes, while Section 3.3 focuses on the development of learning and forgetting curves. Section 3.4 considers the influence of induced learning or training and also addresses cross-training.

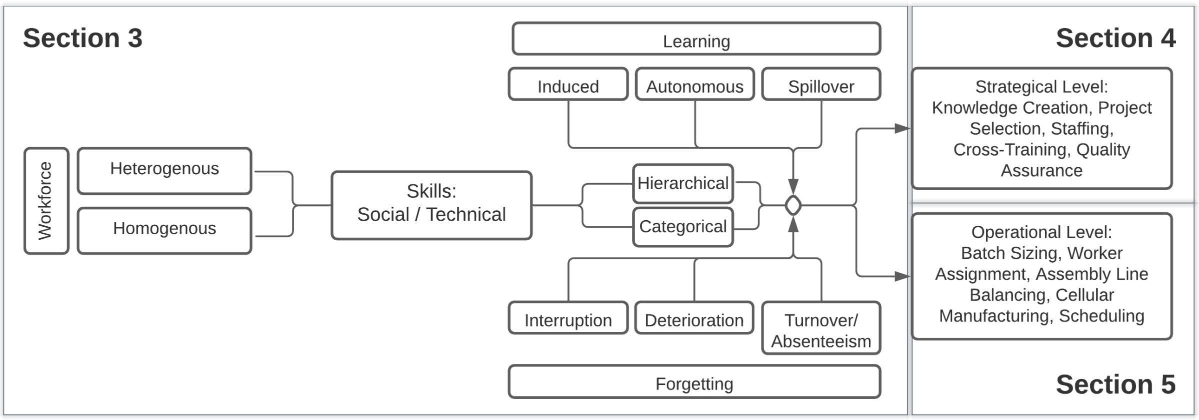

Figure 3: Aspects of skill development decisions

3.1 Learning

In 1936, Wright (1936) discovered that unit processing times decrease at a uniform rate when accumulated production output doubles. Building on his discovery, numerous studies analyzed these underlying relationships in different industries. Yelle (1979) reviewed publications that consider learning, progress, and experience curves, comparing the different models and uniformly denoting them using the now standard term *learning curves*. Dutton and Thomas (1984) considered the results of 200 empirical and theoretical publications and discovered that learning rates vary between 60%-90%, with 80% being the most common rate. Hirsch (1956) found learning rates to be up to 50% higher in labor-paced production environments compared to machine-paced ones. However, these learning rates differ not only with regard to tasks and employees but also between companies and production plants using the same production equipment (Yelle, 1979; Argote and Epple, 1990; Wiersma, 2007; Argote, 2013). Utilizing aggregated learning curves, which do not account for worker heterogeneity and different skills and abilities, leads to an underestimation of the productivity (Shafer et al., 2001; Howick and Eden, 2007). When examining different aspects of worker heterogeneity, Nembhard and Shafer (2008) found that the learning rate, initial experience, and steady-state productivity distinctively influence the output. These factors are further able to mitigate negative effects from, for example, turnover when utilized thoughtfully. Four main factors were found to drive firms' improvement: technological changes, human learning, local industry and firm characteristics, and scale effects (Dutton and Thomas, 1984). In a company, learning happens on the managerial level - due to experience in organizing and planning processes - the tactical level, and the operational level - as a consequence of employee learning (Vits and Gelders, 2002). In contrast, scale effects driven by production volume can be interpreted more as a causal factor that increase the speed of improvement and experience gains (Vits and Gelders, 2002). Li and Rajagopalan (1998) suggested including not only production volume but also the interplay between learning effects, price decisions, demand, and knowledge depreciation into production planning. Because both the time needed to pursue tasks and the amount of waste production decrease with repetition, the costs incurred also decrease (Lapré et al., 2000; Chen et al., 2010) whereas product quality increases (De Bruecker et al., 2015). Moreover, learning influences the rate of non-conforming items, which in turn affects the need for rework (Ittner et al., 2001) and the quality of such rework (Giri and Glock, 2017).

When searching for factors that characterize an environment which stimulates the learning process, Wiersma (2007) identified the slack time available for learning, product heterogeneity, and a mix of temporary and permanent workers. Other important factors for knowledge gathering and learning are decision autonomy and organizational experience (Haas, 2006). While task repetition is known to be one main driver for learning-by-doing, Schilling et al. (2003) found that small variations in tasks lead to higher learning rates relative to pure specialization. In addition to individual learning, team learning also influences productivity (Reagans et al., 2005). Bennour and Crestani (2007) developed a model that allows individual as well as collective competencies to be included into process performance measurement. On the other hand, Letmathe et al. (2012) hint that information feedback on the task performance leads to information overload.

3.2 Forgetting

As a counterpart to learning, different aspects of *forgetting* are known to influence production performance negatively (Globerson, 1987; Li and Rajagopalan, 1998). These effects may arise in monotonous production environments with consecutive repetition of similar tasks and movements, due to ergonomic factors, a lack of motivation (Anzanello et al., 2014), boredom (Azizi et al., 2010) or fatigue (Digiesi et al., 2009; Dode et al., 2016). Boredom can also lead to dissatisfaction and absenteeism of employees, accidents, and decreased productivity due to a loss of interest in the task (Azizi et al., 2010). In contrast, experience with the production task, analytical skills, and social interaction have a positive impact on productivity (Kiassat et al., 2014). While night shifts, as well as work on Mondays and Fridays, increase failure rates in production, adding shift experts and reducing production rates may be utilized as intervention methods that prevent these forgetting effects (Kiassat et al., 2014). A more prominent source of forgetting is the interruption of production processes. Empirical research found different factors that influence forgetting caused by task interruption. Bailey (1989), Globerson et al. (1989), Dar-El et al. (1995), and Schultz et al. (2003) independently provide insights on the amount of knowledge forgotten, which depends on the number of interruptions, the duration of the interruptions, and the knowledge acquired previously (Jaber et al., 2003). Different drivers that have been identified include the loss of information from the immediate memory (Delasay et al., 2019), a break in work rhythm (Schultz et al., 2003), and a general loss of knowledge about the underlying production task. Interruptions can occur when cross-trained workers are reallocated to another product or station (Jaber et al., 2003), when changes in production, technology, or product design are introduced (Vits et al., 2006; Jaber et al., 2003), or when production is disrupted (Howick and Eden, 2007; Wang et al., 2013). Such disruption can occur due to bottlenecks caused by suppliers (Wang et al., 2013), machine failures, or planned and unplanned maintenance activities (Marmier et al., 2009).

3.3 Learning and Forgetting Curves

The first quantitative learning curve is the log-linear model, also referred to as the Wright Learning Curve (WLC) (Wright, 1936). Specifically the function $T_n = T_1 * n^{-a}$ describes the processing time T_n, of the n^{th} unit of a product, dependent on the time T_1, needed to produce the first unit, as well as the learning rate l which defines the coefficient $a \equiv \log(l)/\log(2)$. Extensive research has been carried out on learning curves, refining the assumptions made and evaluating the reliability of the proposed concepts (Yelle, 1979). Since different survey articles have already analyzed these models in depth, we only provide a short overview. For more detailed evaluations, consider Yelle (1979), Hackett (1983), Badiru (1992), Nembhard and Uzumeri (2000), Anzanello and Fogliatto (2011), and Grosse et al. (2015).

Learning Curves Assuming that processing times also depend on machine times that are not influenced by learning, De Jong (1957) modified the WLC by considering a plateau effect to prevent processing times from converging to zero. To that end, he included an incomprehensibility factor, $0 \leq M \leq 1$ into his Plateau Learning Curve (PLC) to assure a minimum standard processing time $T_1 * M$. Another approach to incorporating plateau effects is discussed in Baloff (1971), who simply defines a steady-state processing time C. Li and Rajagopalan (1998) provided an endogenous explanation for the plateau effect by including a depreciation rate for knowledge into the learning curve to cover i.e. turnover effects. The Stanford-B curve by Asher (1956) incorporates prior experience, while the S-shaped model by Carr (1946) accounts for a slow start-up phase due to changes in methods, design, and technology (Baloff, 1971). Anzanello and Fogliatto (2011) and Grosse et al. (2015) reviewed different exponential and hyperbolic learning curves, which consider either decreases in processing times or increases in production efficiency. Smunt (1999) provided a continuous formulation for the log-learning model which allows an estimation of the productivity at any point in time, instead of at discrete steps which are used, for example, by the WLC a consequence of production units. By incorporating learning effects for any necessary rework Jaber and Guiffrida (2004) developed the Quality Learning Curve (QLC) as an extension to the WLC. In later publications the QLC was extended, first through inclusion of an out-of-control state of the system that produced defect items until the restoration of production (Jaber and Guiffrida, 2008), and second by extending this model to include multiple production stages (Jaber and Khan, 2010). A company-data-based comparison by Ittner et al. (2001) showed that learning curves that include not only quality investments but also learning-by-doing effects on defect rates provide more accurate estimations in comparison to models that omit the latter. A deterministic model by Sáenz-Royo and Salas-Fumás (2013) combines learning - in terms of total factor productivity as a consequence of an increasing stock of knowledge - with a Cobb-Douglas function, capturing exogenous improvement factors in terms of capital investment and labor supply. Their model captures different possible shapes in the resulting learning curves.

Shafiei-Monfared and Jenab (2011) accounted for the inherent different characteristics of tasks by introducing a learning curve that includes two parameters that influence the learning behavior: the task complexity and the required cognitive ability. The underlying curve consists of a logarithmic learning part for the initial periods and a linear part that describes plateauing processing times. Dar-El et al. (1995) provided a dual phase learning model (DPLM) by splitting the task processing time and the learning coefficient into a cognitive and a motor part. Although many different models have been proposed, different empirical and computational studies have found the basic WLC the most appropriate to capture employee learning (Yelle, 1979; Globerson, 1987; Globerson and Gold, 1997; Dar-El et al., 1995; Hansen and Grunow, 2015).

Forgetting Curves In addition to the general drivers that lead to forgetting, Jaber et al. (2003) also accumulated criteria connecting learning and forgetting curves. These indicate that the learning and the forgetting rate are mirror images and both therefore depend on the complexity of the underlying task. In addition, the rate at which workers relearn after forgetting equals the original learning rate. Finally, Jaber et al. (2003) state that power-based models are capable of capturing forgetting effects.

Nembhard and Osothsilp (2001) presented an extensive comparison of different models capturing forgetting effects. They divide the models into two categories: deterministic and statistical models. While statistical models need an upfront estimation of parameters to calculate the effect of forgetting, deterministic models directly calculate the effects of forgetting, similarly to the WLC. They express forgetting by using a function $T_x = T_1 * x^f$. Here, T_1 is the time needed for the first unit which could be processed after the interruption, x the number of potential output units during the break, and f the forgetting rate. Carlson and Rowe (1976) introduced the Variable Regression Variable Forgetting model (VRVF) with a variable time T_1 accounting for the previously gained experience and a fixed forgetting rate f. By using a forgetting rate that depends on the learning rate, Jaber and Bonney (1996) presented the learn-forget curve model (LFCM). Comparing both effects, Jaber et al. (2003) found the LFCM captured more forgetting criteria, because the rate at which forgetting occurs depends on the learning rate at the time of an interruption. Consequently, both curves will be mirror images. When comparing the VRVF and LFCM in a computational study, the authors found only small deviations from real data when using the LFCM for predictions. Jaber and Sikström (2004) compared different learn-forget curve models with respect to different learning scenarios that account either for cognitive or motor tasks. For this purpose, they calculated prediction values for different lengths of interruption and initial processing times. Results show that learning rates influence the prediction performance of the models.

As an extension, Jaber and Kher (2002) combined the LFCM with the dual phase learning model (DPLM) in a dual phase learn-forget model (DPLFM) that distinguishes between cognitive and motor tasks. Zamiska et al. (2007) showed that this distinction influences deployment policies as well as the effect of upfront training, which counters forgetting. Not accounting for this distinction can therefore lead to fewer machine transfers due to more forgetting. Alamri and Balkhi (2007) introduced a generalized learn-forget curve model (GLFCM) by including an arbitrary demand rate and deterioration for items in storage, which may reduce the inventory level over time, into the LFCM. Mazzola et al. (1998) considered combined learning and forgetting effects in a multi-product setting. Here, workers forget if the number of repetitions does not reach a given threshold. Learning effects in turn are recorded only if a minimum number of repetitions is exceeded. Hence, the intermediate range purely maintains the knowledge level. In contrast Kim and Seo (2009) modeled forgetting as depreciation. The amount of knowledge does not depend on the time or number of interruptions, and the authors instead assumed knowledge depreciation to take place during the production of one unit of a product. Thus, the amount of time that passes from starting the production of one unit until the beginning of the next unit defines the amount forgotten, which assumes that each unit consists of an infinite number of small dissimilar operations. As a consequence, forgetting effects are present during production. Nevertheless, the stock of knowledge increases with each unit processed.

Parameter Estimation Oftentimes it is not possible to accurately estimate learning rates using historical production data (Boucher and Li, 2016), given that these data can incorporate different long- and short-term improvements; these improvements can consist of single improvement policies or of steady improvement processes (Dutton and Thomas, 1984). Two approaches that increase the estimation quality are certain levels of data aggregation as well as carefully including error terms. Smunt and Watts (2003) utilized minor levels of data aggregation via regression analysis to use production data for estimating learning rates. Uzumeri and Nembhard (1998) fitted personalized performance data in order to derive learning curve parameters for a hyperbolic learning curve. A two-step approach was used to first fit the individual data to learning curves and then calculate the best-fit estimates to describe the overall worker pool. Estimating these parameters from historical data yields significant deviations from reality if the error term utilized is an exogenous variable that does not influence the learning rate itself. To obtain better estimates and more accurate production planning, Boucher and Li (2016) considered an endogenous error term for the WLC.

3.4 Training

Dutton and Thomas (1984) distinguished two types of learning; autonomous learning and induced learning. *Autonomous learning*, also referred to as *learning-by-doing*, is considered to be free of managerial influences and happens somewhat automatically as a consequence of task repetition (Terwiesch and Bohn, 2001). *Induced learning*, on the other hand, summarizes improvements in production performance due to an investment, i.e. in training, knowledge, changes in the production environment or processes (Biskup, 2008), or deliberate experiments (Terwiesch and Bohn, 2001). Employee training can be further categorized as *endogenous* or *online* training that takes place during production, and *exogenous* or *offline* training that is independent of production (Vits and Gelders, 2002). A survey by Upton and Kim (1998) found that companies base their decision about whether to introduce up-front offline learning or online learning on their own experience with these concepts, instead of evaluating which procedure would best fit the production environment. Büke et al. (2016) argue that the choice of the right amount of training measures should be based on the underlying training costs. Despite the positive aspects of training initiatives, higher salaries for experienced workers (De Bruecker et al., 2015) and the interplay of training and holding costs need to be taken into account (Valeva et al., 2017b; Sleptchenko et al., 2019). In this context, Valeva et al. (2017a) presented a production planning model assigning workers with different learning rates, steady-state productivity, and prior experience to training measures or tasks. The underlying production environment is characterized by stochastic demand which can be met by production or inventory stock, as such stocks allow for buffer capacities.

3.4.1 Cross-Training

De Bruecker et al. (2015) divided employee skills into *hierarchical* and *categorical skills*. Hierarchical skills allow employees with a higher skill level to perform a certain task better. Categorical skills, however, allow workers to pursue a broader range of production activities and operate several machines (De Bruecker et al., 2015). While hierarchical skills are reflected in learning curves and can be achieved by autonomous learning, multiple skills demand specific cross-training or job-rotation (Ortega, 2001). Rogers et al. (2011), Xu et al. (2011) and Qin et al. (2015) analyzed cross-training as a means to achieve a multi-skilled workforce with increased flexibility and capability to react to changes in the production environment. Rogers et al. (2011) identified labor flexibility as one of six factors influencing manufacturing flexibility that can yield a competitive advantage. Multi-skilled workers can counter delays as a consequence of expected and unexpected absenteeism of coworkers (Inman et al., 2004; Olivella and Nembhard, 2016), who otherwise need to be replaced by untrained temporary workers (Cohen, 2012). Moreover, the production system's performance can be increased by cross-trained employees working in bottleneck stations (Hopp et al., 2004; McCreery et al., 2004; Sennott et al., 2006) by reducing the amount of work in progress (Hopp et al., 2004; Bokhorst, 2011) and idle times of machines. Further, production capacity, average productivity, and employee motivation increase (Nembhard, 2007). Job-rotation in production can also be used to foster motivation by countering boredom (Ortega, 2001; Bhadury and Radovilsky, 2006; Azizi et al., 2010). Cross-training affects production costs, quality, and time positively, and allows for more product variety (Hopp and Van Oyen, 2004). Generally speaking, firms often face a trade-off between high productivity due to learning and training and meeting the demand. This trade-off is reinforced by demand volatility that decreases average productivity (Anderson, 2001). The value of a flexible workforce therefore increases with higher demand volatility (Campbell, 1999; McCreery et al., 2004), as cross-training allows companies to counter demand fluctuation and other external variations (Nembhard, 2007). It is not important whether the breadth (number of machines, tasks) or the depth (level of skill) of cross-training is considered, as the resulting effects were found to be interchangeable (Campbell, 1999). Cross-training is particularly beneficial when high labor utilization, variability in processing times, and worker absenteeism are present (Yang, 2007).

However, cross-training can also have disadvantages. Whereas it improves flexibility and increase buffers against different types of volatility, it suppresses positive effects of employee specialization. While product variety benefits from cross-training, higher task complexity benefits from having parallel work teams of specialized workers (McCreery et al., 2004). More complex tasks yield slower performance gains through lower learning and higher forgetting rates; therefore specialization and restrictive deployment policies are favorable (McCreery et al., 2004). Demand uncertainty and worker attendance both require more flexibility and, hence, lead to more cross-training, a higher staffing level, and less specialization of workers (Easton, 2014). Nevertheless, several studies found that small levels of cross-training already yield flexibility gains comparable to full cross-training (Sennott et al., 2006; Yang and Kuo, 2007; Gnanlet and Gilland, 2014; Akşin et al., 2015). Qin et al. (2015) identified five types of costs connected to cross-training: lower productivity, quality losses due to forgetting effects, transfer and switching costs, training costs, and increased wages paid to higher-skilled employees. Moreover, non-monetary costs arise due to transfer delays (Xu et al., 2011) when switching a worker to another machine or time spent in offline training away from production. Thus, the amount of cross-training must be calculated carefully. Kher et al. (1999) showed that high turnover and forgetting rates make even a small amount of cross-training infeasible, as the environment does offset effects of higher workforce flexibility. Under such conditions, upfront training measures also cannot foster flexibility (Kher et al., 1999). To reap gains from a cross-trained workforce, Costa and Miralles (2009) utilized job-rotation goals by maximizing the number of different tasks pursued by each worker while maintaining sufficient levels of productivity and quality. A study by Houghton and Portougal (2005) suggested combining the specialized workers of multiple production lines to obtain one joint worker pool of multi-skilled workers and reduce production costs in Just-In-Time (JIT) production environments. Bokhorst and Gaalman (2009) analyzed cross-training in the context of a dual resource-constraint system, where production is restricted by workers and machines with different capabilities. The authors found that pooling the workforce by full cross-training is beneficial only if mean processing times of different products exhibit little variation. Therefore, they suggested cross-training or pooling for similar tasks and similar machines only. Overall, the positive and negative factors that are present in the underlying production system must be taken into account carefully when deciding about cross-training policies.

3.4.2 Cross-Training Policies

Cross-training policies focus on assessing how many employees should be trained in various skills (Xu et al., 2011). These policies span a variety of approaches ranging from the specialization of all workers to a single task over to full cross-training environments, where all workers are enabled to pursue every single operation (Akşin et al., 2015). An example of a policy with a high level of cross-training is the use of nested environments. On the lowest level, an employee possesses only a basic skill. An employee on the next higher level has the same basic skills plus an additional one. With each level in this hierarchy, such new skills are added. Employees at the highest level are able to pursue all tasks (Akşin et al., 2015). For other examples of policies, such as adjacent or overflow structures, we refer to Akşin et al. (2015). Policies that demand a lower level of cross-training include the cherry-picking of workers or skill chaining (Yang and Kuo, 2007). In cherry-picking policies, workers from other stations are trained to support a bottleneck station; thus, they can be cherry-picked to that station (Yang and Kuo, 2007). Jordan and Graves (1995) introduced skill chaining by enabling each worker to perform their task and the task of their successor in the production process. Such a chain is called 'complete' if the last worker in the chain is able to perform the task of the first worker (Jordan and Graves, 1995; Inman et al., 2004). Several studies have analyzed cross-training policies under different circumstances, and there is general agreement that skill chaining is the most efficient cross-training policy (Hopp et al., 2004; Inman et al., 2004; Yue et al., 2008; Gnanlet and Gilland, 2014; Akşin et al., 2015). Inman et al. (2004) found lost sales from an automotive assembly line to be comparable for full and chained cross-training. In addition, a long chain outperforms several small chains regardless of the scenario (Yue et al., 2008) and the queuing policy (Hopp et al., 2004). Overall, a better clustering of skills can lead to decreased service time variability and inventory reduction (Sleptchenko et al., 2019). Regardless of the potential benefits of cross-training, company skill targets can be used in an environment with high learning rates to foster the specialization of workers while maintaining a broad skill portfolio in the company without cross-training workers (Heimerl and Kolisch, 2010).

Yue et al. (2008) emphasized that cross-training decisions, such as determining the number of skills per worker, the distribution of skills to employees, and the way in which skill chaining is introduced must be made carefully. These decisions need to align with the learning and forgetting behavior of the workers, and individual learning rates need to be considered (Yue et al., 2008). Based on a simulation study, Mccreery and Krajewski (1999) suggested that the level of cross-training and the worker deployment policies cannot be determined without considering the product variety and task complexity of the underlying production environment. Bokhorst (2011) showed that an appropriate and lower level of work in progress can help maintain cross-training levels. This counteracts the employees' tendency to only use their preferred skill set. However, assigning workers to machines which best meet their skills when the majority of workers are cross-trained can lead to blocking proficient machines with inefficient workers (Yang, 2007). A model to assess the optimal amount of cross-training for given levels of worker absenteeism and demand variation

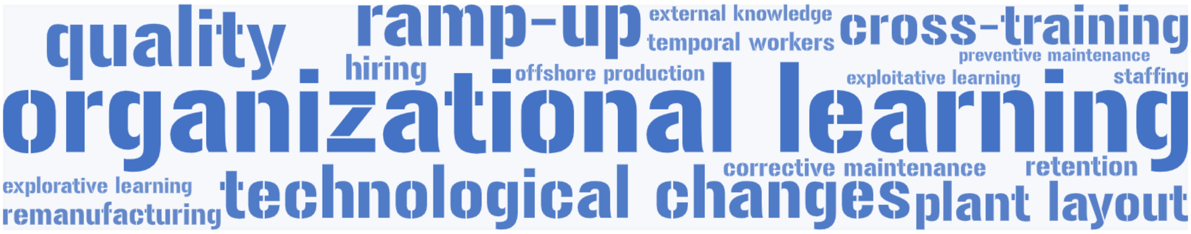

Figure 4: Aspects of strategical decisions

is presented by Olivella and Nembhard (2016). For remanufacturing scrap parts, Sleptchenko et al. (2019) assigned skills to workers under consideration of the trade-off between costs for cross-training and holding or backorder costs. For a comprehensive review of cross-training, which includes more models, we refer to De Bruecker et al. (2015) and Qin et al. (2015).

4 Strategic Decisions Affected by Competence Management

Organizational learning unites the different decision areas which manage the knowledge creation process in companies (Vits and Gelders, 2002). As depicted in Figure 4, these encompass the production layout of a firm, out-sourcing decisions, skill requirements, knowledge creation, change management, staffing and training decisions, and project selection. This section focuses on strategic aspects of these decisions related to knowledge creation.

4.1 Production Design

In addition to the prerequisite competencies that employees possess, the production setting also determines to what extent firms can leverage skill development. To support managerial decisions about plant layouts, Franceschini and Galetto (2003) developed an experimental approach that derives a composite learning curve considering several serial or parallel blocks of production that exhibit different learning properties. Different composite serial and parallel elements of production can be combined in a model to compare distinct production layouts with respect to learning, costs, and quality management in terms of reducing scrap parts. Fioretti (2007) adapted the minimal cost path model, first introduced by Huberman (1997), to support companies to assess the learning potentials provided by their workforce, equipment, and production tasks. Since the profitability of a product depends on the employee assigned to the required tasks, Ortega (2001) argued that job rotation could be used to generate more knowledge about the whole workforce by observation and evaluation of production. Bock (2008) considered decisions on outsourcing production. When task complexity is low, high cost savings from low wages can be achieved. Otherwise, potential low skill levels of offshore workers can hinder efficient production. Results from Heimerl and Kolisch (2010) support this finding by showing that it is the most efficient to outsource those tasks which incur the lowest costs.

4.2 Organizational Knowledge Creation

Organizational knowledge creation generally recognizes two distinct concepts. Exploitative learning focuses on refinements and gradual improvements of existing products. Explorative learning, on the other hand, seeks to identify and implement new inventions (Li et al., 2013b; Tamayo-Torres et al., 2014). As components of organizational learning, the impacts of explorative and exploitative learning on new product development are compared in a study by Li et al. (2013b). They suggested a planned mix of both learning approaches as well as a working environment that provides employees with time and freedom to foster new product development and to avoid the familiarity trap of exploitative learning. Tamayo-Torres et al. (2014) used structural equation models to assess the influence of an ISO 9001:2000 certification on manufacturing flexibility and organizational learning. Contrary to their expectations, the ISO certification does not reduce manufacturing flexibility; instead it has a significant positive influence on both learning dimensions, explorative and exploitative. Lapré and Van Wassenhove (2001) found that management involvement and intra-departmental knowledge are means to accelerate the learning curve when transferring experimental knowledge to real production lines. Learning effects can be triggered by endogenous as well as exogenous factors (Dutton and Thomas, 1984). Kogan et al. (2017) used equilibrium games to compare the influence of in-house and spillover learning from other companies, under different learning and forgetting rates. They showed that spillover learning from other companies contributes to the company's competitiveness in addition to the company's internal proprietary learning. Huang et al. (2008) provided evidence on the influence of both internal learning and external learning on mass customization capabilities as a consequence of problem-solving activities with suppliers and customers. This relationship is further mediated by the firm's process implementation efficiency, i.e. the capability to develop new processes and implement changes in technology and equipment. As a source of external knowledge, Haunschild and Rhee (2004) considered recalls from the automotive industry. They found that learning has a greater impact when these recalls are voluntary. To leverage suppliers' learning effects, companies can split the first period's order between two companies (Basu et al., 2018). In the second period, suppliers bid to gain the contract for the following periods. This encourages suppliers to invest in an efficient production ramp-up and fosters learning processes. Argote and Hora (2017) focused on the transfer and retention of organizational knowledge within companies. This knowledge is embedded in the members, tools, and tasks of a company. In other words, tacit and explicit knowledge can be transferred along a network defined among these dimensions.

4.3 Change Management and Production Ramp-Up

Employee skill development is of particular interest when changes in production occur. As a consequence of these changes, workers have to adapt to new working conditions, i.e. after the acquisition of production equipment, production ramp-ups, or general adjustments in production workflows (Biskup, 2008). Such changes often lead to disruptions of the production process (Carrillo and Gaimon, 2004; Howick and Eden, 2007), decrease the existing knowledge of employees (Vits et al., 2006), and may lead to fatigue effects that impact product quality (Dode et al., 2016). As a result, the introduction of technology, production, and product changes requires careful planning.

The implementation of such changes is further prone to uncertainties (Carrillo and Gaimon, 2004) and should be synchronized with the learning rate of employees and the demand for products (Chambers, 2004). While higher learning rates can lead to earlier implementation of necessary changes, high demand can result in a postponed adoption at the time the learning curve's plateau is reached. (Chambers, 2004). Aside from necessary product changes to align with customer wishes, investment in new production equipment and technologies can increase production efficacy and decrease production costs (Vits et al., 2006). Several models have been developed to support process changes or generate insights on managing these changes.

To assess the costs of changes in technology or production processes, Nadeau et al. (2010) introduced a static process-based cost model. Their model incorporated various operational drivers such as reject rates, downtimes of production, and cycle time learning. Howick and Eden (2007) showed that disaggregating the organizational learning curve to capture individual learning and forgetting effects leads to more accurate estimates of the impact that process changes may have. Pan and Li (2016) presented an optimal control model minimizing the production costs, which depend on the accumulated knowledge due to learning-by-doing and the investment in innovation. The interplay of investments on process changes to increase capacity, knowledge acquisition, and learning rates was considered by Vits et al. (2006). Their results indicate that the optimal process change level increases with the amount of knowledge accumulated by training initiated to prepare for changes as well as the process change learning rate. On the other hand, the optimal investment decreases when the production capacity is already at a high level. The same authors extend their study by considering an investment in process knowledge (Vits et al., 2006). Here, an opposite effect was identified. The investment in process knowledge, by hiring employees or utilizing training measures, increases with production capacity and decreases with previously gained experience (Vits et al., 2007). Carrillo and Gaimon (2004) considered the trade-off between investment in training and process changes. Both are connected with uncertainties and contribute to the production capacity. Their model allows maximization of the expected profit and reaching an expected knowledge target while minimizing the uncertainty.

Terwiesch and Bohn (2001) analyzed the interplay of learning from offline experiments, high capacity utilization, and yields in the early stages of production. Results show that the time-to-volume, i.e. more efficient production capacity utilization due to experience, should be prioritized. Therefore, capacity should be reduced in the early phase to invest in speed and yield improvements (Terwiesch and Bohn, 2001). Alvarez and Cerda (2003) maximized the discounted profit over the ramp-up periods to determine the optimal output flow. Hereby, investments or losses can be assessed in early periods of production as well as when the full productivity is reached. Demeester and Qi (2005) presented a model for allocating training resources between two production lines in the case where a product is being replaced by a new generation of the product. Here, the incremental productivity gains due to learning effects for the original product decrease as well as the importance of the original product and the demand for it. A production-planning model for managing the ramp-up of new production is presented by Glock et al. (2012). Following a numerical analysis, the authors suggested synchronizing production and demand by establishing a constant production rate or reallocating employees. This avoids production interruptions, which in turn leads to minimal costs (Glock et al., 2012). Since the results depend on the length of the ramp-up phase, this model should only be utilized until steady-state productivity has been reached. Hansen and Grunow (2015) introduced an extensive capacity planning model which determines the number and location of new production lines and the inventory built upfront when the production capacity is based on the experience gained further. For this purpose, the authors model experience as a function of cumulative production output in a ramp-up curve.

4.4 Quality Assurance and Maintenance

Production quality is an important factor that impacts not only customer satisfaction but also the costs that arise when screening for, storing, reworking, or disposing of imperfect items (Alamri et al., 2016). Learning effects can help decrease the rate of defective items (Kiassat et al., 2014; Giri and Glock, 2017; Alamri et al., 2016), reduce waste production, and speed up rework times (Jaber and Bonney, 2003). Vörös (2006) considered the joint impact of product price and quality investments on demand. As a consequence of a decrease in demand over time when competitors enter the market, the cost reduction of these investments needs to exceed the reductions in revenue. In addition to learning-by-doing, the author emphasized the importance of continuous improvement and derived investment strategies and optimum quality and price paths. A study by Wang et al. (2013) suggests utilizing investments in quality improvements during supplier disruptions in order to counteract foregone opportunities of autonomous quality improvement.

In addition to learning effects and investments in equipment and training, production performance is further dependent on machine availability. Machine availability is influenced by production schedules and breakdowns. To reduce downtimes of the production system, maintenance activities need to be pursued (Tarakci et al., 2009) and a distinction is made between preventive maintenance and corrective maintenance. While preventive maintenance consists of planned activities that anticipate and prevent machine failures, the corrective maintenance restores system functionality after often unexpected machine breakdowns (Pan et al., 2014). Vahedi Nouri et al. (2013) scheduled jobs and preventive maintenance in a flow shop environment with learning and different job sequences. Higher learning effects for costs and the time involved in preventive maintenance activities increase the frequency of such activities, whereas learning from failures allows for longer maintenance cycles because failure rates decrease (Tarakci, 2016). Including both types into environments with constant failure rates, scheduled preventive maintenance activities are necessary. This contrasts with cases without learning, which demand maintenance intervals of equal length (Tarakci, 2016). Preventive and corrective maintenance activities with learning and forgetting effects for the processing times of jobs are considered in a single-machine setting by Pan et al. (2014). The authors derive inter- and intra-group schedules for jobs and preventive maintenance that minimize the expected makespan when unexpected breakdowns may occur. Marmier et al. (2009) accounted for uncertainty in processing times by proposing an approach that inserts corrective maintenance activities into an existing schedule while considering distinct employee competencies. Azadeh et al. (2013) developed a method to derive the best policies for scheduling maintenance activities when learning effects are considered. Since these services are oftentimes outsourced, (Tarakci et al., 2009) provided insights on contracts that maximize the manufacturer's and the contractor's profits.

4.5 Staffing

4.5.1 Required Skill Sets

To plan employees' skill development, companies first need to determine which competencies or skills are required for production. Siskos et al. (2007) developed a framework to evaluate knowledge and skills relevant for the information technology sector that includes both formal studies and informal knowledge gained due to experience. The resulting framework can be used to classify applicants and generate training policies. Franchini et al. (2001) presented a decision support system to evaluate skill demand, based on a schedule calculated with respect to technical resources and workload. Further, employee skills were defined, modeled, and linked to machines to derive the required skill distribution. Tiwari et al. (2009) formulated a labor assignment problem to account for cross-trained workers and different skills in a project scheduling problem. The output of the proposed model allows the identification of critical bottleneck skills that can be used to determine cross-training decisions. A different approach was introduced by Gutjahr et al. (2010), who presented a multi-objective optimization model for project selection. First, a project portfolio is selected; as a second step, workers are assigned to projects by taking the influence of different employee competencies on the tasks and production speed into account. Their model also included learning-by-doing based on the time invested and linear knowledge depreciation over time. Li et al. (2000) considered a set extension problem for competencies. In this regard the optimal steps to extend a worker's set of competencies to a desired broader one are derived while minimizing the training costs. Specifically, they incorporated intermediate skills needed to reach a certain other skill, compound skills that require certain basic skills, and cyclic connections between skills.

4.5.2 Staffing models

Aside from training employees to the desired skill level, companies can also hire experienced workers with the required skill sets (De Bruecker et al., 2015). In a production environment with high turnover rates, the negative effects on production output can be countered by employing workers with higher initial experience (Nembhard and Shafer, 2008). On the other hand, temporary or inexperienced employees may be paid lower wages (Anderson, 2001; Cambini and Riccardi, 2009; Techawiboonwong et al., 2006; Corominas et al., 2012; De Bruecker et al., 2015). Staffing models can help estimate the number of workers and skills needed. Since the actual skills of workers are often unknown, Arlotto et al. (2014) took into account that the real qualifications of employees become visible with task repetition. They incorporated hiring and firing decisions with stochastic competencies, and employee turnover into a multi-arm bandit problem. They found it worthwhile to retain workers for a longer period of time in order to assess and exploit their full potential. Active screening of employee competencies and employing higher retention rates can significantly decrease costs and increase productivity (Arlotto et al., 2014). Ortega (2001) suggested job rotation as a means to assess the qualification of workers and to discover proficient worker-machine matches. However, the authors argue that the benefits of job rotation decline for senior workers. In several simulation studies for assembly line performance, Shafer et al. (2001) found that higher previous experience is positively related to higher steady-state experience when modeling different learning and forgetting patterns. When planning retention policies, a focus on higher steady-state productivity can positively influence the production output (Nembhard and Shafer, 2008).

Most models that determine the number of workers to train, hire, and lay off distinguish between employees with lower skill levels (apprentices, temporary or external workers) (Anderson, 2001; Cambini and Riccardi, 2009; Techawiboonwong et al., 2006; Corominas et al., 2012) and experienced workers (De Bruecker et al., 2015). Further restrictions considered are overtime, stochastic demand, and shortage costs (De Bruecker et al., 2015). Anderson (2001) included apprentice workers and experienced workers in an optimal control model to derive staffing policies for hiring and layoff decisions under stochastic demand. According to their findings, firms with either long business cycles or long training periods should smooth their policies for hiring and retention. In addition to such general insights, different approaches to calculate the workforce composition with respect to the production environment have also been presented. A model by Cambini and Riccardi (2009) considers hiring temporal or external workers with low skills and internal workers with higher skills. Techawiboonwong et al. (2006) allow temporal workers to be skilled or unskilled and include overtime as well as task deployment decisions. The approach by Corominas et al. (2012) allows for assessing the benefits of hiring new employees who need to undergo training sessions, and laying off senior workers while taking cash decisions and costs for laying off employees based on their contract into account. Lastly, Mirzapour Al-E-Hashem et al. (2011) presented a detailed production planning model considering the whole supply chain with multiple suppliers, manufacturers, costumers, sites, periods, and products with uncertainty. Shortages in all stages were minimized first, followed by the total losses along the supply chain.

In contrast to the extensive research carried out on cross-training, few publications focus on categorical skills (Bordoloi and Matsuo, 2001; Wirojanagud et al., 2007; Fowler et al., 2008; Özlük et al., 2010). Wirojanagud et al. (2007) considered a heterogeneous workforce with different general cognitive abilities (categorical skills) and determined the number of workers to hire, lay off, and cross-train in each period. Fowler et al. (2008) presented a heuristic and a genetic algorithm to solve the problem introduced by Wirojanagud et al. (2007). Özlük et al. (2010) determined optimal staffing requirements by considering apprentices, capable of performing two tasks out of the three available, and senior workers, capable of doing all three production tasks. They suggest that instead of actively managing training decisions, a cross-trained workforce should be generated by determining the required staff mix. A heuristic to solve the MIP that accounts for monetary incentives for overtime hours and customer flexibility was then utilized to balance work and reduce peak workload, while minimizing costs (Özlük et al., 2010). Bordoloi and Matsuo (2001) determined the optimal steady-state level of workers with different experience levels. They obtained an optimal hiring and retention policy for a fully cross-trained workforce with nested categorical skills under random production yields and uncertain and high turnover rates. They found that optimal skill mix policies underestimate the number of experienced workers necessary to train new employees on the job and therefore do not contribute to production. Cai and Li (2000) considered staff scheduling decisions by first minimizing the costs for assigning employees to shifts while meeting the demand. Second, they maximized the monetary surplus among the periods. Finally, they considered a balanced solution with minimal surplus variations over multiple periods.

4.6 Summary

Competencies influence various strategical organizational decisions. These range from deciding on how to create and manage new knowledge and products, to organizing the knowledge distribution within a company, to introducing process changes, and to making workforce and quality decisions. Crucial factors are the upfront determination of the competencies and skills needed for production, the learning potential of the production environment, and the potential sources that might inhibit efficiency gains. Therefore, not only the composition of the workforce itself is relevant, but also the design of production lines, outsourcing and contracting decisions, and technological changes play an important role. The majority of aspects depend on the tasks' complexity, which determines the potential for learning and the prior experience of the workforce. Complex production tasks are connected to lower learning rates and can benefit from in-house production pursued by specialized experienced employees in serial production lines, as well as from an environment with low turnover and change rates. Simple motor or low-cost tasks, however, are better suited for parallel production and outsourcing, or can be pursued by temporal or inexperienced workers. Worker experience and accumulated knowledge impact the introduction of changes in production and the timing of training. Studies show that investments in changes should be postponed until some knowledge of the production process is established to avoid losses due to forgetting, while employee training is most beneficial in the early phase of production. The task complexity, turnover rate, and product variety are essential when deciding about cross-training employees. Generally speaking, however, numerous studies agree that moderate levels of cross-training yield higher flexibility and can outperform pure specialization as well as full cross-training and full flexibility.

5 Operational Decisions Affected by Competence Management

Since the impact of employee competencies depends on the production environment, the remainder of this section is clustered according to various environments; assembly lines, batch sizing, cellular manufacturing, machine scheduling, and worker assignment problems,.

5.1 Batch Sizing

Economic Order Quantity (EOQ) models determine the lot size of production runs while minimizing the total costs, including holding and ordering costs. While the classical EOQ model assumes constant demand over time, dynamic lot-sizing accounts for demand variations. Human labor can impact batch production in different ways. Setup (Chiu and Chen, 2005) and processing time reductions can be achieved due to learning, while forgetting effects arise when switching between batches (Jaber and Bonney, 2003; Teyarachakul et al., 2014). While forgetting effects yield larger batch sizes, learning effects (particularly for setup times), holding costs and deterioration of stored items reduce the optimal lot size (Jaber and Bonney, 2007, 2001). Chiu and Chen (2005) found that learning and forgetting effects in processing times and setups increase the optimal batch sizes, independent of demand variation patterns. The steady-state behavior under learning and forgetting with interruptions has been analyzed by Teyarachakul et al. (2014). When considering fixed batch sizes and demand rates, low skill levels lead to shorter breaks and therefore less forgetting. These results comply with a study by Jaber and Bonney (2003) which suggests that smaller batches lead to shorter breaks and fewer forgetting effects. For accurate planning, batch sizes and convergence behavior therefore need to be based on the initial skill levels of workers (Teyarachakul et al., 2014). Neidigh and Harrison (2010) assessed total forgetting between lots of different sizes. Instead of determining a fixed lot size, their model allows for variable lots while meeting a given demand over multiple periods. The authors further extended their model to fit a multi-product environment (Neidigh and Harrison, 2013). Here, production in larger batches is aspired in order to benefit from learning whenever due dates allow for it. However, producing in smaller batches leads to higher control costs (e.g., for managing batch production or shipments, congesting the distribution channels). Therefore, Jaber et al. (2009) included these entropy costs alongside learning and forgetting into a EOQ model. Jaber and Bonney (2007) distinguished between cognitive and motor tasks by incorporating the dual phase learn-forget model (DPLFM) into an EOQ model. Their results emphasize that neglecting the differences in task types can lead to unreliable batch sizes and high error costs. Pratsini and Marks (2001) considered a multi-item environment with setup time learning and cross-learning effects between similar tasks. The authors analyzed different policies in a simulation study. Although learning effects due to batch production suggest a lot-by-lot production of similar products, demand satisfaction and holding costs make simple policies that allocate production capacity equally among product types more beneficial.

Monitoring production quality is especially important for batch production. Identifying defective items at the end of a production run and implementing process improvements to increase quality will result in decreasing lot sizes Urban (1998). Smaller batches are appropriate even in the presence of forgetting effects and without setup times learning effects (Urban, 1998). In contrast, dividing costs for rework into fixed material costs and labor costs subject to learning leads to larger batch sizes (Jaber and Bonney, 2003). Alamri et al. (2016) considered an EOQ model with items that need 100% screening due to their deteriorating and perishable nature. As the authors' model accounts for storage, rework, or disposal costs of defect items; defect rates decrease with learning. A step-by-step approach for continuous improvement cycles is presented. The model can be used with different demand patterns and learning curves. A closed loop-chain model with stochastic production returns, learning, and forgetting effects, where demand depends on the sales price, was introduced by Giri and Glock (2017). Fast learning and slow forgetting results in higher recovery rates, and plateau effects in production can be utilized to improve learning due to investments in change (Giri and Glock, 2017). Jaber et al. (2010) considered the effect of coordinating lot sizes along a three-level supply chain with a supplier, a manufacturer, and a retailer. Learning processes reduce setup times, rework, as well as costs and increase capacity along the supply chain. Although the cost savings are comparable to those from coordination without learning, a contrary effect on the lot and order size was found. Accounting for learning effects results in smaller batches, whereas coordination normally leads to larger lots (Jaber et al., 2010). When considering overall costs, there is no significant impact of learning and discounting the stream of labor cost over time on total costs (Jaber and Bonney, 2001). However, optimal batch sizes do change. Ben-Daya and Hariga (2003) considered an inventory review model with investments in lead time reduction, processing time learning, and lot sizing. In a computational study, effects on the expected total costs were analyzed. Demand variation, cost of capital, and holding costs have a significant influence on the total expected costs, and lead-time reduction investments are significant in some cases. However, processing time learning has no impact compared to set-up time learning, even when total forgetting between lots is accounted for (Ben-Daya and Hariga, 2003). Feng and Chan (2019) included up- and downstream interest-free credits to stimulate demand while production learning is considered. Both effects increase the lot size and decrease the selling price, yet lead to a higher total profit value. Generally, it can be assumed that the batch size increases when the setup costs are reduced and decreases with variable unit costs. For further literature on lot sizing and learning, we refer to Neidigh and Harrison (2010).

5.2 Worker Assignment

Classical worker assignment problems aim to minimize total costs and completion times, or to maximize profit by assigning a set of tasks to workers (Bhadury and Radovilsky, 2006). Assigning tasks to workers with respect to their individual learning behavior reduces production time and costs (Nembhard, 2001). A heuristic by Nembhard (2001) indicates that workers with more gradual learning rates reach higher steady-state productivity. Therefore, small tasks are assigned to faster learners and large tasks to slower learners. In general, when selecting workers prior to assigning tasks, policies should account for prior experience instead of the overall production output of employees, as these are subject to learning and forgetting (Nembhard and Bentefouet, 2014). Anzanello and Fogliatto (2007) provided an approach that groups products to families based on quantitative and qualitative measures and fits learning curve parameters for different groups to assign product families to assembly line teams in short and long-run scenarios. Hewitt et al. (2015) utilized a reformulation technique to overcome the non-linearity of learning curves. Although the authors considered a specific learning and forgetting model, the approach can be applied to other learning curves as well, such as a hyperbolic, logistic, or exponential curve. The authors showed that the solutions of the non-convex problem are equivalent to the optimal solutions of the original non-linear problem.

If workers possess distinct skills, taking these abilities into account is crucial. Since competencies are often unknown, Guillaume et al. (2014) took uncertainties with regard to the competence levels as well as interaction effects between different competencies into account while minimizing the decision-maker's uncertainty.

For assessing the value of assignment decisions over multiple periods with uncertain processing times and demand in future periods, Chen et al. (2018) considered a learning curve by Nembhard and Osothsilp (2005) and presented an approximate dynamic programming approach by fitting linear basis functions in each period. Results of a computational study show that productivity gains are already determined in early periods of the planning horizon and that cross-trained workforces deliver superior results. The authors emphasize that their model can be used with any learning curve instead of the one by Nembhard and Osothsilp (2005). Olivella et al. (2013) incorporated cross-training goals for individual workers and cross-learning effects between different tasks to maximize production output while accounting for due dates of jobs. Brusco (2015) combined maximizing utility, by minimizing shortages, with desirability in terms of assignment targets. A small reduction in utility already yields higher levels of desirability, which can include cross-training or career goals (Brusco, 2015).

Along with mere skill requirements which enable workers to pursue tasks, different human factors have also been incorporated into assignment problems. In a two-step approach, Sayın and Karabatı (2007) assigned workers to departments in order to maximize the departments' utility. Here, utility is again measured in terms of shortage. Their model is based on maximizing skill development and minimizing deviation from the optimal utility simultaneously. For a parallel multi-period production environment, Nembhard and Bentefouet (2012) analyzed the structure of optimal assignments when employees learn. Their model suggests that the specialization of workers yields maximum output when learning, forgetting, and learning from similar tasks are considered. Nevertheless, the authors emphasize the importance of cross-training and suggest utilizing their model to estimate the costs for a multi-skilled workforce (Nembhard and Bentefouet, 2012). A similar approach to reducing the computational complexity and incorporating the non-linear learning curves is used by Jin et al. (2018) to form teams of workers and assign tasks to teams. Kim and Nembhard (2013) derived assignment policies based on learning and forgetting characteristics of employees. In these policies, heterogeneous workers are assigned to tasks while minimizing the number or workers (Kim and Nembhard, 2013).

Nembhard and Bentefouet (2014) proposed a holistic model which accounts for serial as well as parallel lines and different flexibility levels based on a generalist to specialist ratio. Workers are first selected from a homogeneous pool, and are subsequently assigned to tasks which are scheduled. In addition to learning-by-doing, Jin et al. (2018) considered tacit knowledge transfer as employees learn by observing co-workers in their team. Ağralı et al. (2017) took governmental labor restrictions, individual employee contracts as well as overtime hours and holidays into account to maximize employee satisfaction in a MIP model. Corominas et al. (2010) accounted for spillover learning from similar tasks when assigning workers to tasks over different periods.

Bhadury and Radovilsky (2006) presented an assignment problem minimizing the total costs of assigning tasks and employee boredom. For this purpose, the number of consecutive repetitions, the maximum number of repetitions, and a combination of both are considered. Including not only job rotation but also related penalty costs leads to a more sophisticated and cost-efficient rotation scheme over multiple periods (Bhadury and Radovilsky, 2006). Azizi et al. (2010) considered not only boredom with repetition but also forgetting effects due to an interruption as a consequence of job rotation. Therefore, their heuristic approach minimizes the delay with respect to the standard processing times in terms of productivity reduction caused by a lack of motivation and skills at the same time (Azizi et al., 2010). Explicit job-rotation goals to maintain cross-training levels were used by McDonald et al. (2009). Their assignment model minimizes the net present costs for initial training, incremental training, inventory, and poor quality. Further discussion on assigning jobs with respect to competencies can be found in Guillaume et al. (2014) and Brusco (2015).

5.3 Assembly Line Balancing

Assembly or serial production lines route tasks through precedence-constrained stages of production (Askin and Chen, 2006), where each product is divided into different small production steps. Since workers are assigned to one task type, they operate in a highly repetitive environment which provides avenues for learning (Bukchin and Cohen, 2013; Otto and Otto, 2014). Cohen et al. (2006) found that serial production lines have a shorter ramp-up phase compared to parallel production but come with lower steady-state productivity and higher risks for health-related incidents (Neumann and Medbo, 2017). Typical problems with the use of assembly lines concern idle times, i.e. blockage and starvation. If a product cannot travel downstream because the successor station is not available, the current station is blocked. Starvation occurs if the preceding station cannot provide a new task (item) to the next station (Cohen et al., 2006). As these bottleneck stations impact the output of the whole line, Assembly Line Balancing (ALB) is an important goal that aims to obtain a balanced distribution of work to employees or stations (Askin and Chen, 2006; Cohen et al., 2006; Bukchin and Cohen, 2013).

Both absenteeism and employee turnover have a tremendous impact on serial production. Hiring temporary workers imposes a trade-off between lower direct labor costs and an increase in costs as a consequence of lower learning, higher forgetting, and lower overall skill levels (Stratman et al., 2004). As a result, inexperienced temporary or permanent workers may reduce the productivity of the assembly line (Stratman et al., 2004; Bukchin and Cohen, 2013). To reduce the costs for a pool of backup workers and to avoid assigning temporary workers, Cohen (2012) proposed employing a cross-trained foreman for each production line. This person can flexibly replace an absent coworker and support all stations to reduce bottlenecks during normal production. Nevertheless, different experience levels of employees (Bukchin and Cohen, 2013), as well as unavoidable differences in task times can lead to an uneven work distribution (Askin and Chen, 2006), which results in asynchronous flow lines (Sennott et al., 2006). One way of balancing assembly lines is building up inventory buffers between stations to store Work in Progress (WIP), as this counters the disruptive effects and avoids an underutilization of the workforce (Askin and Chen, 2006). Learning and forgetting effects in turn influence the optimal inventory levels for different policies of buffer capacities (Biel and Glock, 2018). Buffer capacities that counter incidental variability can be misused if workers become tired at the end of a shift and cause productivity to decrease (Digiesi et al., 2009). When deciding on such buffers, all stages of a production line must be considered (Biel and Glock, 2018). Dynamic Load Balancing (DLB) concepts focus on allocating task more flexibly to workers (Bentefouet and Nembhard, 2013). Here, the dynamic nature of employee skills and cross-training is utilized to reduce idle times and cycle times, to minimize the makespan (Cohen et al., 2006), to maximize yields (Askin and Chen, 2006), and to counter absenteeism. If switching costs are also considered, the amount of work sharing and flexible task assignments depends on the level of worker heterogeneity and worker performance levels (Bentefouet and Nembhard, 2013). Again, a low level of cross-training often outperforms both full specialization and full cross-training (Felan and Fry, 2001; Sennott et al., 2006; Yang and Kuo, 2007).

Because of the reasons outlined above, assembly line production policies for assigning workers to tasks are of special importance. In a production line without work-sharing, upstream workers become more efficient due to more experience. In such an environment, an unbalanced distribution of the workload, according to the different performance levels of employees, leads to significant savings (Cohen et al., 2006). Moreover, assigning workers to their most efficient task can lead to machine blocking if more capacity is needed at another bottleneck station (Yang and Kuo, 2007). In a bucket brigade system, however, workers can be ordered according to their efficiency such that the worker with the highest steady-state productivity operates the most downstream station. This policy relies on preemption and full cross-training as the downstream worker pulls the task from their predecessor in the system at the time the former is finished (Bartholdi and Eisenstein, 1996; Buzacott, 2002; Armbruster et al., 2007). Armbruster et al. (2007) proposed a switching policy for assigning to an existing production line a new worker who gains experience according to an individual task-dependent learning curve. A comparison of policies that do not demand full cross-training, (i.e. cherry-picking) shows that chained cross-training often delivers superior results (Hopp and Van Oyen, 2004; Inman et al., 2004). While most policies consider assigning workers within a single production line, the bubble allocation policies of Wang et al. (2016) showed that assigning a pool of heterogeneous workers to different parallel lines and simultaneously accounting for worker absenteeism can lead to improved line balancing.

Extensions to the Simple Assembly Line Load Balancing Problem (SALBP) which incorporate learning and heuristics have been presented by Hamta et al. (2013) and Otto and Otto (2014). Motivated by a shared work shelter for people with disabilities, Costa and Miralles (2009) combined ALB with maximizing the number of different tasks pursued by a worker (job-rotation) while ensuring profitability.

(Allwood and Lee, 2004) analyzed knowledge-intensive problem-solving tasks in maintenance activities that restore production of the whole line after a breakdown and found that specialization outperforms job-rotation in this situation. Since cycle times are further determined by the availability and quality of supplied items, Lolli et al. (2016) considered autonomous and induced learning of suppliers and their effect on non-conforming item rates. Their model allocates training measures to suppliers over multiple periods minimizing prevention (training), appraisal (inspection), and failure costs. Wan and Yan (2015) generated schedules for a multi-stage assembly line with a tree structure and different product types. They used a reconfiguration heuristic to reassign teams of workers to meet changing demand while maintaining minimal production and reconfiguration costs, which account for earliness and training.

5.4 Cellular Manufacturing

In group technology, dissimilar machines are clustered into manufacturing cells to produce families of parts (Eckstein and Rohleder, 1998; Shahvari and Logendran, 2018). These cells are designed to improve production by reducing costs and increasing production performance, exploiting production similarities in terms of processing requirements (Shahvari and Logendran, 2018), such as reduced setups and improved material handling (Jensen, 2000). When considering the impact of human labor, higher learning due to task similarities reduces flow times and results in lower capacity utilization (Eckstein and Rohleder, 1998). Cellular manufacturing, can therefore achieve lower staffing and cross-training levels while maintaining full labor flexibility within a cell (Jensen, 2000).

Surplus time capacities can be utilized for continuous improvement or maintenance routines and to enhance product quality (Eckstein and Rohleder, 1998). When analyzing the effectiveness of manufacturing cells compared to flow-shop production, cellular manufacturing was found to be beneficial in production settings for an uneven demand mix, high learning rates and low staffing levels (Eckstein and Rohleder, 1998; Jensen, 2000). Since workers in a cell need to cooperate, social skills like conflict management (Chakravorty and Hales, 2008) and team working abilities (Norman and Needy, 2010) are important.

Chakravorty and Hales (2008) examined the impact of human interactions when forming new cells. During the first phase of introduction, human and technical problems exist. While problems driven by social interaction and hierarchy dominate this phase, only technical problems persist in the second phase until full productivity is reached (Chakravorty and Hales, 2008). Similar aspects were taken into account by Azadeh et al. (2016), who incorporated personality traits into their cell formation model to minimize decision-making problems within cells due to incompatibility of personalities. Their model also accounts for technical decisions, material handling as well as the training, hiring, and retention of workers (Azadeh et al., 2016).

A holistic three-step approach by Süer and Tummaluri (2008) assigns workers to operations, forms cells of employees, and assigns tasks to employees within a cell. For the last step, two heuristics are presented, whereas a single heuristic accounts for worker skills. Norman and Needy (2010) included technical and human skills (e.g. leadership, communication, or team working skills) into an MIP assigning workers to cells and training sessions to workers. Results of a computational study emphasize the importance of incorporating human skills and individual training schemes (Norman and Needy, 2010). Kannan and Jensen (2004) found that the choice of the most beneficial deployment policy of workers to cells depends on the individual learning rates of employees. Ying and Tsai (2017) presented a two-stage heuristic approach in order to jointly minimize the training costs and standard deviation of working hours of employees when assigning workers to cells. Slomp and Suresh (2005) provided a two-stage heuristic to solve a goal-programming model that minimizes personnel costs while assuring a desired level of multi-functionality due to cross-training. For a chronological review of additional literature on cellular manufacturing and human factors, we refer to Azadeh et al. (2016).

5.5 Machine Scheduling

Scheduling assigns jobs to machines and is supposed to generate an optimal production plan for each machine while minimizing or maximizing a given objective function. In this setting, the processing times of jobs can benefit from learning effects of preceding jobs (Biskup, 1999, 2008; Azzouz et al., 2018). For single machine scheduling problems, extensive research has been carried out on the consequences of learning effects for production, see for example the surveys by Biskup (2008), Janiak and Rudek (2010), and Azzouz et al. (2018).

Biskup (2008) categorized the underlying learning effects into *position-based* and *time-based* effects. These effects emerge from the different characteristics of the underlying production environment and can be motivated in two ways. First, position-based effects may account for the learning process of employees during machine setups only in a machine-paced production environment (Biskup, 2008). Therefore, *position-based* learning effects expect knowledge creation to depend solely on the number r of tasks previously scheduled (Biskup, 1999). Second, the inherent nature of jobs influences the learning potential. While some jobs consist of a number of distinct tasks and movements, other monotonous, highly repetitive jobs allow for constant learning during the whole processing time (Yang and Kuo, 2007). Thus, *time-based* learning effects additionally account for the time spent in production by including the processing times p_j of the $r-1$ jobs processed prior (Kuo and Yang, 2006).

Table 1: Learning Effects Single-Machine Scheduling

Position-based (Biskup, 1999)	Time-based (Kuo and Yang, 2006)
$p_{j,r} := p_j \cdot r^a$	$p_{j,r} := p_j \cdot \left(1 + \sum_{k=1}^{r-1} p_{[k]}\right)^a$

Based on these approaches, numerous extensions and alternative formulations for the learning effects have been presented. For the position-based effect, job-dependent learning rates (Mosheiov and Sidney, 2003), explicit setup time learning (Pargar and Zandieh, 2012; Koulamas and Kyparisis, 2008), plateau effects (Cheng et al., 2013), induced learning (Biskup and Simons, 2004), controllable processing times (Oron, 2016; Wang and Wang, 2015), deteriorating processing times (Wang and Cheng, 2007) and a linear learning effect (Xu et al., 2008) have been introduced. In contrast, the literature on time-based effects focuses more intensely on how the processing times of jobs impact learning. Consequently, logarithmic (Cheng et al., 2009), fractional (Koulamas and Kyparisis, 2007) and exponential (Wang et al., 2009) reformulations have been developed. Further publications account for actual processing times (Yang and Kuo, 2007), i.e. processing times already discounted by learning effects, and actual processing times with job-dependent learning (Yang and Kuo, 2007; Jiang et al., 2013). The only extension comparable to models with a position-based learning effect is the consideration of plateau effects (Cheng et al., 2011).

Uniting numerous of the above approaches, a general integral-based approach by Lai and Lee (2011) modeled both position- and time-based effects. A model independent of these time- or position-based effects by Anzanello and Fogliatto (2010) excluded explicit learning effects from the optimization process to reduce computational complexity. Hyperbolic learning curves are fitted to job and worker characteristics to derive processing times that include learning effects. Janiak and Rudek (2010) developed a more complex model by breaking down learning to individual skill levels that affect each job differently.

Forgetting effects are rarely considered in the context of machine scheduling with deterio-ration-based forgetting effects (Lai and Lee, 2013, 2014; Wu et al., 2015, 2016; Dondeti and Mohanty, 1998) being more prominent. A few articles cover interruption-based forgetting effects that either focus on batch sizing and scheduling (Pan et al., 2014; Yang and Chand, 2008; Anzanello et al., 2014) or consider multi-stage production systems (Li et al., 2018b).

When considering objective functions, minimizing the makespan $C_{\max}$ and total completion time $\sum C_j$ are solved by the Shortest-Processing-Time-First (SPT)-rule for the majority of the problems mentioned above. A reformulation as an assignment problem delivers optimal solutions for job-dependent processing time and position-based learning, while actual processing times and individual learning rates for jobs result in a NP-complete problem. Moreover, the computational complexity for the weighted total completion time $\sum w_j C_J$, the maximum lateness $\mathrm{L}_j := \{C_j - d_j\}$, the maximum tardiness $T_j := \max\{0, C_j - d_j\}$, and the number of tardy jobs $\sum U_j$ increases further if learning effects impact the processing times. Without learning, these objectives were minimized efficiently by sorting rules, such as the Weighted-Shortest-Processing-Time-First and the Earliest-Due-Date-First (EDD). When including learning effects, only special cases of these problems stay solvable. However, the single-machine problem minimizing the total tardiness $\sum T_j$ is already known to be NP-complete. Nevertheless, for a number of computationally intractable cases Branch and Bound (B&B) and heuristic algorithms have been developed. Table 2 lists publications concerned with scheduling and skill development that incorporate learning or forgetting effects. For a comprehensive and more detailed overview, we refer to Heuser et al. (2022).

Table 2: Publications Clustered by Learning and Forgetting Effects

Effect	Publication
	Learning
Positions-Based	Biskup (1999); Mosheiov (2001a,b); Mosheiov and Sidney (2003); Lee (2004); Mosheiov and Sidney (2005); Wang (2006); Koulamas and Kyparisis (2007); Lin (2007); Wang and Cheng (2007); Xu et al. (2008); Chang et al. (2009); Cheng et al. (2009); Wu and Lee (2009); Yang and Kuo (2009); Koulamas (2010); Pargar and Zandieh (2012); Lai and Lee (2013); Lee and Chung (2013); Qian and Steiner (2013); Wang and Wang (2015); Oron (2016); Wang et al. (2017); Wu et al. (2018)
Time-Based	Janiak and Rudek (2009); Koulamas and Kyparisis (2007); Yang and Kuo (2007); Jiang et al. (2013); Koulamas and Kyparisis (2007, 2008); Cheng et al. (2009); Wang et al. (2009); Kuo and Yang (2006); Wang et al. (2008); Dondeti and Mohanty (1998); Lai and Lee (2013); Li et al. (2013a)
Other	Lai and Lee (2011); Janiak and Rudek (2010); Anzanello and Fogliatto (2010)
	Learning and Forgetting
Deterioration-Based	Lai and Lee (2013, 2014); Wu et al. (2015, 2016); Dondeti and Mohanty (1998)
Interruption-Based	Pan et al. (2014); Yang and Chand (2008); Anzanello et al. (2014); Li et al. (2018a)

5.6 Summary

The incorporation of learning effects naturally emphasized different factors depending on the production environment. An overview of the different aspects covered (dark blue) as well as gaps in the existing literature (gray) is presented in Figure 5. Therefore, some aspects that do have an impact but are not covered by research may offer avenues for further research:

- While learning effects are incorporated in the majority of environments, character traits and interaction effects with coworkers have largely been neglected in the literature. The latter in turn can lead to unsatisfied employees, with reduced motivation or boredom resulting in forgetting effects or higher turnover rates. Since employees increasingly seek fulfillment in their employment, personal preferences and social skills will be of special importance in the future.
- As changing customer preferences force production to shift to mass customization and reduce product life cycles, shared production lines gain importance. However, forgetting effects

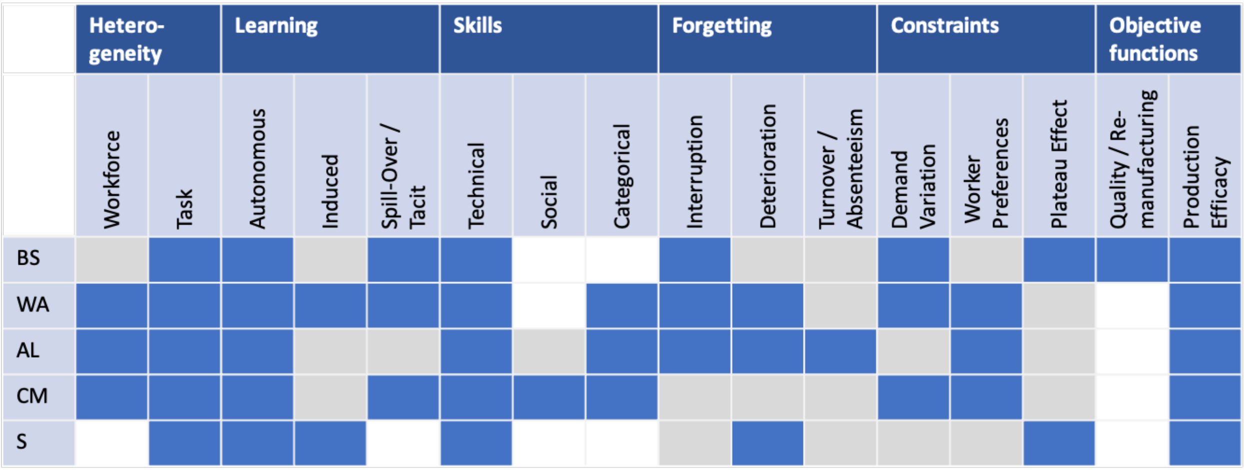

Figure 5: Aspects of competence management considered in production planning: Batch Sizing (BS), Worker Assignment (WA), Assembly Line (AL), Cellular Manufacturing (CM), Machine Scheduling (S)

driven by production task interruptions are only incorporated when considering batch sizing, assembly line balancing, or cellular manufacturing. We believe that including these forgetting effects provides further opportunities for improving existing models for small batch production and single-machine scheduling.

- In this vein, including spill-over or cross-learning effects provides another avenue for further research. Different tasks come with different complexities and demands for other skill sets. Nevertheless, a distinction between tasks is usually made without considering the underlying differences in the learning potentials of jobs, and therefore neglecting differences in learning rates.

- When considering different job types, the existing literature predominantly considers categorical skills only. Existing models usually assume that workers are cross-trained but they do not allow for different levels of productivity within a skill category. Models that combine both hierarchical and categorical skills might allow for more precise prediction.

- Future jobs will require more diverse forms of knowledge as a consequence of shifted requirements due to technological developments and automation (Autor, 2015; Davies et al., 2017; Neumann et al., 2021). However, when and how to provide this knowledge, e.g. in terms of training measures, needs to be considered in more detail.

- A common and rather surprising research shortcoming concerning learning curves is the exclusion of plateau effects. Throughout all environments, most models allow processing times to converge to zero with repetition.

- So far, aspects of digitization and the interaction of human and artificial intelligence have hardly been addressed by the operations management literature on competence development. This is remarkable, as the most important changes in the production of the future are expected to occur in these areas (Dogru and Keskin, 2020).

6 Conclusion

Human factors have been considered extensively in different manufacturing contexts. Case and simulation studies have provided insights on the impact of personality traits, different skill sets, and environments that foster learning in production. Research on learning curves has presented detailed models describing and accounting for such factors. However, mathematical models and problem formulations often demand simplifications to achieve computational tractability. Instead of focusing on one area, this article provides a comprehensive overview of the consideration of competencies in different areas that are important for manufacturing. We note that the underlying aim and method of this survey necessarily limit its scope. In particular our approach includes mainly research conducted in the last two decades and published in selected journals. These articles, however, build on results and insights from earlier research articles or important contributions from other journals.

Our survey first presents the dynamics behind skill development in production together with the derived learning and forgetting models and the research that builds on these models. In this vein, skills or competencies, as well as their influence on the workforce and their development through learning due to training or experience, and forgetting are described. Next, we reviewed how the dynamics behind skill development impact strategic decisions within companies. In particular, we considered research related to organizational knowledge creation, change management, production ramp-ups, quality assurance, maintenance, and staffing. Finally, we also reviewed the unique challenges related to competence management that arise in different production environments. Here, we distinguish between batch sizing, assembly line balancing, worker assignment, cellular manufacturing, and machine scheduling.

As a result, researchers and practitioners can identify key characteristics that require careful consideration. Figure 6 describes the interplay between the three areas distinguished here. Skill development (as considered in Section 3), impacts the organizational decisions (Section 4) as well as the operational planning (Section 5). Thus, competence management influences companies' decisions from the creation of knowledge and its management to the objects relevant for production. Different production systems, outsourcing and maintenance decisions, as well as the product's design itself provide distinct learning potentials. Next, the timing for implementing changes must be evaluated carefully. Timing can, for example, include switching from an old product to an updated version or implementing new technologies. Here, learning requirements and phasing-out of existing and no longer needed knowledge must be weighed. Introducing a new production line or plant calls for workforce and staffing decisions. These entail hiring, retention, and training decisions tailored to the production environment, as well as establishing the production tasks and their complexity. Finally the development of competencies, technical, and social skills influences operational production planning and optimization in different production environments.

Several avenues for future research are already provided in the individual sections. However, we would like to highlight concepts from the empirical research that existing models might benefit from. Accounting for technical advances, for example by incorporating digital work instructions, allows companies to deploy training sessions more flexibly and provides superior learning results compared to conventional methods (Letmathe and Rößler, 2021). Moreover, influence factors on

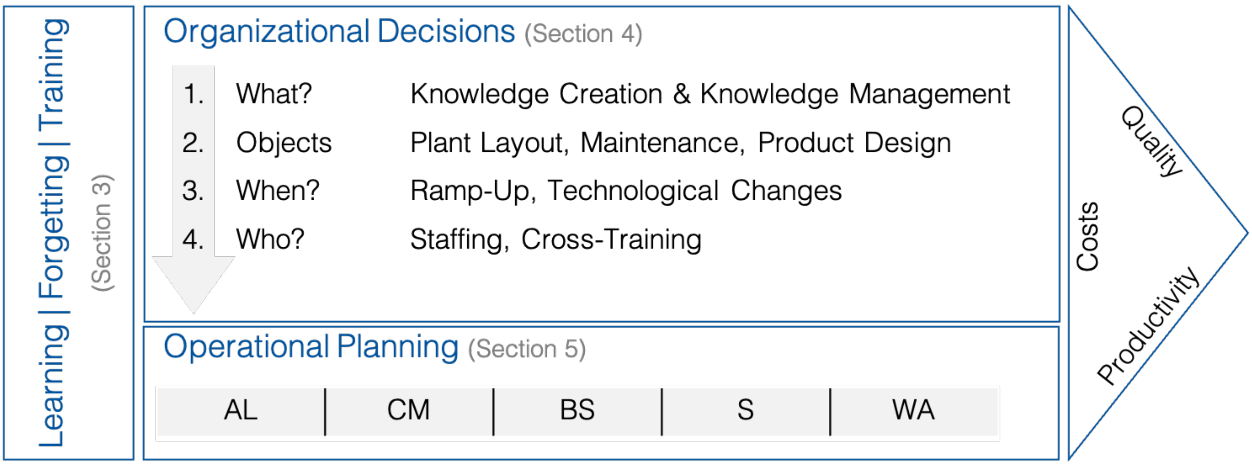

Figure 6: Decision areas affected by employee skill development

learning-by-doing, such as cross-learning effects between similar tasks (Pratsini and Marks, 2001), spillover learning from coworkers (Letmathe et al., 2012), and feedback information, could be included more broadly. This also holds for factors that might increase forgetting effects and thus harm production performance, like ergonomic factors (Anzanello et al., 2014) and cognitive load. It can certainly be seen as particularly surprising that highly relevant newer developments have hardly found their way into the literature on competence development in the production sector so far. This applies in particular to the increasing digitization of many production systems and also the use of artificial intelligence. It is generally expected that the latter will revolutionize many production systems in the future (Dogru and Keskin, 2020; Fügener et al., 2021). An important aspect with regard to this overview is hybrid intelligence, which involves the collaboration and interaction of artificial and human intelligence.

Overall, we believe that the broad area of competence management provides numerous promising areas for integrated OR models that can lead to impactful research. Therefore, we believe this review will help the reader to assess relevant literature related to competence management.

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Research Paper 2: Skill Development in the Field of Machine Scheduling - A Structured Literature Review

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Abstract Human competencies are seen as a main driver of competitive advantages of enterprises. This article provides a state-of-the-art overview of research related to competence management in the field of operational research. For this purpose, the term competence management is used as an umbrella term to integrate different quantitative approaches in this field. The structured literature review is based on seven keywords and includes articles published between 1998 and 2019 in nine major operational research and operational management journals (Journal of Operational Research, International Journal of Production Research, International Journal of Production Economics, Management Science, Operations Research, Omega, Journal of Operations Management, Production and Operations Management, and Manufacturing and Service Operations Management). Further relevant literature considering competence-related topics and machine scheduling problems is also included. The publications included in this review are analyzed in-depth with regard to theoretical results on employee skill development. Moreover, a unified notation is introduced covering different models, machine environments, and objectives. To the best of our knowledge, this is the first review to jointly consider learning, forgetting, and training aspects. Moreover, the review also highlights substantial research gaps and avenues for future research.

1 Introduction

It is widely recognized that production processes are impacted by efficiency gains over time (Yelle, 1979). In this context, the term 'efficiency gains' unites improvements driven by different sources which can be categorized as follows: technological change, human learning, characteristics of a company or local industry and scale effects (Dutton and Thomas, 1984). Some efficiency gains result in lower costs per output unit and/or higher productivity. Efficiency gains in production were first described in 1936 by Wright (1936). He observed that the time needed for production decreases at a uniform rate, the learning or progress rate, as the production output doubles. Building on this result, several studies found evidence for learning effects in a variety of industries. Dutton and Thomas (1984) examined 200 studies analyzing learning effects in production to derive insights on the variation in learning rates between different industries. Such differences are not only recognized when comparing industries or companies. Further, studies imply that these differences persist between plants belonging to the same company located in one country, utilizing the same equipment to produce the same product (Argote and Epple, 1990).

Since learning when performing production processes depends on human labor, taking employee development into account is of key importance, when planning production (Qin et al., 2015). Learning does not only materialize in efficiency gains but also in increases to employee competencies. Hence, managing the workforce and evaluating which competencies are relevant now and in the future can be crucial for gaining a competitive advantage for companies (Meyer et al., 2015). In this vein, '*Competencies [...] can be described as self-organization dispositions*' (Erpenbeck and Michel (2006), p.128). They unite a person's knowledge, skills, experience, and personality-related characteristics (Erpenbeck, 2007). Compared to skills, for example, competencies are not easily measurable since they are expressed through higher performance and can only be viewed in the results of an action (Erpenbeck and Michel, 2006). Therefore, hiring employees with the required competencies is connected to uncertainties regarding to their true qualifications (Arlotto et al., 2014). The performance of an employee, on the other hand, can be increased by experience when performing a production task which generates knowledge over time (Meyer et al., 2015). Experience can be acquired automatically due to task repetition (De Bruecker et al., 2015). In terms of competence management not only employee skill development by autonomous learning or learning-by-doing due to process repetition needs to be considered. Efficiency gains through induced learning in terms of external or internal training are also important for developing employee competencies (Chen et al., 2010). Training measures can be used to explicitly transfer knowledge and, hence, obtain a multi-skilled, cross-trained workforce or increase worker productivity and enhance workforce flexibility (Qin et al., 2015). Utilizing training to strengthen the workforce's skills and competencies is a managerial decision connected with different types of costs, e.g., direct costs for the training measures or indirect cost in terms of forgone production time (De Bruecker et al., 2015). In contrast to learning-by-doing, efficiency gains due to formal learning can be generated deliberately and allow firms to accelerate the learning curve (Lapré and Van Wassenhove, 2001).

In addition to autonomous and induced learning, forgetting effects can reverse prior learning effects (Jaber et al., 2003). Forgetting mostly occurs if the production process is interrupted for a substantial amount of time (Globerson, 1987). Different factors have been proven to influence the amount of knowledge forgotten as well as the relearning curve of employees, e.g. the number of interruptions, the duration of an interruption and the experience gained prior (Jaber et al., 2003). Moreover, negative consequences of task repetition, for example, ergonomic factors (Anzanello et al., 2014), employees boredom (Azizi et al., 2010), and fatigue (Dondeti and Mohanty, 1998) can also decrease workers' performance. Thus, they are considered as a special case of forgetting effects.

Since the efficiency of workers impacts production cost, speed, and waste production (Lapré et al., 2000; Chen et al., 2010), it is important to take the dynamic nature of employee skills into account when turning to production planning. Since learning and forgetting effects can be evoked by changes in the production environment they influence production efficiency and are thus relevant for short term planning (Dutton and Thomas, 1984). Such changes can include new employees entering the production process, a new product design, or new equipment and machines. Moreover, production ramp-ups, i.e. introducing new processes or production lines, are heavily impacted by skill development, since full capacity utilization is not yet possible. Employees get introduced to new production tasks and need to learn rapidly in order to reach a high productivity level (Terwiesch and Bohn, 2001). Biskup (2008) emphasized the importance of including learning effects into scheduling research since efficiency gains through learning affect short-term as well as long-term production outcomes and can yield a strategic advantage for companies. In this vein also forgetting effects and accurately timed training measures countering these effects need to be considered (Jaber et al., 2003).

Based on the importance of employee development for production planning we aim to answer the research question: *Which concepts of competence management have been considered in machine scheduling models?* The term 'competence management' is used to unite different concepts with regard to employee development. To provide an overview of the current state of research we conducted a structured literature review. In contrast to related survey articles, which concentrate only on employee learning processes, we aim to provide an exhaustive overview on topics relevant for the broader field of competence management. Therefore, databases were searched for articles published in the last 20 years containing at least one of seven competence-related keywords. Building on the insights presented we derived *competencies, experience, skills, learning, forgetting, training* and *hiring* as keywords for the search process. To emphasize theoretical results that are also applicable for practitioners, we primary focused on journals operating on the interface of management science, operational management, and operational research.

When considering other relevant literature reviews we retrieved only articles focusing solely on learning processes. Hence, we included reviews by Biskup (2008), a more recent survey by Azzouz et al. (2018) who present a cartography on learning problems, and an overview by Janiak and Rudek (2010) who focused on the computational complexity of already considered problems. In addition to considering learning effects this article reviews also a number of other competence-related terms.

These are relevant to assess employees' development fully and have, to the best of our knowledge, not been analyzed so far. Moreover, we present a unified notation for different learning and forgetting effects. Further, we analyze the models considered with regard to their validity in the context of employee development and demonstrate scheduling problems these models have been applied to.

The remainder of the paper is structured as follows: Section 2 provides a brief overview on the search process. Section 4 describes and clusters the effects of skill development analyzed in the articles. The underlying scheduling problems are described in Section 5. Finally, Section 5.3 closes with a discussion and outlines future research opportunities.

2 Methodology and Review Process

To provide a state-of-the-art overview on topics related to competence management and employee skill development in the context of machine scheduling we conducted a structured literature review. The method utilized is based on the approach from Okoli and Schabram (2010) and uses the taxonomy of Cooper (1988) to classify the purpose of the survey. Following their approach we defined a time window for the publications included and selected databases, journals, and keywords restricting the search process. In order to be able to report the distinct models in sufficient detail and provide an comprehensive overview, we decided to focus on publications dealing with machine scheduling problems separately in this paper.

For our search, we selected two databases *Elsevier* and *Ebsco Host* to retrieve articles published in nine journals from January 1st, 1998 till January 13th, 2019. The advanced search of *Elsevier* was used to identify articles from the *European Journal of Operational Research, the International Journal of Production Economics, the Journal of Operations Management* and *Omega*. The *Ebsco Host* database was used to screen the *International Journal of Production Research, Management Science, Operations Research, Production and Operations Management* and *Manufacturing & Service Operations Management*. The journals were chosen based on their high quality and relevance in management science, operational management, and operational research. Since these journals concentrate on the interface of the mentioned research areas, they are relevant for both researchers and practitioners.

Furthermore we chose 17 keywords related to competence management and skill development. Since several search terms could be reduced to a common word included we retrieved seven search terms: *competence/ies [competence management, competence development], experience, skill/s [employee skill/s, skill development], learning [learning curve, autonomous learning, learning-by-doing, absorptive learning, induced learning], training [cross-training], forgetting, and hiring.* We screened title, abstract, and the authors' keywords for the above search terms.

Our search resulted in 2398 articles, which underwent an initial screening, to evaluate their overall relevance for our research question. Following the pre-screening process, 216 journal articles were selected for further screening. In an in-depth screening process, these remaining publications were fully read and categorized. From those, the articles addressing the field of machine scheduling are analyzed in the subsequent sections of this paper. In addition to the selected publications we included relevant articles fro the field and built on earlier high quality literature reviews, as well as related literature published by authors frequently appearing in the search process. A large percentage of the publications focuses on learning processes in production. Since forgetting can be viewed as the counterpart to learning it plays a crucial role in production planning as well. Nevertheless, the underlying effects appear to be under-researched in the context of scheduling. For this reason we conducted a second search to retrieve models including forgetting effects which was based on the publication of Yang and Chand (2008). Considering *experience, skills, competence,* and *hiring* we did not receive any results.

Based on the findings from our searches, the following sections concentrate, more accurately speaking, on employee skill development, which entails learning, based on experience in the production task, forgetting and training, instead of competence management.

3 Scheduling Problems and Notation

Machine scheduling problems aim to support decision processes by seeking optimal allocations of a set of jobs $j \in \{1, ..., n\}$ to a set of machines $i \in \{1, ..., m\}$ or workers (Pinedo, 2012). The permutations π of jobs either minimize or maximize given objective functions. To classify the underlying machine environment α, constraints β and objective functions γ the three field notation $\alpha|\beta|\gamma$ by Graham et al. (1979) is used.

Machine Environments Compared to a single-machine production ($\alpha = 1$), parallel machine environments allow processing jobs on different machines. These machines can either be identical (P_m), related (Q_m) which means that the machines' speeds are in a proportional relation or unrelated (R_m). For unrelated machines, the speeds for processing different jobs are not aligned. Moreover, it is possible that a job can only be processed on certain machines. Another multi-machine environment is given when considering flow-shop problems. For a classical flow-shop problem, jobs have to be processed on $m = |M|$ different machines in a given order. Jobs that have been processed on one machine queue to be processed on the succeeding machine. If these queues operate under the First-in-First-out (FiFo)-rule the problem is referred to as a permutation (*prmu*) flow-shop problem (Pinedo, 2012). This type of problem can be considered as being ordered (*ord*) if for processing times $p_{i,j}$ on machine i and $p_{i+1,j}$ on machine $i+1$ holds: $p_{i,j} \leq p_{i+1,j}$ and $p_{i,j} \leq p_{i,k} \Rightarrow p_{i+1,j} \leq p_{i+1,k}$ for all $j, k \in \{1, ..., n\}$. In this vein, proportional (*prp*) processing times are given if $p_{i,j} = c \cdot p_{i+1,j}$ for $c \geq 1$ holds (Koulamas and Kyparisis, 2007).

Multi-stage flow-shop ($\mathrm{MF}_{s,m}$) problems are special cases of flow-shop problems. First, jobs have to be completed on all machines at one stage before being available for being processed on the successive stage. Note that the processing order within each of the stages is not important. A hybrid-flow-shop (HFS) combines properties of parallel machine environments and flow-shop production lines. Parallel, not necessarily identical machines, are included in at least one stage of a permutation flow-shop problem to avoid bottlenecks by providing sufficient capacity. The jobs to be scheduled follow the same route but can further skip one or more production steps. Even for small problem sizes, hybrid-flow-shops are oftentimes *NP-hard*. We refer to Ruiz and Vázquez-Rodríguez (2010) for a review of HFS problems without learning effects.

In group scheduling problems jobs are first clustered into groups (called job families) according to their similarities. As a consequence, jobs belonging to a family yield efficiency gains when being performed in direct sequence or temporal proximity, e.g., due to setup time reductions or learning effects. Jobs of one family are often produced in batches to exploit these potential gains (Shahvari and Logendran, 2018).

Objective Functions A number of single or multi-criteria objective functions have been formulated which concentrate on the completion times and due dates of jobs (Pinedo, 2012). Henceforth, the main objective functions relevant for this article are introduced. For the sake of convenience multi-objective functions will be presented in Section 5.

Completion time related objectives focus on the time C_j, i.e. when job j is completed. In this regard the makespan $C_{max} \equiv \max\{C_1, ..., C_j\}$ defined as the time needed until the last job in a given schedule is completed is a widely used performance measure. Especially for flow-shop problems, routing jobs through different stages of production and reducing the makespan yields a lower level of Work in Progress (WIP) (Pargar and Zandieh, 2012). Reducing WIP decreases storage costs and set up times, since intermediate products do not need to be stored or re-fetched for continuing their production process. The makespan for the basic single-machine problem, without learning and further restrictions, is minimized by any arbitrary order of jobs. A related objective function is to minimize the sum of completions times $TC \equiv \sum_{j=1}^{n} C_j$, also referred to as the minimization of the total completion time or total flow time for multi-stage problems. The total completion time explicitly accounts for completion time of each single job, and thus inventory or holding costs relevant when jobs are completed before their output can be processed to the next production stage. These costs decrease if more jobs are finished earlier (Pinedo, 2012). The objective function is optimized when as many jobs as possible are completed early. Thus, a common solution is processing the smallest jobs first, according to the Shortest-Processing-Time-First (SPT)-rule. Hence, the same applies for the sum of the squared completion times $\sum_{j=1}^{n} C_j^2$ as a special case of the sum of the kth power of completion times $\sum_{j=1}^{n} C_j^k$, with $k > 1$. Further variations are the total weighted completion time $TWC \equiv \sum_{j=1}^{n} w_j \cdot C_j$, and the discounted total completion time $\sum_{j=1}^{n} w_j \cdot (1 - e^{-\gamma \cdot C_j})$ with $\gamma \in (0, 1)$. These objectives further allow to prioritize jobs by setting weights and discount rates. When omitting learning effects, these objectives are minimized by the Weighted-Shortest-Processing-Time-First (WSPT) and the Weighted-Discounted-Shortest-Processing-Time-First (WDSPT) rule (Pinedo, 2012).

Measuring performance based on the completion times sheds light on the shop floor's productivity but neglects considering customer satisfaction. By setting due dates d_j it is possible to assess if completion times are aligned with customer requests. Objective functions which include due dates measure the earliness $E_j \equiv \max_{j \in J}\{0, d_j - C_j\}$ and the lateness $L_j \equiv C_j - dj$ of jobs, as well as the tardiness $T_j \equiv \max_{j \in J}\{0, C_j - d_j\} = \max_{j \in J}\{0, L_j\}$. Further measures are the maximum lateness $L_{\max} \equiv max_{j \in J}\{L_j\}$, the maximum tardiness $T_{\max} \equiv max_{j \in J}\{T_j\}$, the total tardiness $\sum_{j \in J} T_j$

and the number of tardy jobs $\sum_{j\in J} U_j$ (with $U_j = 1$ if $C_j > d_j$ and $U_j = 0$ otherwise). These objectives are usually connected with unit penalties and also refer to a common due date $d_j = d$ for all jobs. Heuristics solving those problems are the Earliest-Due-Date-First (EDD)-rule, which sorts jobs by increasing due dates and *Moore's Algorithm*. This algorithm ALGO interchanges the position of a large job from a EDD-schedule to obtain an optimal solution for the number of tardy jobs. Again, solving problems minimizing the maximum lateness or the number of tardy jobs is often only possible when assuming $aggregableconditions/constraintsformachinescheduling(agg)$ for the due dates, that is $p_i \leq p_j \Rightarrow d_i \leq d_j$, or assuming a common due date or processing time for all jobs.

4 Skill Development

Figure 1 summarizes the types of learning and forgetting effects considered in the context of machine scheduling problems. In this vein, Section 4.1 focuses on the learning effects in production. Section 4.1.1 provides definitions for position-based learning effects while Section 4.1.2 focuses on time-based effects. Section 4.2 introduces forgetting effects while Section 4.2.1 deals with deterioration-based and Section 4.2.2 with interruption-based forgetting effects. Different variants of learning effect models, e.g. log-linear or logarithmic, are listed in horizontal order in Figure 1. Extensions and further conditions included in learning or forgetting effects, such as plateau effects or job-dependence, are provided in vertical order. The rhombus indicates for which production environment effects are presented in the literature.

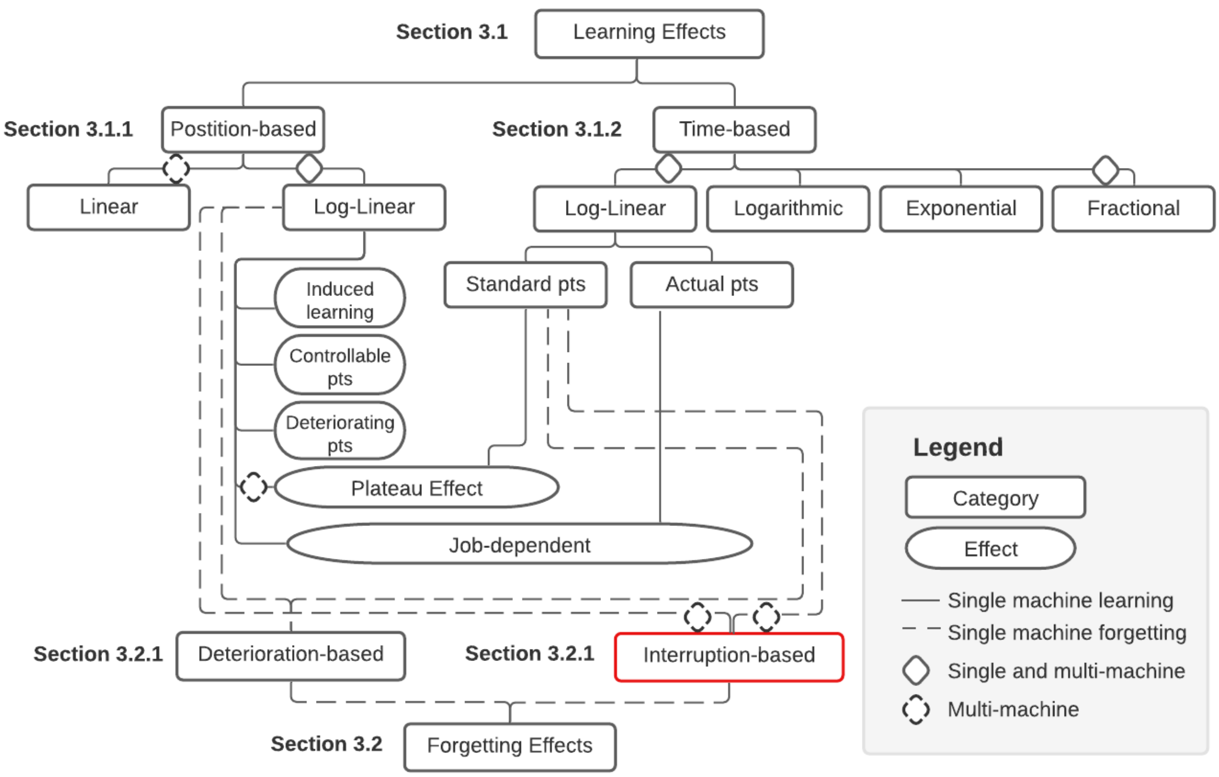

Figure 1: Interplay of learning and forgetting effects provided for machine scheduling

Table 1: Denotation for Machine Scheduling Problems with Learning Effects

LE	Learning Effects	F	Forgetting
g	general effect	g	general effect
t	time-based effect	i	interruption-based
p	position-based effect	d	deterioration-based
pl	linear position-based effect		
exp	exponential effect		
log	logarithmic effect		
$plat$	plateau learning effect		
j	job-dependent		
A	actual processing time-dependent		
det	deteriorating processing times		
con	controllable processing times		

Regardless of their different basic assumptions, learning and forgetting include efficiency gains and loses in terms of decreasing or increasing standard processing times p_j with respect to a sequence π of jobs scheduled. Thus the learning effect can be described as further constraint β to a given problem in the three field notation.

Before turning to the models presented in the publications, we briefly describe the notation used in this article. First, models including a position-based learning effect and, thereafter, models with time-based learning effects are described. In order to distinguish different types of effects we establish a notation, which can easily be extended to incorporate future models of skill development. The presented abbreviations are based on the notation of Learning (LE) utilized in early articles that addressed the combination of learning and scheduling (Mosheiov, 2001b; Biskup, 1999). To account for forgetting effects we further use the abbreviation F. Moreover, we introduce different indices to distinguish families of learning effects, e.g., position-based (LE_p) and time-based (LE_t). Within the individual families the abbreviation LE is extended to characterize the underlying machine environment, e.g., single-machine (LE), flow-shop (LEF) or parallel machines (LEP). Forgetting effects are denoted by a F. A conbination of learning and forgetting effects can be described by $LE{+}F$. Table 2 provides the notation introduced within the this article and definition of the effects respectively. For an overview of the indices, variables and parameters used in the models, we refer to Table 1.

4.1 Learning Effects

Wright (1936) based the first learning curve model on observations in the airplane manufacturing industry. According to his famous log-linear model, the time needed to produce one unit of a product decreases at a uniform rate l, the learning rate, when the number of already processed output n doubles. Utilizing the learning coefficient $a \equiv \log_2(l) \leq 0$ the time needed to produce the nth unit of a product is defined as

$$T_n \equiv T_1 \cdot n^a,$$

with T_1 denoting the time needed to produce the first unit, also referred to as the standard processing time. Building on this result, numerous refinements and model alternatives have been developed. A comparison of exponential and hyperbolic learning curves to the log-linear model by Wright (1936) is provided by Anzanello and Fogliatto (2011) and Grosse et al. (2015), while Smunt (1999) considered a continuous learning model. Regardless of its simplicity the Wright Learning Curve (WLC) is considered appropriate to capture employee learning effects (Yelle, 1979; Globerson, 1987; Globerson and Gold, 1997; Dar-El et al., 1995; Hansen and Grunow, 2015). Extensions to the basic learning curves consider for example, the prior experience of employees (Asher, 1956) while others account for plateau effects (De Jong, 1957; Baloff, 1971), which freeze processing times for number of task repetitions and therefore allow for step-wise learning. To account for differences in task requirements (Shafiei-Monfared and Jenab, 2011) included the two parameters 'task complexity' and 'worker's cognitive ability' whereas (Dar-El et al., 1995) split tasks explicitly in a cognitive and a motor part which are effected differently by learning. Other aspects considered in the context of learning are spill-over (Corominas et al., 2010; Letmathe and Rößler, 2019) and cross-learning (Pratsini and Marks, 2001) as well as production quality (Ittner et al., 2001; Jaber and Guiffrida, 2008; Jaber and Khan, 2010) and rework tasks (Jaber and Guiffrida, 2004).

Learning effects have been embedded into machine scheduling literature in various ways. These differ not only with regard to their formulation but also to their complexity. Anzanello and Fogliatto (2010) for example considered processing times with learning effects as prior given to calculating the optimal schedule. They obtained processing times for different jobs and workers by fitting hyperbolic learning curves to worker and job combinations. In this context, they clustered jobs with similar sizes and complexity into families, assessing performance data for each worker with regard to different families.

In contrast, Janiak and Rudek (2010) provided a model with increased complexity by breaking down learning effects to a skill-based level instead. This allows a more detailed consideration of diverse jobs, as well as learning effects of jobs, which consists of more than one task. Therefore, an experience vector $\overrightarrow{E}(v_1)$ was introduced, that accounts for different skills $k \in \{1, .., K\}$ a worker can gain by processing a job j, which increases the knowledge by e_j. The authors first formulated a learning model, which takes different levels of abilities into account. These in turn, influence the processing times $p_j^A\left(\overrightarrow{E}(v-1)\right) = p_j - \overrightarrow{b}_j \cdot \min\{\overrightarrow{E}(v-1), g_j\}$. The vector of parameters $\overrightarrow{b_j} \in \mathbb{R}^k$, the learning threshold g_j and $\overrightarrow{E}_j$ are all rational. By restricting the variable $\overrightarrow{E}_j,\ e_j \in 0, 1$ to be binary and setting the threshold g_j to 1 the authors reduce the complexity of the original $NP-hard$ problem.

Besides these exceptions, machine scheduling literature mainly distinguishes two types of learning based on the underlying production environment: *position-based* and *time-based* learning effects (Biskup, 2008). Position-based effects are based on the jobs position in a given schedule and neglect the processing time of the jobs already processed. Time-based effects in contrast take the whole time spend in production into account by considering the processing of previous jobs. Both effects can be interpreted as variations of the WLC. This twofold view conforms with the results of a study by Hirsch (1956), who found learning rates in human labor-paced environments to be up to 50 % higher compared to machine-paced progress rates. De Jong (1957) further stated that human labor-paced assembly lines offer more potential for learning compared to machine-paced productions. The following sections are devoted to the different learning effects introduced.

4.1.1 Position-Based Learning Effects

Position-based learning effects, first introduced by Biskup (1999), assume that learning occurs solely in between the performance of two production processes, or the processing of two jobs respectively. Such an approach refers to a machine-paced production with human learning only present for machine setups, cleaning, or machine maintenance (Biskup, 2008). Another justification for position-based learning lies in the nature of the task. If jobs itself consist of a number of different operations learning effects can only be observed after the completion of a job.
Biskup (1999) defined the actual processing time of job j processed on position r in a schedule π with learning coefficient $a \leq 0$ as

$$p_{j,r} \equiv p_j \cdot r^a.$$

This *position-based* learning effects connects efficiency gains, in terms of reductions in jobs standard processing time p_j with the jobs position. These effects are independent of the length of the previously processed jobs. Assuming identical processing times for all jobs and in line with empirical studies, we can assume a logarithmic learning curve corresponding to the model of Wright (1936).

Throughout this article, problems including a *position-based* learning effect are identified by an index p. Hence, the above described model by Biskup (1999) is denoted by LE_p. On m parallel identical machines (P_m) the processing times (LEP_p) can be written as $p_{i,j,r} \equiv p_j \cdot r^a \cdot x_{i,j,r}$ with $x_{i,j,r}$ indicating if job j is processed on machine i in position r (Mosheiov, 2001a,b). This learning effect can be extended by generalizing the formulation by Lee (2004) to a two-machine flow-shop problem where jobs have different standard processing times $p_{i,j}$ on each machine i. This effect was introduced for flow-shop problems with m machines. The resulting processing times with learning effect are given by $p_{i,j,r} \equiv \sum_{i=1}^{m} p_{i,j} \cdot r^a \cdot x_{i,j,r}$, referred to as LEF_p. Wu et al. (2018) presented a position-based learning effect ($LEMF_p$) for a multi-stage flow-shop problem with two machines in the first stage and one in the second. They only considered the jobs position r in the second-stage. Nevertheless, the processing times on the two machines of the first stage are also affected by this position. Thus, the actual processing times on machine i are defined as $p^A_{i,j} = p_{i,j} \cdot r^\alpha$. The completion time of job j is given by $C_{[r],j} \equiv \max\{S_1 + p_{1,j} \cdot r^\alpha, S_2 + p_{2,j} \cdot r^\alpha, S_3\} + p_{3,j} \cdot r^\alpha$ with start time S_i on machine i (Wu et al., 2018). For a hybrid flow-shop group scheduling problem, the learning effect $LEHF_{p,g}$ is given by $p^s_{g,j,i,r} = p^s_{g,j,i} \cdot r^a$ if job j belonging to group g is processed on machine i at stage s Shahvari and Logendran (2018).

Job-Dependent Learning Studies show that the inherent nature of a job influences the efficiency gains realized due to learning effects. The distinction between cognitive and motor tasks (Zamiska et al., 2007) as well as the number of operations and the overall complexity have been named as factors for job-dependent effects. Mosheiov and Sidney (2003) extended the base model above by assuming that different jobs j can possess distinct learning coefficients $\alpha_j < 0$ resulting in $p_{j,r} \equiv p_j \cdot r^{\alpha_j}$ for single-machine scheduling problems. By including a speed factor h_i for machine

i the processing time $p_{i,j,r} \equiv p_j \cdot r^{\alpha_j} \cdot h_i$ can be used for parallel unrelated machines (Q_m). The afore-described effects are denoted by $LE_{p,j}$ and $LEQ_{p,j}$. Moreover, the family of job dependent position-based learning effect is denoted by $LE_{p,j}$.

Setup Time Learning Pargar and Zandieh (2012) included the job dependent learning coefficients α_j described above to model sequence-dependent setup times. By separating setup and processing times, this approach explicitly models the assumption that learning is mainly present in machine setups in many position-based learning publications. Since they consider a hybrid flow-shop problem, the setup time of a job j processed after job i on position r in stage t is defined as $s_{i,j,r,t} \equiv s_{i,j,t} \cdot r^{\alpha_j}$. By dropping the stage index t, the effect $LE_{p,j,setup}$ could be used for a single-machine problem.

Koulamas and Kyparisis (2008) introduced sequence-dependent setup times (s_{psd}), which depend on the total production time of the already scheduled jobs $s_{[r]} = \gamma \cdot \sum_{i=1}^{r-1} p_{[i]}, j = 2, ..., n, s_{[1]} = 0$, and a normalization constant $\gamma \geq 0$. They further assumed that with each unit processed setup time learning can be observed. Therefore, they restricted γ to the interval $(0, 1)$ and modified the setup times to obtain a position-based learning effect $LE_{p,setup}$. The setup time of the job scheduled on position r is defined as $s_{[r]} = \gamma^{(r-1)} \sum_{i=1}^{j-1} p_{[i]}$, for $j = 2, ..., n$, with $s_{[1]} = 0$. Note that this learning effect is job-independent.

Plateau Learning The above learning models share a common shortcoming, in that a large enough number of repetitions forces the processing times to unrealistically converge to zero. To overcome this problem, learning models that include a plateau effect have been developed. Cheng et al. (2013) introduced a so-called truncated learning effect $LE_{p,plat}$ by including a truncation parameter $\gamma \in (0, 1)$ restricting the processing time to being at least of the size $\gamma \cdot p_j$, independent of the jobs position. For flow-shop problems in general, the learning effect can be rewritten as $p_{j,i,r} \equiv p_{j,i} \cdot \max\{r^{\alpha}, \gamma\}$, denoted by $LEF_{p,plat}$ with $\alpha < 0$. Again, by dropping the machine index i this learning effect is easily applicable to single-machine problems.

Induced and Autonomous Learning Biskup and Simons (2004) combined the autonomous learning effect above with induced learning $LE_{p,induced}$. Induced learning, in turn, summarizes learning effects caused by managerial actions and decisions, e.g., training measures or investment in new equipment. It thus allows to actively impact the production efficiency directly and accelerate the learning curve (Lapré and Van Wassenhove, 2001). In this vein, a convex cost function $k(x)$, which includes costs of such measures in the objective function, which aims to minimize the sum of the 'regular' production costs and costs of induced learning. Although induced learning is costly it positively impacts (reduces) the learning rate l by a percentage $0 \leq x \leq x_{max} < 1$ and hence 'regular' productions costs. This results in the learning rate $(1-x) \cdot l$ and, further, processing times $p_j, r \equiv p_j \cdot r^{log_2((1-x) \cdot l)}$ after an investment in induced learning of $k(x)$.

Controllable Processing Times and Learning Similar to induced learning, deliberate efficiency gains can be achieved by controllable processing times. In certain production processes, the processing times of jobs can be influenced due to the allocation of certain resources. In this vein, a compression rate u_j is included, which reduces the processing times based on the amount of resources employed. Oron (2016) combined the effect of controllable processing times and position-based learning by introducing a convex processing time function $p_{i,j,r}(u_j) = (\frac{w_{i,j,r}}{u_j})^k$, which depends on the amount $u_j > 0$ of a resource allocated to job j and a positive constant k. Here, the learning effect is embodied in the workload $w_{i,j,r}$ of job j on machine i depending on the position r in the schedule. As we receive an indirect position-based learning effect $LE_{\overline{p},con}$, the notation $\overline{p}$ is utilized. By dropping the index i this model can also be used for single-machine problems. Note, that controllable processing times in comparison to induced learning do not affect the learning coefficient a but the workload of a single job. Wang and Wang (2015) considered a related effect on a single-machine by explicitly including a positions-based and job-dependent learning effect when modeling the job's workload. Hereto, the workload $w_{i,j,r} = w_{j,r}$ is replaced by $w_j \cdot r^{a_j}$ with $a_j \leq 0$ leading to the formulation $p_{j,r}(u_j) = (\frac{w_j \cdot r^{a_j}}{u_j})^k$ denoted by $LE_{p,con}$. For a comprehensive review of articles on controllable processing times, we refer to Wang and Wang (2015).

Deterioration and Learning Deteriorating jobs are characterized by increasing processing times, i.e. a job needs more time to be completed the later it is started. These kinds of problems are, for example, relevant in fire fighting, emergency room scheduling, or if machines included in the production quickly wear out (Qian and Steiner, 2013). Wang and Cheng (2007) adapted the classical single-machine scheduling problem with deterioration by modifying a common standard processing time $p_j = p$ (for all jobs j) by adding a position-based learning effect. This leads to processing times $p_{j,r} = (p + w_j \cdot S_j) \cdot r^a$, with starting times $S_j > 0$ of job j and growth rates $w_j \geq 0$ of job j. A more general formulation of this problem utilizes a common growth rate $w > 0$ but individual standard processing times p_j for all jobs, resulting in $p_{j,r} \equiv (p_j + w \cdot S_j)r^a$ (Wang, 2006). Note, that both formulations are based on a job-independent learning rate a. Position-based learning effects with deterioration are further denoted by $LE_{p,deterioration}$ (Wang, 2006; Qian and Steiner, 2013). Note that we distinguish between deterioration processing times and deterioration-based forgetting which will be introduced in Section 4.2.1.

Linear Position-Based Learning The only position-based learning effect that does not correspond to the logarithmic WLC is a linear effect LEF_{pl} introduced by (Wang and Xia, 2005). For flow-shop problems, the processing times are $p_{i,j,r} \equiv p_{i,j} \cdot (\overline{a} - \overline{b} \cdot r)$, with parameters $\overline{a} > 0$, $\overline{b} \geq 0$, so that $\overline{a} - \overline{b} \cdot r$ is a decreasing function and $\overline{a} - (n+1) \cdot \overline{b} > 0$ to assure positive processing times. Again this model can be applied to single-machine problems by dropping the index i (Wang and Xia, 2005). Compared to the logarithmic model, the linear model (Wang and Xia, 2005) does not consider the diminishing effects of learning. It is implicitly assumed that the amount workers learn is constant over the whole production horizon. That means processing times decline according to a constant rate with each repetition. This assumption is not in line with the findings from empirical studies on human learning, since efficiency gains from learning are highest when producing the first units and decrease over time with further repetitions (Yelle, 1979; Dutton and Thomas, 1984; Wright, 1936).

4.1.2 Time-Based Learning Effects

In contrast to position-based effects, another stream of literature assumes that learning takes place when a job is actually performed, i.e. during the processing time of a job. This concept considers labor-intensive environments where the production process is largely carried out by human labor learning effects therefore occur during the execution time. In this context, homogeneous production processes where the main characteristics of a job do not change are a key requirement. In other words jobs consists of only one, repeated operation and the individual jobs differ solely with regard to their length and number of embedded task repetitions (Yang and Kuo, 2007). To assess the resulting processing times or costs, the learning effect is based on the sum of (prior) processing times, also referred to as the *time-based* effect. Hence, larger (i.e. more time-consuming) jobs have a greater impact on employee's learning compared to smaller (i.e. less time-consuming) jobs.

Time-based learning effects can again be interpreted as a special case of the logarithmic concept by (Wright, 1936). Kuo and Yang (2006) defined a time-based learning effect (LE_t), depending on the standard processing times of the preceding jobs, by

$$p_{j,r} \equiv p_j \cdot \left(1 + \sum_{k=1}^{r-1} p_{[k]}\right)^a .$$

Henceforth, we utilize the index t to denote learning formulations depending on the processing times.

Actual Processing-Time-Dependent Learning Yang and Kuo (2007) modified the original model by Kuo and Yang (2006) by taking into account that the jobs scheduled prior were already subject to learning effects. They assumed that one job does not consist of a number of identical parts but, nevertheless, learning takes place to a certain extent. Therefore, the actual processing times p_r^A instead of the standard processing times of the preceding jobs are considered. This leads to the following definition: $p_{j,r} \equiv p_j \cdot (1 + \sum_{k=1}^{(r-1)} p_{[k]}^A)^a$.

Actual Processing-Time-Dependent Learning with Job-Dependent Learning Similar to position-based learning, Jiang et al. (2013) substituted the learning coefficient a by job-dependent coefficients a_j leading to $p_{j,r} \equiv p_j^{a_j} \cdot (1 + \sum_{k=1}^{(r-1)} p_{[k]^A})$. We denote the actual processing time-dependent learning effects by $LE_{t,A}$ and $LE_{t,A,j}$ respectively (Yang and Kuo, 2007; Jiang et al., 2013).

Plateau Processing-Time-Dependent Learning Cheng et al. (2011) extended the time-dependent learning effect to satisfy a plateau or truncation condition ($LE_{t,plat}$). Another approach equivalent to the plateau effect for position-based effects also uses a parameter $\gamma \in (0, 1)$ to restricts the processing times form decreasing arbitrarily. The resulting processing time for job j on the rth position is $p_{j,r} \equiv p_j \cdot \max\{(1 + \sum_{k=1}^{r-1} p_{[k]})^\alpha, \gamma\}$.

Logarithmic, Time-Based Learning By considering the logarithm of the standard processing times Cheng et al. (2009) mitigated the prior processing times' effect. The resulting learning effect $LE_{t,log}$ leads to a processing time $p_{j,r} \equiv p_j \cdot (1+\sum_{k=1}^{r-1} \ln(p_k))^a$. Note that the sum of the processing times decreases and, thus, the learning effect. The presented model respects, as also stated by the authors, the diminishing returns form learning. However, due to the second logarithmic effect utilizing this approach is more complex for practitioners. It is also necessary to adjust the learning rate, empirically observed in production, to the nested logarithmic effects in order to obtain proper results.

Fractional, Time-Based Learning Koulamas and Kyparisis (2007) developed a learning effect with processing times, depending on the proportion of jobs that still have to be executed. For this purpose, the total standard processing time of all jobs is used to calculate the time-based percentage of jobs that still have to be processed. The actual processing times of a job on position r are defined as $p_{j,[r]} \equiv p_j \cdot \left(\frac{\sum_{k=r}^{n} p_{[k]}}{\sum_{k=1}^{n} p_k}\right)^{\beta}$. Since the percentage calculated is in $(0, 1)$, the learning coefficient $a \leq 0$ considered in the previous problems is replaced by a positive real number $\beta \geq 1$. For flow-shop problems the formulation has been extended as follows: $p_{i,j,[r]} \equiv p_{i,j} \cdot \left(\frac{\sum_{k=r}^{n} p_{i,[k]}}{\sum_{k=1}^{n} p_{i,k}}\right)^{\beta}$, with $\beta \geq 1$ (Koulamas and Kyparisis, 2007).

Exponential, Time-Based Learning Wang et al. (2009) proposed an exponential, time-based learning model $LE_{t,exp,plat}$. Here, the completion times $C_j \equiv \sum_{k=1}^{r-1} s_{[k]} + p_{[k]}^A$ are based on the actual processing times, with learning effects $p_j^A = p_{j,r} = p_j \cdot (\overline{a} \cdot \gamma^{\sum_{k=1}^{r-1} p_{[k]}} + \overline{b})$ and past-sequence-dependent setup times $s_r = \delta \cdot \sum_{k=1}^{r-1} p_{[k]}^A$. Thus the learning affects both, setup times and processing times. The parameters $\overline{a}$, $\overline{b} \geq 0$ with $\overline{a} + \overline{b} = 1$ and $0 < \gamma \leq 1$ need to be estimated empirically while $\delta \geq 0$ is a normalizing constant. Interestingly, the actual processing times, including learning, are considered in the setup times. For calculating the actual processing times itself, however, only the standard processing times are utilized. Moreover, the model includes a plateau effect by approximating the exponential effect through a linear function. As a consequence, a job needs at least $p_j \cdot \overline{b}$ time units. Hence, a logarithmic learning effect, for both setup times and processing times, with plateau effects in presented.

4.1.3 Other Learning Formulations

In addition to the previously described approaches, some models, matching neither of the two categories, have been developed. Among them, some models do not include unambiguous functional formulations of learning curves but allow for a number of different continuous functions and therefor a variety of different learning curves. For example, a generalization including the position-based learning effect LE_p by Biskup (1999) and time-based effect LE_t by Kuo and Yang (2006) was introduced by Lai and Lee (2011). For this purpose, a function $f(0, \infty) \times \mathbb{N} \rightarrow (0, 1]$ is used to model the general learning effect LE_g with the processing times

$$p_{j,r} \equiv p_j \cdot f\left(\sum_{k=1}^{r-1} \beta_k p_{[k]}, r\right).$$

The learning function f needs to be differentiable with respect to x, non-increasing with respect to x and y, and the derivative $(\delta/\delta x)f(x, y_0)$ needs to be non-decreasing with respect to x (for y_0 fixed) and $f(0, 1) = 1$. Although the processing times require a time-based input factor, it is possible to model position-based learning effects. A list of existing models forming subcases of this problem class can be found in Lai and Lee (2011).

Table 2 (page 115) contains all *position-based* and *time-based* learning effects explained above, as well as the general learning effect, using the notation introduced before. Equal to the alternative formulations presented a number of other time-based models have been developed. Since, these come with more requirements for the production planner while yielding none or little benefits we limit this overview to the above examples. For more models consult the following review articles (Janiak and Rudek, 2010; Azzouz et al., 2018; Biskup, 2008).

4.2 Forgetting Effects

Compared to the variety of scheduling models that include different learning effects, publications that focus not only on learning but also on forgetting are rare. Forgetting effects are a counterpart to learning, in that they decrease workers efficiency due to losses of knowledge on the production task (Globerson, 1987). Omitting forgetting effects therefore leads to an underestimation of the actual processing times of jobs. Consequently, the retrieved production planning can be inaccurate (Jaber et al., 2003). Forgetting effects are predominantly assumed to arise if the production process is interrupted (Globerson, 1987; Jaber et al., 2003). Another stream of research in this area of publications considers human-based productivity losses that start influencing the processing times after a certain number of repetitions or time of production. The resulting efficiency losses are partly interpreted as temporal forgetting effects, which resemble deterioration or fatigue effects. Both effects are considered in this section, and we distinguish between *deterioration-based* and *interruption-based* forgetting.

4.2.1 Deterioration-based Forgetting Effects

Besides realizing efficiency gains, learning effects foster the specialization of employee due to repeating a limited number of tasks. In turn, specialization of employees can lead to ergonomic incidents and reduce motivation or productivity since workers pursue a single task or movement repeatedly (Azizi et al., 2010; Dondeti and Mohanty, 1998; Anzanello et al., 2014). Often production already has overcome the steep part of the learning curve at that time, and employees are familiar with the production tasks. Because the main learning process is already completed, it is assumed that losses due to interrupting the production process are rather small. Therefore, possible ways to overcome the resulting problems are job rotations between jobs of different complexity or physical movements required (Azizi et al., 2010). Models focusing on efficiency losses with a high number of repetitions or certain production time can also be considered as special cases of scheduling problems with deteriorating task-processing times (Lai and Lee, 2013).

Dondeti and Mohanty (1998) considered learning and forgetting $(LE + F)_g$ effects based on fatigue. A continuous and monotonically increasing function $F(u) = \int_0^u f(x)dx$ was used to describe

Table 2: Explicitly Modeled Learning and Forgetting Effects dealt with in Scheduling Problems

Position in the Schedule		
Position (LE_p)	$p_{j,r} \equiv p_j \cdot r^a$	Biskup (1999)
Position F_m (LEF_p)	$p_{j,i,r} \equiv p_{j,i} \cdot r^a$	Lee (2004)
Position P_m (LEP_p)	$p_{j,r} \equiv p_j \cdot r^a \cdot x_{i,j,r}$	Mosheiov (2001b) Mosheiov (2001a)
Position MF_p ($LEMF_p$)	$p_{j,i,r} \equiv p_{j,i} \cdot r_m^{\alpha},\ r_m \in \pi_m$	Wu et al. (2018)
Position MF_p ($LEMF_p$)	$p^s_{j,i,g,r} \equiv p^s_{j,i,g} \cdot r^a$	Shahvari and Logendran (2018)
Position, Job-dependent ($LE_{p,j}$)	$p_{j,r} \equiv p_j \cdot r^{\alpha_j}$	Mosheiov and Sidney (2003)
Position, Job-dependent Q_m ($LEQ_{p,j}$)	$p_{i,j,r} \equiv p_j \cdot r^{\alpha_j} \cdot h_i$	Mosheiov and Sidney (2003)
Position, Job-dependent HF_m ($LE_{p,j,setup}$)	$s_{ijrt} \equiv s_{i,j,t} \cdot r^{\alpha_j}$	Pargar and Zandieh (2012)
Position, Job-dependent, Setup Times ($LE_{t,setup}$)	$s_{[j]} \equiv \gamma^{(j-1)} \sum_{k=1}^{j-1} p_{[k]}$ * **	Koulamas and Kyparisis (2008)
Plateau Position Learning F_m ($LEF_{p,plat}$)	$p_{j,i,r} \equiv p_{j,i} \cdot \max\{r^{\alpha}, \gamma\}, \gamma \in (0,1)$	Cheng et al. (2013)
Induced and Autonomous learning ($LE_{p,induced}$)	$p_j, r \equiv p_j \cdot r^{log_2((1-x)\cdot l)}$, $0 < x \le x_{max}$	Biskup and Simons (2004)
Position, Controllable processing times ($LE_{\overline{p},con}$)	$p_{i,j,r}(u_j) \equiv \frac{w_{i,j,r}}{u_j}^k$	Oron (2016)
Position, Controllable processing times ($LE_{p,con}$)	$p_{j,r}(u_j) \equiv (\frac{w_j \cdot r^{a_j}}{u_j})^k$	Wang and Wang (2015)
Position, Deterioration ($LE_{p,det}$)	$p_{j,r} \equiv (p_j + w \cdot S_j)r^a$	Wang (2006); Qian and Steiner (2013); Yang and Kuo (2009)
Position, Job-dependent Deterioration (LE_{p,det_j})	$p_{j,r} \equiv (p_0 + w_j \cdot S_j)r^a$	Wang and Cheng (2007)
Position, Linear-Effect* F_m (LEF_{pl})	$p_{i,j,r} \equiv p_{i,j} \cdot (a - b \cdot r)$	Wang and Xia (2005)
Time-dependent		
Time** (LE_t)	$p_{j,r} \equiv p_j(1 + \sum_{k=1}^{r-1} p_{[k]})^a$	Li et al. (2013) Kuo and Yang (2006)
Time (LEF_t)	$p_{i,j,r} \equiv p_{i,j}(1 + \sum_{k=1}^{r-1} p_{i,[k]})^a$	Wang et al. (2008) Li et al. (2013)
Time, Actual Processing Times ($LE_{t,A}$)	$p_{j,r} \equiv (1 + \sum_{k=1}^{(r-1)} p_{[k]^A}) * p_j^a$	Jiang et al. (2013)
Time, Actual Processing Times, Job-dependent ($LE_{t,A,j}$)	$p_{j,r} \equiv (1 + \sum_{k=1}^{(r-1)} p_{[k]^A}) \cdot p_j^{a_j}$	Yang and Chand (2008)
Time, Plateau-effect ($LE_{t,plat}$)	$p_{j,r} \equiv p_j \cdot \{\left(1 + \sum_{k=1}^{r-1} p_{[k]}\right)^{\alpha}, \gamma\},\ \gamma \in (0,1)$	Cheng et al. (2011)
Time, Proportional ($LE_{t,frac}$)	$p_{j,r} \equiv p_j \cdot \left(\frac{\sum_{k=r}^{n} p_{[k]}}{\sum_{k=1}^{n} p_k}\right)^{\beta},\ \beta \ge 1$	Koulamas and Kyparisis (2007)
Times, Proportional F_m ($LEF_{t,frac}$)	$p_{i,j,[r]} \equiv p_{i,j} \cdot (\frac{\sum_{k=r}^{n} p_{i,[k]}}{\sum_{k=1}^{n} p_{i,k}})^{\beta}$, with $\beta \ge 1$	Koulamas and Kyparisis (2007)
Times, Exponential ($LE_{t,exp}$)	$p_{j,r} \equiv (\gamma \cdot c^{\sum_{k=1}^{r-1} p_{[k]}} + \delta)$	Wang et al. (2009)
Times, Logarithmic ($LE_{t,log}$)	$p_{j,r} \equiv (1 + \sum_{k=1}^{(r-1)} \ln(p_{[k]})) \cdot p_j^a$	Cheng et al. (2009)
General Learning Effect (LE_g)	$p_{j,r} \equiv p_j \cdot f(\sum_{k=1}^{r-1} \beta_k p_{[k]}, r)$	Lai and Lee (2011)

*$a > 0,\ b \ge 0,\ (a - b \cdot r),\ a - (n+1) \cdot b > 0$ to assure a learning effect and positive processing times (Xu et al., 2008); **In order to assure a proper learning effect for the time-based processing times $p_{j,i,r} \equiv p_j(1 + \sum_{k=1}^{r-1} p_{[k]})^a$ a 1 is included, so that $0 \le (1 + \sum_{k=1}^{r-1} p_{[k]})^a \le 1$ (Kuo and Yang, 2006). *** $j = 2, ..., n, s_{[1]} = 0, \gamma \in (0,1)$

the time needed to process u units. Since the only requirement for the derivative function $f(u)$, describing the rate at which unit u is processed, is to be positive, it can incorporate learning and forgetting effects or even both effects (Dondeti and Mohanty, 1998). The resulting forgetting effect can influence the processing times at any point of production.

Lai and Lee (2013) developed a model $(LE + F)_{p,sum,g}$ that combines learning and forgetting effects for single-machine problems utilizing a general formulation. The model can be seen as an extension to the general learning model LE_g by the same authors described in Section 4.1.3 Lai and Lee (2011). Here, the standard processing times are multiplied both by a non-negative, non-increasing, differentiable learning function $f(\sum_{k=1}^{r-1} \beta_k \cdot p_{[k]}, r)$ and by a forgetting function $g(r)$ with the same properties. In contrast to the $(LE + F_g)$ model by Dondeti and Mohanty (1998), forgetting occurs if a certain threshold of prior processed jobs is reached. Since the position in the schedule determines the amount of knowledge forgotten, the resulting effect can be understood as a position-based forgetting effect. The authors calculated processing time as follows:

$$p_{j,r} \equiv \begin{cases} p_j \cdot f\left(\sum_{k=1}^{r-1} \beta_k \cdot p_{[k]}, r\right) & if\ r \leq m \\ p_j \cdot \left[f\left(\sum_{k=1}^{r-1} \beta_k \cdot p_{[k]}, r\right) \cdot g(r)\right] & if\ r > m \end{cases}$$

This formulation allows for a variety of learning and forgetting effects. In particular the following learning effects LE_t and $LE_{t,frac}$ are special cases of their formulation.

Wu et al. (2016) propose an integral-based approach $(LE + F)_{p,int,g}$ using two non-increasing, non-negative functions. In contrast to the previous model, they do not multiply the learning and forgetting effect but consider the following summation when calculating the processing times:

$$p_{j,r} \equiv \begin{cases} p_j \cdot \left[1 - \sum_{l=1}^{r-1} \int_0^{\sum_{k=1}^{l} \beta_k \cdot p_{[k]}} f(x,y)dx\right] & if\ r \leq m \\ p_j \cdot \left[1 - \sum_{l=1}^{r-1} \int_0^{\sum_{k=1}^{l} \beta_k \cdot p_{[k]}} f(x,y)dx + \sum_{l=1}^{r-m-1} \int_0^{\sum_{k=1}^{l} \beta_k \cdot p_{[k]}} g(x,y)dx\right] & if\ r > m \end{cases}$$

A similar approach is also used by Lai and Lee (2014). They replaced the sum over the forgetting function again by an integral.

Wu et al. (2015) extend the integral-based approach by modifying the threshold for forgetting. Instead of referring to the number of previously processed jobs they, further, accounted for the duration of the processed jobs by considering the sum of prior processing times. This approach $(LE + F)_{t,int,g}$ can be interpreted as a time-based forgetting effect. In their formulation, the standard processing times are multiplied by $(1 - \int f(x) + \int g(x))$, omitting the summation over the forgetting effects.

$$p_{j,r} \equiv \begin{cases} p_j \cdot [1 - \int_0^{\sum_{k=1}^{r-1} p_{[k]}} f(x)dx] & if\ \sum_{k=1}^{r-1} p_{[k]} \leq k_0 \\ p_j \cdot [1 - \int_0^{\sum_{k=1}^{r-1} p_{[k]}} f(x)dx + \int_0^{\sum_{k=1}^{r-1} p_{[k]}^{-k_0}} g(x)dx] & if\ \sum_{k=1}^{r-1} p_{[k]} > k_0 \end{cases}$$

Models that are based on general learning and forgetting effects can be found in Lai and Lee

(2013), Lai and Lee (2014), Wu et al. (2015) and Wu et al. (2016).

4.2.2 Interruption-Based Forgetting Effects

As already mentioned, the forgetting effects outlined above do not depend on interruptions of the production process. However, broad strands of the literature see interruptions as main drivers of forgetting (Globerson, 1987). Jaber et al. (2003) named some factors that can influence the amount forgotten. These comprise, for example, the amount of knowledge previously acquired , the length and number of interruptions or the learning rate (Jaber et al., 2003). Moreover, the activities pursued during the interruption can influence the performance when resuming production. Positive effects that decrease the amount forgotten are related production activities or sleep (Globerson, 1987).

Li et al. (2018) were the first to introduce a forgetting effect ($(LE_{p,t,plat,experience} + F_{inter,exp})F$) for flow-shop problems, which is not comparable with a deterioration effect. In their model, they accounted for forgetting effects based on workers interrupting or being interrupted when performing a task. The interruptions arise when employees need to wait for new jobs to arrive to continue processing products. In this vein, the effect of forgetting is based on idle times on the second machine in a two-machine flow-shop problem. First, the actual processing times

$$p_{j,r} \equiv p_j \cdot \max\{(1-\omega) \cdot \left(1 - \frac{\sum_{k=1}^{r-1} p[k]}{\sum_{k=1}^{n} p_k}\right)^{\beta} \cdot r^{a_2}, \Theta\} = p_j \cdot L(p, r-1, \Theta)$$

on each machine are caused by learning effects only. Here, a time-based learning effect (with coefficient $\beta > 1$) is combined with position-based learning (coefficient $a \leq 0$). Moreover, the model allows for employee heterogeneity since an experience parameter $\omega \in (0, 1]$ is included. Moreover, a plateau effect for learning is realized by restricting the processing times to be at least $p_j \cdot \Theta$. Io extend this model to include forgetting effects, a forgetting parameter $\sigma > 0$ and a measure I_k depicting the idle time before the kth job are introduced. The combined effect of learning and forgetting results in the processing times

$$p_{j,r} \equiv p_j \cdot \left[1 - \underbrace{(1 - L(p, r-1, \theta))}_{\text{learning}} \cdot \underbrace{e^{-\sigma \sum_{k=1}^{r} I_{[k]}}}_{\text{forgetting}}\right].$$

This presented model includes a number of relevant factors for describing employees' skill development: prior experience, plateau effects, and interruption-based forgetting. This model can also be used for single-machine problems with idle times and does not only apply to for flow-shop environments. Moreover, the forgetting function used can be combined with other learning effects and utilized for other production scenarios. Note that we changed the coefficient σ to being positive. Li et al. (2018) described the parameter σ to described to be negative. In this case unlearning (negative) learning, but not forgetting effects could be present. Moreover the authors themselves choose σ to be positive in their numerical example as well.

Batch-Sizing Yusriski et al. (2015) considered a learning and forgetting effect $(L+F)_{t,batch}$ for batch sizing. They emphasize that batch production research mainly focused on determining the batch sizes but has neglected finding an optimal sequence for the derived batches. Therefore, the introduced a model that aims to jointly determine both the number and size of batches as well as a 'batch' schedule. During the processing of one batch, learning effects are time-based, taking all previously processed batches Q_i into account. Forgetting effects depend on the number of units Y_i of one batch that could be processed during the length of an interruption due to the setup of batch i. This number of units is further normalized by dividing it by the number Y_i of units processed during a maximum interruption.

$$T_{[i]} = \min \left\{ \max \left\{ p \cdot \left(1 + \sum_{k=i}^{N} Q_{k+1}\right)^{-m} \cdot \left(1 + \sum_{k=i}^{N} \frac{X_k}{Y_i}\right)^{f(i)} - 1, v \right\}, w \right\}$$

Moreover, the forgetting slope$f(i)$ depends on the learning rate utilized as well as the previously processed batches and interruptions. Lastly, plateau effects v for learning and w for forgetting restrict processing times to a fixed range.

Yang and Chand (2008) also considered a batch sizing problem with learning and forgetting $(LE+F)_{p,batch,f}$ incorporating jobs that can belong to different families g. The underlying learning effect is position-based with $p_{j,r,g} = p_{j,g} \cdot r^{a_g}$ for the jth job of family g processed on the rth position in the current batch. Note, that each job has an individual processing time, and each group g an individual learning rate $a_g \leq 0$. Forgetting is incorporated in three ways. First, total forgetting between batches of different families is assumed. In this case, the processing time of job j is given by the equation above and does only consider the position r in the current batch. Second, no forgetting between two batches of one family is assumed. Hence, the total number of jobs from a family produced previously, regardless of the batch, contribute to the learning effect $p_{j,r,g,v} \equiv p_{j,g} \cdot (r + \sum_{k=1}^{v-1} \delta_{k,g})$ when job j is part of the vth batch of family g and $\delta_{v,g}$ describes the number of jobs from g in batch v. Finally, the number of jobs in the current batch and the number of previously completed batches lead to experience gains. Therefore, the position-index v, denoting the position of the batch of group g the job is part of, is equipped with a learning coefficient $c_g \in (a_g, 0)$. The following effect arises $p_{j,r,g,v} = p_{j,g} \cdot r^{a_j} \cdot v^{c_g}$. Here, it is important to choose c_g so that it is not beneficial to split the families into arbitrary small batches, that is, one batch for each job. In addition to this effect, the model includes also setup times.

Pan et al. (2014) proposed a single-machine batch and group scheduling problem with groups consisting of similar jobs, which consist of a number of identical parts. Therefore, they introduced two types of sequence-dependent setup times, intra- and inter-group setups switching between two jobs or groups. They assumed forgetting $(F_{p,exp,batch,f})$ to occur if the employee switches between jobs and groups. Therefore, an exponential forgetting effect is based on the similarity $r^i_{j,j+1}$, of two consecutive jobs j and $j-1$, a forgetting parameter ϕ and the basic job setup time s

$$f(r^i_{j,j+1}, s) \equiv 1 - exp(-\phi \cdot (1 - r^i_{j,j+1},) \cdot s).$$

For each job respectively, this effect is then multiplied by the accumulated learning effect, which is the standard processing time minus the actual processing time. Finally, the resulting term is added to the processing times with learning effect. A similar forgetting effect is derived for switching between two groups of jobs. To account for the earlier learning and forgetting effects, a recursive formulation is used. Additionally, predictable preventive and stochastic corrective maintenance operations are included.

Since batch-sizing models with forgetting are mostly applicable to specific problems only and are generally very complex, they are not summarized in a separate table. The other forgetting models we discussed are summarized in Table 3.

4.3 Concluding Summary on Learning and Forgetting Effects

Learning Effects A number of distinct learning effects have been presented which are generally based either on the number of previously processed jobs (position-based) or the time spent in production (time-based).

For the position-based effect different conditions and aspects of skill development have been considered, i.e. job-dependence, induced learning, controllable processing times, deteriorating processing times, plateau effects, as well as learning effects for setup times and different multi-machine environments. Compared to the position-based effect, instead of refinements or extensions alternative model formulations have been introduced for the time-based effect. These models include more parameters estimated empirically. As a consequence the learning process that can be observed in production, in terms of the learning rate, needs to be split among several parameters. A model by Wang et al. (2009) for example requires four parameters. The authors do not guide practitioners in estimating these parameters nor provide any intuition. Without empirical evidence demonstrating the relevance of these alternative formulations the models presented offer only limited benefits for practitioners.

Concerning both categories of learning effects generally at most one aspect of skill development is considered in each model. Therefore, most effects allow processing times to decline to zero, do not consider the actual processing times of jobs, disregard job-dependencies, neglect training measures, and consider single-skill jobs only. In addition to the natural improvement of workers' skills only few publications take induced improvements into account. Thus positive impacts of employee training have been widely ignored. Only the model by Biskup and Simons (2004) allows for employee training measures to influence the workers' performance. Since training sessions and knowledge can be provided more easily and efficiently due to means of digitization they should be considered in the scheduling literature (Letmathe and Rößler, 2021). Richer models could to one end combine different properties, or include aspects that influence learning on the shop floor such as ergonomic factors (Anzanello et al., 2014), feedback information, cognitive load, information overload, spillover (Letmathe et al., 2012) or cross-learning (Pratsini and Marks, 2001), and effects of the production environment. All of these aspects can potentially improve the practical relevance of existing models and can lead to better learning outcomes relevant for managing the learning

Table 3: Forgetting Models

Deterioration-Based Forgetting		
General Learning and Forgetting Effect $(LE+F)_g$	$F(u) \equiv \int_0^u f(x)dx$	(Dondeti and Mohanty, 1998)
General Learning Effect with Position-Based Forgetting $(LE+F)_{p,sum,g}$	$p_{j,r} \equiv \begin{cases} p_j \cdot f\left(\sum_{k=1}^{r-1} \beta_k \cdot p_{[k]}, r\right) & if\ r \leq m \\ p_j \cdot \left[f\left(\sum_{k=1}^{r-1} \beta_k \cdot p_{[k]}, r\right) \cdot g(r)\right] & if\ r > m \end{cases}$	(Lai and Lee, 2013)
General Learning Effect with Position-Based Forgetting $(LE+F)_{p,int,g}$	$p_{j,r} \equiv \begin{cases} p_j \cdot \left[1 - \sum_{l=1}^{r-1} \int_0^{\sum_{k=1}^{l} \beta_k \cdot p_{[k]}} f(x,y)dx\right] & if\ r \leq m \\ p_j \cdot \left[1 - \sum_{l=1}^{r-1} \int_0^{\sum_{k=1}^{l} \beta_k \cdot p_{[k]}} f(x,y)dx + \sum_{l=1}^{r-m-1} \int_0^{\sum_{k=1}^{l} \beta_k \cdot p_{[k]}} g(x,y)dx\right] & if\ r > m \end{cases}$	(Wu et al., 2016)
General Learning Effect with Time-Based Forgetting $(LE+F)_{t,int,g}$	$p_{j,r} \equiv \begin{cases} p_j \cdot [1 - \int_0^{\sum_{k=1}^{r-1} p_{[k]}} f(x)dx] & if\ \sum_{k=1}^{r-1} p_{[k]} \leq k_0 \\ p_j \cdot [1 - \int_0^{\sum_{k=1}^{r-1} p_{[k]}} f(x)dx + \int_0^{\sum_{k=1}^{r-1} p_{[k]}^{-k_0}} g(x)dx] & if\ \sum_{k=1}^{r-1} p_{[k]} > k_0 \end{cases}$	(Wu et al., 2015)
Interruption-Based Forgetting		
$LE_{p,t,experience}$	$p_{j,r} \equiv p_j \cdot \max\{(1-\omega) \cdot \left(1 - \frac{\sum_{k=1}^{r-1} p[k]}{\sum_{k=1}^{n} p_k}\right)^{\beta} \cdot r^{a_2}, \Theta\} = p_j \cdot L(p, r-1, \Theta)$	Li et al. (2018)
Interruption-Based, Exponential Forgetting $(LE_{p,t,experience} + F_{inter})$	$p_{j,r} \equiv p_j \cdot [1 - \underbrace{(1 - L(p, r-1, \theta))}_{\text{learning}} \cdot \underbrace{e^{-\sigma \sum_{k=1}^{r} I_{[k]}}}_{\text{forgetting}}]$	

curve. Morevoer, refinements for multi-machine environments could include individual learning rates for different machines or workers. Such a distinction is relevant, as processing times and learning effects need to reflect the operators' skills and not only the job characteristics (Nembhard and Bentefouet, 2012).

Learning and Effects Effects The deterioration of skills caused by forgetting effects or by changes in the production process, (e.g., due to the introduction of new product designs, machines, or workers, are rarely considered). Despite the fact that previous research confirms the existence of forgetting effects in production and emphasizes its importance in production planning (Jaber et al., 2003), only a few articles include both learning and forgetting effects. We found they mostly either consider forgetting effects solely based on deterioration or are specialized in terms of their constraints and not generally transferable to other settings. Even though production process interruptions and changes are known to be the main drivers for forgetting effects, in single-machine scheduling the effect of forgetting is often modeled as a special case of deterioration. A threshold based on the total processing time or number of prior jobs is defined, and forgetting emerges only if this threshold is exceeded. As a consequence employees suffer from losses in efficiency after a certain production time which resembles productivity declines due to effects of boredom, fatigue or ergonomic factors. These effects are mainly relevant for highly specialized workers who have already overcome the steep part of the learning curve and gained familiarity with the production process. Job rotations is a common means to counteract such problems. These, in turn, lead to interruption-based forgetting effects if workers are new to the production process and learn how to perform the required jobs. Since new products replace products at the end of their life cycles (Otto and Otto, 2014) and new production lines are introduced frequently, it is even more important to account for these interruption-based forgetting effects. Even for batch scheduling problems, models that analyze interruption-based forgetting effects when turning from one part family to another are examined. Table 4 shows that compared to publications on learning effects, only a few articles also consider forgetting. From those, the models that include deterioration-based forgetting are not applicable to multi-machine environments. Although, models for interruption-based forgetting were presented for single- and multi-machine problems, these solely focus on batch-sizing and -scheduling.

Since the literature on learning effects is quite rich, we are not able to describe all models available. Nevertheless, we provide an overview of the publications most relevant in terms of learning theory and applicability. For further models that include learning effects, we recommend, for example, the reviews by (Biskup, 2008; Azzouz et al., 2018; Janiak and Rudek, 2009).

5 Complexity Results

Numerous publications show that learning and forgetting increase complexity of resulting planning and scheduling problems. As a result some of the problems incorporation learning and forgetting effects have proven to be *NP-complete*. Nevertheless, for the majority of problems approximation algorithms, heuristics or bounds for Branch and Bound (B&B) algorithms have been introduced. This section provides an overview of problems and objective functions already considered as well as

Table 4: Publications Clustered by Learning and Forgetting Effects

	Single-Machine Problems	Multi-Machine Problems
Position-Based Learning Effects	Mosheiov (2001b); Mosheiov and Sidney (2003); Koulamas (2010); Wang and Cheng (2007); Yang and Kuo (2009); Wang (2006); Qian and Steiner (2013); Oron (2016); Biskup (1999); Wang and Wang (2015); Lai and Lee (2013); Mosheiov and Sidney (2005); Lin (2007); Chang et al. (2009); Wang et al. (2017)	Cheng et al. (2009); Koulamas and Kyparisis (2007); Wu et al. (2018); Lee (2004); Mosheiov (2001a); Oron (2016); Wu and Lee (2009); Xu et al. (2008); Lee and Chung (2013); Pargar and Zandieh (2012)
Time-Based Learning Effects	Janiak and Rudek (2009); Koulamas and Kyparisis (2007); Yang and Kuo (2007); Jiang et al. (2013); Koulamas and Kyparisis (2008); Cheng et al. (2009); Wang et al. (2009); Kuo and Yang (2006); Wang et al. (2008); Dondeti and Mohanty (1998); Lai and Lee (2013)	Li et al. (2013); Koulamas and Kyparisis (2007)
Other Learning Effects	Lai and Lee (2011); Janiak and Rudek (2010)	Anzanello and Fogliatto (2010)
Deterioration-Based Forgetting	Lai and Lee (2013, 2014); Wu et al. (2015, 2016); Dondeti and Mohanty (1998)	None
Interruption-Based Forgetting Effects	Pan et al. (2014); Yang and Chand (2008)	Li et al. (2018); Yusriski et al. (2015); Anzanello et al. (2014)

the corresponding complexity results. The results are organized according to the objective functions examined. Section 5.1 focuses on completion time-based objective functions, whereas Section 5.2 considers objectives based on the due dates of jobs. These subsections are further structured based either single- or multi-machine environments. A summary of results with respect to different objectives and single-machine problems is displayed in Table 5 on page 123. A ✓ indicated if an efficient solution method to a problem exists. If only approximation algorithms exist or the problem can solely solved under special constraints these defining constraints are displayed in brackets (✓). Table 5 shows that only for the makespan and the Total Completion Time (TC) polynomial solutions persist for most learning models. Problems with other objectives are only efficiently solvable for special cases. These conditions and solution methods will be discussed in the subsequent subsections. The findings on different objective functions and environments are summarized in tables at the end of each subsection. For this purpose the classification from Section 4 is used in the three field notation.

5.1 Completion Time Related Objectives

5.1.1 Makespan

When including position-based learning effects (LE_p) or (LE_{pl}) into makespan minimization, a minimal schedule can be obtained by the Shortest-Processing-Time-First (SPT)-rule in polynomial time (Mosheiov, 2001b; Wang and Xia, 2005). By reformulating the first problem as an assign-

Table 5: Single-Machine Problems and Learning Effects

	Make-span	Total Completion Time	Total Weighted Completion Time	Maximum Lateness	Maximum Tardiness	Total Tardiness	Number of Tardy Jobs
	$C_{\max}$	$\sum C_j$	$\sum w_j \cdot C_j$	$L_{\max}$	$T_{\max}$	$\sum T_j$	$\sum U_j$
LE_p	✓	✓	(✓ agg_w)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $d = d_j$)
$LE_{p,j}$	✓	✓					(✓ $d = d_j$)
$LE_{p,plat}$	✓*	✓*					
$LE_{p,det}$	✓	✓	(✓ agg_w)				
LE_{pl}	✓	✓					
LE_t	✓	✓	(✓ agg_w)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $d = d_j$)
$LE_{t,A}$	✓	✓	(✓ agg_w)	(✓ $agg_{d=d_j}$)			
$LE_{t,A,j}$	*NP*		*NP*	*SNP*			
$LE_{t,exp}$	✓	✓	(✓ agg_w)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	
$LEC_{t,frac}$	✓	✓	(✓ agg_w)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	
$LE_{t,log}$	✓	✓	(✓ agg_w)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	
$LE + F_{p,sum,g}$	✓	✓	(✓ agg_w)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	
$LE + F_{p,int,g}$	✓	✓	(✓ agg_w)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	(✓ $agg_{d,p}$)	
$LE + F_{t,int,g}$	✓	✓	(✓ agg_w)			(✓ $agg_{d,p}$)	

✓ polynomial time solution for the problem exists; (✓) polynomial time solutions exist for sub-problems; *SNP / NP* problem is *(strongly) NP-Complete*; agg_w aggregable weights; $agg_{d,p}$ aggregable processing times and aggregable due dates; $d = d_j$ common due date, *via interchange argument

ment problem (ASGMT), it remains polynomial solvable in O(n^3) time even when job-dependent learning effects $LE_{p,j}$ (Mosheiov and Sidney, 2003). Koulamas (2010) showed that this problem can further be solved in O($n \cdot \log n$) when assuming lower-bounded learning coefficients and sophisticated learning effects. The latter arise when longer and more complex jobs possess higher learning rates ($p_j \geq p_k \Rightarrow a_j \leq a_k$). Similar results hold when this assumptions is reversed (Koulamas, 2010).

Wang and Cheng (2007) examined deteriorating job processing times with learning effects (LE_{p,det_j}). They considered a unique deterioration parameters w_j for each job but a common standard processing time $p_j = p_0$ for all jobs. The problem without learning can be solved by ordering the jobs according to non-increasing growth rates of processing times. Due to the joint effect of learning and deterioration this Largest-Growth-Rate-First (LGR)-rule is unbounded if learning effects are considered. Therefore, they derive three practical scenarios to solve the problem in polynomial O($n \cdot \log n$) time (Wang and Cheng, 2007). For another special case Wang and Cheng (2007) derived a heuristic. Yang and Kuo (2009), Wang (2006) and Qian and Steiner (2013) showed that the SPT-rule minimizes the makespan when all jobs share a common deterioration parameter $\gamma_j = \gamma$ but individual processing times ($LE_{p,j,det}$). The problem with controllable processing times ($LE_{\overline{p},con}$) can be solved by an algorithm in O(n^3) time (Oron, 2016).

The makespan for the proportional time-based learning effect $LE_{t,frac}$ (Koulamas and Kyparisis, 2007), the exponential learning effect with setup time learning $LE_{t,exp}$ (Wang et al., 2009), the logarithmic formulation $LE_{t,log}$ (Cheng et al., 2009) and the time-based learning effect LE_t (Janiak and Rudek, 2009) are again minimized by the SPT-rule. If the latter learning effect does not depend on the standard but actual processing times of preceding jobs ($LE_{t,A}$), the SPT-rule still provides an optimal solution (Yang and Kuo, 2007). Extending the problem to $LE_{t,A,j}$ and including job-dependent learning coefficients a_j leads to a *NP-Complete* problem which can be reduced to the problem $Partition$ (Jiang et al., 2013) when restricting the processing times to a certain minimal plateau-value.

The problem arising from including the time-based learning effect into the past-sequence-dependent setup times ($LE_{t,setup}$) can be solved by the SPT-rule in $\mathrm{O}(n \cdot \log(n))$ (Koulamas and Kyparisis, 2008).

The three general learning effects with deterioration-based forgetting ($LE + F_{p,sum,g}, LE + F_{p,int,g}, LE + F_{t,int,g}$) that allow for a number of different explicit learning effects are makespan-optimal when ordering the jobs according to the SPT-rule (Wu et al., 2015, 2016; Lai and Lee, 2013, 2014).

Yang and Chand (2008) presented a branch and bound algorithm with lower bounds and scheduling rules as well as a heuristic to minimize the total completion time for a single-machine batch-sizing and scheduling problem with different job families and three stages of learning and forgetting ($(LE+F)_{p,batch,f}$). In this setup, two factors that are normally addressed separately are considered jointly for minimization.

Multi-Machine Environments Minimizing the makespan on related parallel machines (Q_m) can further balance the load between different machines (Pinedo, 2012). The related problem with job-dependent and position-based learning ($LEQ_{p,j}$) can be solved in polynomial time in $\mathrm{O}(n^4)$ by utilizing a reformulation as assignment problem (Mosheiov and Sidney, 2003).

For two-stage flow-shop problems, Koulamas and Kyparisis (2007) showed that the SPT rule is optimal for the special cases *ord* and *prp*, when considering proportional time-based learning effects ($LEF_{t,frac}$). Cheng et al. (2013) studied a position-based plateau learning effect ($LEF_{p,plat}$) and introduced lower bounds and dominance properties for a branch and bound algorithm as well as three genetic algorithms. Moreover, Li et al. (2018) considered a two machine flow-shop problem with exponential learning and a forgetting effect ($(LE+F)F_{t,exp}$) on the second stage if the machine is idle. They propose four heuristics and a branch and bound algorithm with six bounds to derive a near-optimal solution for minimizing the makespan, given that the base problem is already known to be *NP-hard* (Li et al., 2018).

Wu et al. (2018) considered a multi-stage flow-shop problem with two machines on the first stage and an assembly machine on the second stage. Position-based learning effects ($LEMF_p$) are employed on each machine with regard to the jobs' position on the machine on the second stage. Since the base problem without learning effects is already known to be *NP-hard*, a branch and bound algorithm with several dominance properties and a lower bound is used to solve the problem to optimality for small instances. For larger instances, three heuristic algorithms based on the SPT-rule and six meta-heuristics (three Simulated Annealing, three *CSA* algorithms) with two methods to tune parameters are introduced. The solution methods are further evaluated regarding their performance (Wu et al., 2018).

Pan et al. (2014) considered learning and forgetting effects for group scheduling with preventive and stochastic corrective maintenance operations. They also included past-sequence-dependent setup times which account for the similarity of different groups and different jobs. The jobs considered consist of a number of similar parts to be processed, which are subject to a position-based learning effect (LE_p). To account for the parts position within a job, which in turn, is part of a group, the effect was expanded by a second index. In addition, an exponential forgetting effect ($F_{p,exp,batch,g}$) that accounts for the job similarities is analyzed. Since the base problem is known to be *NP-hard* and the presented group scheduling with maintenance operations as well as learning and forgetting considerations is *strongly NP-hard*, the authors present a meta-heuristic based on a genetic algorithm to minimize the expected makespan.

Table 6: Results on Makespan Minimization with Learning and Forgetting Effects

Problem	Solution Method	Paper
$1\|LE_p\|C_{\max}$	SPT, $O(n \cdot \log(n))$	Mosheiov (2001b)
$1\|LE_{p,j}\|C_{\max}$	ASGMT, $O(n^3)$	Mosheiov and Sidney (2003)
$1\|LE_{p,j}, p_i \leq p_j \Rightarrow a_i \geq a_j\|C_{\max}$	SPT, $O(n \cdot log(n))$	Koulamas (2010)
$1\|LE_{p,det_j},\|C_{\max}$	results for subproblems	Wang and Cheng (2007)
$1\|LE_{p,det}\|C_{\max}$	SPT	Yang and Kuo (2009); Wang (2006); Qian and Steiner (2013)
$1\|LE_{p,j,det}\|C_{\max}$	ALGO, $O(n \cdot \log(n))$	Qian and Steiner (2013)
$1\|LE_{\overline{p},con}\|C_{\max}$	ALGO, $O(n^3)$	Oron (2016)
$1\|LE_{pl}\|C_{\max}$	SPT, $O(n \cdot \log(n))$	Wang and Xia (2005)
$1\|LE_t\|C_{\max}$	SPT, $O(n \cdot \log(n))$	See Janiak and Rudek (2009)
$1\|LE_{t,frac}\|C_{\max}$	SPT, $O(n \cdot \log(n))$	Koulamas and Kyparisis (2007)
$1\|LE_{t,A}\|C_{\max}$	SPT, $O(n \cdot \log(n))$,	Yang and Kuo (2007)
$1\|LE_{t,A,j}\|C_{\max}$	$NP-complete$	Jiang et al. (2013)
$1\|LE_{t,setup}\|C_{max}$	SPT, $O(n \cdot \log(n))$	Koulamas and Kyparisis (2008)
$1\|LE_{t,log}\|C_{max}$	SPT, $O(n \cdot \log(n))$	Cheng et al. (2009)
$1\|LE_{t,exp},\ s_i = d \cdot \sum_{i=1}^{r-1} p_{[i]}^A\ \|C_{\max}$	SPT, $O(n \cdot \log(n))$	Wang et al. (2009)
$1\|(LE+F)_g\|C_{\max}$	SPT, $O(n \cdot \log(n))$	Lai and Lee (2013, 2014); Wu et al. (2015, 2016)
$Q_m\|LE_{p,j}\|C_{\max}$	ASGMT, $O(n^4)$	Mosheiov and Sidney (2003)
$F_2\|PLEF_p, prmu\|\sum C_{\max}$	B&B, GA*	Cheng et al. (2013)
$F_2\|LEF_{t,frac}, ord\|C_{\max}$	SPT, $O(n \cdot \log(n))$	Koulamas and Kyparisis (2007)
$F_2\|LEF_{t,frac}, prp\|C_{\max}$	SPT, $O(n \cdot \log(n))$	Koulamas and Kyparisis (2007)
$F_2\|LEF_p, prp\|C_{\max}$	SPT, $O(n \cdot \log(n))$	Koulamas and Kyparisis (2007)
$F_m\|prmu,\ LEF_t\|C_{\max}$	heuristic	Li et al. (2013)
$MF_{2,3}\|LEMF_p\|C_{max}$	NP-hard, heuristics, meta-heuristics, B&B	Wu et al. (2018)

5.1.2 Total Completion Time

The SPT-rule yields an optimal solution minimizing the total completion time (TC) when considering position-based learning effects (LE_p) (Biskup, 1999) and (LE_{pl}) (Wang and Xia, 2005). For job-dependent learning effects ($LE_{p,j}$) the problem stays solvable as assignment problem (Mosheiov and Sidney, 2003). Oron (2016) presented and algorithm to solve ($LE_{p,con}$) in O(n^3). For the deterioration learning effect $LE_{p,det}$, Yang and Kuo (2009) also showed that the SPT-rule minimizes the total completion time, and the sum of the kth power of completion times.Kuo and Yang (2006) proved that minimizing the total completion time with a time-based learning effect (LE_t) is solvable by the SPT-rule. The SPT-rule further delivers an optimal solution for minimizing the sum of the kth power of completion times $\sum C_j^k$ if the learning effect does not depend on the normal but actual processing times of the preceding jobs ($LE_{t,A}$) (Yang and Kuo, 2007). For the alternative proportional time-based learning effect $LE_{t,frac}$ (Koulamas and Kyparisis, 2007) and the logarithmic effect $LE_{t,log}$ (Cheng et al., 2009) the total completion time can be minimized by the SPT-rule. Wang et al. (2009) showed that for their exponential time-based effect $LE_{t,exp}$ with setup time learning, the total completion time and the sum of squared completion times are still solvable by the SPT-rule. When considering time-based learning for past-sequence-dependent setup times, a solution is achieved by the SPT-rule in O($n \cdot \log(n)$) (Koulamas and Kyparisis, 2008).

The general learning and forgetting models $LE{+}F_{p,sum,g}$, $LE{+}F_{p,int,g}$, and $LE{+}F_{t,int,g}$ possess a minimal total completion time when jobs are ordered according to the SPT-rule. Moreover, special cases of the weighted completion time can be solved in polynomial time by the WSPT-rule (Lai and Lee, 2013, 2014; Wu et al., 2015, 2016) when inclduing these learning and forgetting effects. Compared to the total completion time, most results on minimizing the weighted completion time with learning effects consider special cases of the problem which will be described in the following.

When including a deterioration effect with learning ($LE_{p,det}$), the WSPT yields an optimal solution for different special cases with respect to the aggregable agg condition $p_i \leq p_j \Rightarrow w_i \cdot p_i \leq w_j \cdot p_j$ (Yang and Kuo, 2009), aggregable weights $p_i \leq p_j \Rightarrow w_i \geq w_j$, uniform standard processing times $p_j = p$ or proportional processing times with regard to the weights $p_j = k \cdot w_j$ (Wang, 2006). Considering the time-dependent learning effect (LE_t), the WSPT-rule again yields a solution for aggregable weights, uniform standard processing times, and proportional processing times (Wang et al., 2008). Moreover, the results persist for aggregable weights when considering the exponential learning effect $LE_{t,exp}$ with setup time learning (Wang et al., 2009), the logarithmic time-based learning effect $LE_{t,log}$ (Cheng et al., 2009), or actual instead of the standard processing times $LE_{t,A}$ (Yang and Kuo, 2007). Jiang et al. (2013) assessed the complexity of minimizing the total weighted completion time with job-dependent learning coefficients and actual processing times ($LE_{t,A,j}$). This problem is *NP-complete* by reduction on the problem *Partition* (Garey and Johnson, 1979). Nevertheless, when assuming a common processing time $p_j = p$ for all jobs, the problem can be solved by ordering the jobs in non-increasing order of the job-specific weights w_j.

Multi-Machine Environments An optimal schedule for the flow time minimization on parallel identical machines with position-based learning effect (LEP_p) is not guaranteed by the SPT-rule but consists of SPT-sequences on all machines (Mosheiov, 2001b). Mosheiov (2001a) showed that the total completion time on identical parallel machines with position-based processing time learning effect (LEP_p) can be minimizing in polynomial time. They show that number of assignments problems that have to solved is bound. Since each assignment problem can be solved in O(n^3) the problem $P_m|LEP_p|\sum C_j$ is polynomial in n. The author further presented an algorithm for solving this problem for two machines $P_2|LEP_p|\sum C_j$ in O(n^4). Oron (2016) investigated controllable processing times with an indirect, position-based learning effect ($LE_{\overline{p},con}$). The computational effort O(n^{M+2}) is polynomial for a fixed number of machines.

The classical flow-shop problem is known to be *NP-hard* for $m \geq 3$ (Lenstra et al., 1977). Therefore, most results on flow-shop problems concentrate on approximation or branch and bound algorithms. Wu and Lee (2009) considered a position-based learning effect (LEF_p) and developed a dominance rule as well as several lower bounds to reduce the computational effort of branch and bound algorithms for permutation flow-shops. They further conducted computational experiments for different learning rates, job and machine sizes, comparing the efficiency of branch and bound algorithms and heuristics. The branch and bound algorithm performed well for small instances (with up to 16 jobs), while the Framinan and Leisten (FL)-heuristic (Framinan and Leisten, 2003) outperformed other methods for small and large problems (Wu and Lee, 2009). Lee (2004) presented dominance properties and lower bounds for a branch and bound algorithm to solve a two-machine flow-shop problems with position-based learning. Since the base problem is known to be *NP-hard* a two-stage-heuristic is presented to obtain near-optimal solutions for problems with 30 and more jobs to overcome the intractability of the branch and bound algorithm for bigger problem sizes. Koulamas and Kyparisis (2007) showed that the SPT-rule is optimal for minimizing the total flow time for the special cases *ord* and *prp* of the two machine flow-shop problem, when considering the time-based learning effect $LEF_{t,frac}$.

Two types of of position-based learning effects, the commonly used learning effect LEF_p and a linear position effect LEF_{pl} were considered by (Wang and Xia, 2005) and Xu et al. (2008). For both, tight worst-case bounds for the makespan, the total completion time (Wang and Xia, 2005), the sum of squared completion times, the weighted sum of completion times and the discounted total flow time (Xu et al., 2008) are presented. The authors also developed heuristics based on those performing best for the base flow-shop problems without learning. Specifically, a WSPT-rule based on increasing $\frac{\sum_{i=1}^{m} p_{i,j}}{w_j}$, a $WDSPT$-rule based on increasing $\frac{1-e^{-\gamma \cdot L_j}}{w_j \cdot e^{-\gamma \cdot L_j}}$ and a SPT-rule based on increasing $L_j = \sum_{i=1}^{m} p_{i,j}$ for the sum of squared completion times are presented. Li et al. (2013) developed several heuristics and tight worst-case bounds for the above described flow-shop problems as well as the total flow time, considering time-dependent learning effects (LEF_t). It's worth noting that Xu et al. (2008) and Li et al. (2013) considered only busy schedules for their worst-case analyses, that is, schedules with a least one operating machine at any point in time.

Table 7: Results on Total Completion Time and Weighted Total Completion Time Minimization with Learning and Forgetting Effects

Problem	Solution Method	Paper
$1\|LE_p\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Biskup (1999)
$1\|LE_{p,j}\|\sum C_j$	ASGMT, O(n^3)	Mosheiov and Sidney (2003)
$1\|LED_p\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Yang and Kuo (2009)
$1\|LEC_{\overline{p},con}\|\sum C_j$	ALGO, O(n^3)	Oron (2016)
$1\|LE_{pl}\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Wang and Xia (2005)
$1\|LE_{t,frac}\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Koulamas and Kyparisis (2007)
$1\|LE_{t,log}\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Cheng et al. (2009)
$1\|LE_t\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Kuo and Yang (2006)
$1\|LE_{t,A}\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Yang and Kuo (2007)
$1\|LE_{t,exp},\ s_i = d \cdot \sum_{i=1}^{r-1} p_{[i]}^A\ \|C_j$	SPT, O($n \cdot \log(n)$)	Wang et al. (2009)
$1\|LE_{t,setup}\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Koulamas and Kyparisis (2008)
$P_m\|LEP_p\|\sum C_j$	ASGMT, polynomial in n	Mosheiov (2001a)
$P_m\|LEC_p\|\sum C_j$	ALGO, O(n^{M+2})	Oron (2016)
$P_2\|LEP_p\|\sum C_j$	ASGMT, O(n^4)	Mosheiov (2001a)
$F_2\|LEF_p\|\sum C_j$	B&B, Two-Phase heuristic	Lee (2004)
$F_2\|LEF_{t,frac}, ord\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Koulamas and Kyparisis (2007)
$F_2\|LEF_{t,frac}, prp\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Koulamas and Kyparisis (2007)
$F_2\|LEF_p, prp\|\sum C_j$	SPT, O($n \cdot \log(n)$)	Koulamas and Kyparisis (2007)
$F_m\|LEF_p\|\sum C_j$	heuristic(SPT), $O(n \cdot log(n))$	Wang and Xia (2005)
$F_m\|LEF_{pl}\|\sum C_j$	heuristic(SPT), $O(n \cdot log(n))$	Wang and Xia (2005)
$F_m\|prmu,\ LEF_t\|\sum C_j$	heuristic(SPT)	Li et al. (2013)
$F_m\|prmu,\ LEF_p\|\sum C_j$	B&B, heuristics	Wu and Lee (2009)
$1\|LE_{t,A}\|\sum C_j^k$	SPT, O($n \cdot \log(n)$),	Yang and Kuo (2007)
$1\|LE_{t,exp},\ s_i = d \cdot \sum_{i=1}^{r-1} p_{[i]}^A\ \|C_j^2$	SPT, O($n \cdot \log(n)$)	Wang et al. (2009)
$F_m\|prmu,\ LEF_t\|\sum C_j^2$	heuristic(SPT), $O(n \cdot log(n))$	Li et al. (2013)
$F_m\|prmu,\ LEF_p\|\sum C_j^2$	heuristic(SPT), $O(n \cdot log(n))$	Xu et al. (2008)
$F_m\|prmu,\ LEF_{pl}\|\sum C_j^2$	heuristic(SPT), $O(n \cdot log(n))$	Xu et al. (2008)
$F_m\|prmu,\ LEF_p\|\sum w_j(1-\exp^{-\gamma C_j}), \gamma \in (0,1)$	heuristic(WSPT), $O(n \cdot log(n))$	Xu et al. (2008)
$F_m\|prmu,\ LEF_t\|\sum w_j(1-\exp^{-\gamma C_j}), \gamma \in (0,1)$	heuristic(WSPT), $O(n \cdot log(n))$	Li et al. (2013)
$F_m\|prmu,\ LEF_{pl}\|\sum w_j(1-\exp^{-\gamma C_j}), \gamma \in (0,1)$	heuristic(WSPT), $O(n \cdot log(n))$	Xu et al. (2008)
$1\|LE_{p,det}, agg_w\|\sum w_j \cdot C_j$	WSPT, O($n \cdot \log(n)$)	Yang and Kuo (2009) Koulamas (2010)
$1\|LE_t, agg_w\|\sum w_j C_j$	WSPT,O($n \cdot \log(n)$)	Wang et al. (2008)
$1\|LE_{t,log}, agg_w\|\sum w_j C_j$	WSPT,O($n \cdot \log(n)$)	Cheng et al. (2009)
$1\|LE_t, p_j = p\|\sum w_j C_j$	non-increasing order of w_j, O($n \cdot \log(n)$)	Wang et al. (2008)

Problem	Solution Method	Paper
$1\|LE_t, w_j = k \cdot p_j\|\sum w_j C_j$	SPT,O($n \cdot \log(n)$)	Wang et al. (2008)
$1\|LE_{t,A,j}\|\sum w_j \cdot C_j$	$NP-complete$	Jiang et al. (2013)
$1\|LE_{t,A}, agg\|\sum w_j C_j$	WSPT, O($n \cdot \log(n)$)	Yang and Kuo (2007)
$1\|LE_{t,e},\ s_i = d \cdot \sum_{i=1}^{r-1} p_{[i]}^A,\ agg\ p_j,\ w_j\|C_{\max}$	WSPT, O($n \cdot \log(n)$)	Wang et al. (2009)
$F_m\|prmu,\ LEF_t\|\sum w_j C_j$	heuristic (WSPT), $O(n \cdot log(n))$	Li et al. (2013)
$F_m\|prmu,\ LEF_p\|\sum T_j$	B&B, heuristics	Lee and Chung (2013)
$F_m\|prmu,\ LEF_p\|\sum w_j C_j$	heuristic(WSPT), $O(n \cdot log(n))$	Xu et al. (2008)
$F_m\|prmu,\ LEF_{pl}\|\sum w_j C_j$	heuristic(WSPT), $O(n \cdot log(n))$	Xu et al. (2008)

5.1.3 Multi-Criteria Objectives

Utilizing the total completion time and the total weighted completion time a number of multi-criteria objectives can be formulated. Kanet (1981b) introduced the total absolute differences in completion times $TADC \equiv \sum_{j=1}^{n} \sum_{i=1}^{n} |C_j - C_i|$. This objective is for example relevant for providing a comparable service to different costumers with regard to the waiting time, or when aligning response speeds of a computer system independent of the size of data retrieved. The $TADC$ is further modified to the total absolute difference in weighted completion times $TADW \equiv \sum_{j=1}^{n} \sum_{i=1}^{n} |w_j \cdot C_j - w_i \cdot C_i|$ and utilized in the bi-criteria objective function $BC \equiv \delta \cdot \sum_{j=1}^{n} C_j + (1-\delta) \cdot TADC$. Mosheiov (2001b) showed that the bi-criteria objective BC can be solved as an assignment problem when the basic position learning effect LE_p is considered. Moreover, the BC can be solved in O($n \cdot \log(n)$) when deteriorating and job-dependent processing times ($LE_{p,det}$) are considered (Qian and Steiner, 2013).

Oron (2016) studied controllable processing times with indirect position-based learning effect ($LE_{\overline{p},con}$). By managerial decision resources can be allocated to jobs to decrease processing times in addition to the learning effect. He proved that minimizing the total completion time and the bi-criterion objective function $TADC$ with position-based learning and controllable processing times combined to a convex function, and can be solved in polynomial time.

Problems minimizing the objectives $TADC$ and BC with past-sequence-dependent setup times and with time-based learning effect ($LE_{t,setup}$) can be solved in O($n \cdot \log(n)$) (Koulamas and Kyparisis, 2008). Even though the setup time function is non-linear due to the combination with a learning effect, it is possible to solve the above problems to optimality by a sorting rule based on results by Kanet (1981b).

In addition to the objective functions mentioned above, the multi-criteria objectives $MC \equiv w_1 \cdot C_{\max} + w_2 \cdot TC + w_3 \cdot TADC$ and $MWC \equiv w_1 \cdot C_{\max} + w_2 \cdot TW + w_3 \cdot TADW$ were considered in different publications including learning effects, e.g. by Wang and Wang (2015). Note, that for all objectives $w_j \geq 0$ is a constant weight. Position-based learning effects with controllable processing times were further considered for the multi-criteria objectives MC and MCW by Wang and Wang (2015). For both problems, the resource availability u_j for all jobs j is restricted by a constant U, included in a constraint $\sum_{j=1}^{n} u_j \leq U$. Moreover, the inverse problem formulations with these objective functions have also been considered. In this selling, the total amount of resource u_j allocated to job $\sum_{j=1}^{n} u_j$ should be minimized while the objective functions MC and MCW are transformed into constraint $MC \leq R$ and $MCW \leq R$ for an arbitrary but fixed value $R \in \mathbb{R}$. For all four problems considered, Wang and Wang (2015) provided algorithms solving the problems in $O(n^3)$ if job-dependent learning coefficients are utilized and in $O(n \cdot \log(n))$ for a common learning coefficient $a_j = a$.

Table 8: Results on Completion Time related Multi-Criteria Objectives with Learning and Forgetting Effects

Problem	Solution Method	Paper
$1\|LE_p\|BC$	ASGMT, $O(n^3)$	Mosheiov (2001b)
$1\|LE_{p,con}\|MC$	ALGO, $O(n \cdot log(n))$	Wang and Wang (2015)
$1\|LE_{p,con}\|MCW$	ALGO, $O(n \cdot log(n))$	Wang and Wang (2015)
$1\|LE_{p,con}, MC \leq R\| \sum u_j$	ALGO, $O(n \cdot log(n))$	Wang and Wang (2015)
$1\|LE_{p,con}, MCW \leq R\| \sum u_j$	ALGO, $O(n \cdot log(n))$	Wang and Wang (2015)
$1\|LEC_{p,j,con}\|MC$	ALGO, $O(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j,con}\|MCW$	ALGO, $O(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j,con}, MC \leq R\| \sum u_j$	ALGO, $O(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j,con}, MCW \leq R\| \sum u_j$	ALGO, $O(n^3)$	Wang and Wang (2015)
$1\|LE_{p,det}\|BC$	ASGMT, $O(n \cdot \log(n))$	Qian and Steiner (2013)
$1\|LE_{t,setup}\|TADC$	Sorting-Rule $O(n \cdot \log(n))$	Koulamas and Kyparisis (2008)
$1\|LE_{t,setup}\|BC$	Sorting-Rule $O(n \cdot \log(n))$	Koulamas and Kyparisis (2008)

5.2 Due Date

5.2.1 Earliness, Tardiness, Lateness

Since the position-based learning effect (LE_p) can be modeled by the general learning and forgetting formulation ($LE + F_g$), the maximum lateness, total tardiness $\sum T_j$ and maximum tardiness $T_{\max}$ can be solved by the EDD-rule when assuming aggregable due dates(Lai and Lee, 2013). Mosheiov and Sidney (2005) proposed an algorithm minimizing the number of tardy jobs with a position-based learning effect and job-dependent learning coefficient ($LE_{p,j}$) in $O(n \cdot \log(n))$ if a common due date is assumed. They stated that the proposed algorithm can be applied to any position-based processing learning effects with non-negative processing times. The problem is *NP-hard* if two different due dates are considered and even *strongly NP-hard* with a variable number of different due dates (Lin, 2007). With position-based learning and deterioration ($LE_{p,det}$), the problem with a maximum lateness objective can be solved in polynomial time for aggregable due dates, a common processing time or proportional weights (Wang, 2006).

The maximum lateness for the exponential time-based learning effect with setup time learning ($LE_{t,exp}$) can be minimized by the EDD- or SPT-rule when considering special cases, e.g. aggregable conditions for the due dates Wang et al. (2009). For the time-based learning effects $LE_{t,log}$

(Cheng et al., 2009), $LE_{t,frac}$, and LE_t, the maximum lateness and total tardiness can be solved in polynomial time using the EDD if the processing times and due dates are aggregable (Lai and Lee, 2013). Wang et al. (2008) also considered the maximum lateness and number of tardy jobs for the later learning effect LE_t. They show that classic solution methods for the base problem do not deliver optimal results and develop heuristics with tight bounds and polynomial methods for special cases. The results for different constraints can be found in Table 9. Li and Wang (2015) presented counter-examples for other finding by Wang et al. (2008). These concern aggregable processing times and aggregable due dates. For minimizing the number of tardy jobs, two heuristics calculating near-optimal solutions have been introduced; a modification of the FL-algorithm (Framinan and Leisten, 2003) and a variation of *Moore's Algorithm* (Wang et al., 2017). Moreover, a branch and bound algorithm has been presented to solve the given problem to optimality (Wang et al., 2017). Jiang et al. (2013) assessed the complexity of minimizing the maximum lateness with job- dependent learning coefficients and actual processing times learning ($LE_{t,j,A}$). By reduction to *3-Partition* the problem is *strongly NP-complete*. Nevertheless, an optimal schedule can be found by the SPT-rule when considering a common due date $d_j = d$ (Jiang et al., 2013).

Dondeti and Mohanty (1998) showed that the maximum tardiness for their proposed continuous learning and fatigue effects $(LE + F)_g$ is minimized by the EDD-rule and the number of tardy jobs by the *Moore-Hodgeson Algorithm*. Minimizing the total weighted tardiness on a single-machine with this continuous learning and fatigue effect ($(LE + F)_g$) is *NP-hard*. The authors reduced the computational effort by formulating the problem as a nested knapsack problem and transforming it into a graph for a maximum-weighted path problem (Dondeti and Mohanty, 1998). When learning followed by deterioration-based forgetting ($LE+F_{p,sum,g}$, $LE+F_{p,int,g}$, $LE+F_{t,int,g}$) is considered the maximum tardiness, the sum of tardy jobs and the maximum lateness can also be solved in polynomial time by the EDD-rule if aggregable processing times and aggregable due dates are assumed (Lai and Lee, 2013, 2014; Wu et al., 2015, 2016).

Multi-Machine Environments Anzanello et al. (2014) separated the learning effect from the scheduling decision. Here no explicit learning effect can be defined, as processing times are derived upfront by fitting hyperbolic learning curves to worker-task combinations. For this purpose, task complexity, task repetition, and model complexity as well as workers' abilities are considered. A batch scheduling rule taking ergonomic factors work balancing, and complexity balancing among different machines into account while reducing the total weighted tardiness is introduced. Moreover, Anzanello et al. (2014) applied the developed method to a shoe manufacturer to derive empirical insights on the performance.

Lee and Chung (2013) analyzed a permutation flow-shop problem developing a dominance property and lower bounds to improve the performance of a branch and bound algorithm to minimize the total tardiness with position-based learning effect (LEF_p). Moreover, they provided a heuristic algorithm to obtain near optimal solutions for problem sizes containing more than 18 jobs (Lee and Chung, 2013). Vahedi Nouri et al. (2013) considered the same setting and learning effect (LEF_p) but also included flexible maintenance operations in their problem formulation. For minimizing jointly the total tardiness and the costs for delays due to machine maintenance, they present a heuristic and meta-heuristic based on a simulated annealing algorithm.

Table 9: Results on Due Date Objectives with Learning and Forgetting Effects

Problem	Solution Method	Paper
$1\|LE_p, agg_{d_j}\|L_{\max}$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2013)
$1\|LE_p, agg_{d_j}\|T_{\max}$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2013)
$1\|LE_p, agg_{d_j}\|\sum T_j$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2013)
$1\|LE_{p,j}, d_j = d\|\sum U_j$	ALGO, $O(n \cdot \log(n))$	Mosheiov and Sidney (2005)
$1\|LE_{p,j}\|\sum U_j$	strongly NP-hard	Lin (2007)
$1\|LE_p, d_j = d\|f(d,\sigma) = \sum E_j + T_j$	ALGO, $O(n \cdot \log(n))$ if $A < a < 0$	Chang et al. (2009)
$1\|LE_p, a < 0\|f(d,\pi) = \sum(E_{[j]} + T_{[j]})$	ALGO $O(n \cdot log(n))$ if $B^a < a < 0$	Chang et al. (2009)
$1\|LE_p, a > 0\|f(d,\pi) = \sum(E_{[j]} + T_{[j]})$	ALGO $O(n \cdot log(n))$ if $A^a > a > 0$	Chang et al. (2009)
$1\|LE_t, agg_{d_j}\|L_{\max}$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2013)
$1\|LE_t, agg_{d_j}\|T_{\max}$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2013)
$1\|LE_t, agg_{d_j}\|\sum T_j$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2013)
$1\|LE_t, agg_d : p_i \leq p_j \rightarrow di \leq d_j\|L_{\max}$	EDD, $O(n \cdot \log(n))$	Wang et al. (2008)
$1\|LE_t, p_j = p\|L_{\max}$	EDD, $O(n \cdot \log(n))$	Wang et al. (2008)
$1\|LE_t, p_j = p\|\sum U_j$	EDD, $O(n \cdot \log(n))$	Wang et al. (2008)
$1\|LE_t, d_j = d\|\sum U_j$	SPT, $O(n \cdot \log(n))$	Wang et al. (2008)
$1\|LE_t\|\sum U_j$	B&B, heuristic	Wang et al. (2017)
$1\|LE_{t,j,A}\|L_{\max}$	$strongly\ NP-complete$	Jiang et al. (2013)
$1\|(LE+F)_g\|T_{\max}$	EDD	Dondeti and Mohanty (1998)
$1\|(LE+F)_g\|\sum U_j$	ALGO	Dondeti and Mohanty (1998)
$1\|(LE+F)_g\|$job penalty problem	ALGO	Dondeti and Mohanty (1998)
$1\|LE_{t,A}, d_j = d\|L_{\max}$	SPT, $O(n \cdot \log(n))$	Jiang et al. (2013)
$1\|LE_{t,exp},\ s_i = d \cdot \sum_{i=1}^{r-1} p_{[i]}^A,\ agg\ p_j,\ d_j\|L_{\max}$	EDD, $O(n \cdot \log(n))$	Wang et al. (2009)
$1\|LE_{t,log}, p_j\ and\ d_j\ agg\|T_{max}$	EDD, $O(n \cdot \log(n))$	Cheng et al. (2009)
$1\|LE_{t,log}, p_j\ and\ d_j\ agg\|L_{max}$	EDD, $O(n \cdot \log(n))$	Cheng et al. (2009)
$1\|LE_{t,log}, p_j\ and\ d_j\ agg\|\sum T_j$	EDD, $O(n \cdot \log(n))$	Cheng et al. (2009)
$1\|L+F_b,\ p_i\ and\ d_i\ agg\|\sum T_j$	EDD, $O(n \cdot \log(n))$	Wu et al. (2015, 2016)
$1\|L+F_b,\ p_i\ and\ d_i\ agg\|L_{\max}$	EDD, $O(n \cdot \log(n))$	Wu et al. (2015)
$1\|L+F_b,\ p_i\ and\ d_i\ agg\|L_{\max}$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2014, 2013)
$1\|L+F_b,\ p_i\ and\ d_i\ agg\|\sum T_j$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2014, 2013)
$1\|L+F_b,\ p_i\ and\ d_i\ agg\|T_{\max}$	EDD, $O(n \cdot \log(n))$	Lai and Lee (2014, 2013)
$HF_m\|LEF_p(setup)\|w_1 C_{\max} + w_2 \sum T_j$	meta-heuristic	Pargar and Zandieh (2012)

5.2.2 Multi-Criteria Objectives and Due Date Assignment Problems

Panwalkar et al. (1982) formulated a due date assignment problem (DDA) objective function without learning. It combines selecting a common due date d for all jobs with unit penalties $w_1,\ w_2,\ w_3 \geq 0$ for the due date d, the earliness E_j and the tardiness T_j of a job as follows:

$$DDA \equiv \sum(w_1 \cdot d + w_2 \cdot E_j + w_3 \cdot T_j).$$

By setting the parameters for the unit penalties, a number of distinct objective function arise, e.g., with $w_1 = 0$ and $w_2 = w_3 = 1$ we receive the Kanet objective function $\sum E_j + T_j$ (Kanet, 1981a). A more general approach has been introduced by Qian and Steiner (2013). They considered a common product matrix formulation, which is able to represent the cost functions belonging to a range of different scheduling problems e.g., different due date assignment problems.

Moreover, these problems can be classified according to the due dates required Wang and Wang (2015). In case, a common due date for all jobs is requested, the problem can be denoted by DDA(CON), which equals the formulation by Panwalkar et al. (1982). If an individual, unrestricted due date is assigned to each job the problem is denoted by DDA(DIF). For due dates satisfying the slack condition $d_j = p_j + q$, where $q \geq 0$ is a decision variable, the notation DDA(SLK) is used.

With position-based learning (LE_p), the due date assignment problem (DDA) and the variation $DDAc = (\sum w_1 C_j + w_2 E_j + w_3 T_j)$ remain polynomially solvable when formulated as assignment problems (Biskup, 1999; Mosheiov, 2001b). Mosheiov and Sidney (2003) showed that minimizing the DDA problem with job-dependent, position-based learning effect ($LE_{p,j}$) can, again, be formulated as an assignment problem and thus be solved efficiently ($O(n^3)$). Qian and Steiner (2013) considered a position-based learning effect with deterioration ($LE_{p,det}$) and extensions to the due date assignment problem (DDA). They provided an $O(n \cdot \log(n))$ algorithm solving the objectives $DDA + w_4 \cdot C_{\max}$ and $DDA + w_4 \cdot \sum C_j$ for a common due date DDA(CON), due dates with a slack DDA(SLK) condition, individual due dates DDA(DIF) and due dates given in terms of a common time window DDA(CONW) for completing the jobs: $[\underline{d}, \overline{d} = \underline{d} + D]$ (Qian and Steiner, 2013). Modeling position-based learning explicitly into the controllable processing times ($LE_{p,con}$) with the objective functions DDA(CON), DDA(SLK), and DDA(DIF), Wang and Wang (2015) analyzed a number of due date assignment problems. In their model, the amount of resource u_j available for intentionally decreasing processing times is restricted to $\sum_{j=1}^{n} u_j \leq U$. Moreover, they considered the inverse problem formulations to all objective functions by minimizing the total amount of resource $\sum_{j=1}^{N} u_j$ allocated to individual jobs u_j and restricting the values of the original objective functions by transforming them into a constraint $Obj \leq R$ with arbitrary $R \in \mathbb{R}$. They provided algorithms solving the problems in $O(n^3)$ if job-dependent learning coefficients are utilized and in $O(n \cdot \log(n))$ for a common learning coefficient $a_j = a$.

Chang et al. (2009) analyzed the objective function $(\sum E_{[j]} + T[j])$ (Kanet, 1981a) and position-based learning effect LE_p. By allowing the learning coefficient a to be strictly negative or positive, they further to model aging effects with a learning factor $a < 0$ or aging rate $a > 0$ and proposed a $O(n\log n)$ solution method resulting in a common due date and an optimal schedule. For both effects, learning and aging, an optimal sequence π of jobs was obtained by two algorithms presented if and only if the learning and aging coefficients take values within a certain range. Additionally, they demonstrated how to calculate these respective boundaries and presented solution methods if the first job of a sequence is fixed. In this vein, Biskup and Simons (2004) further included a cost function $k(x)$ for an investment in induced learning. This function yields cost per percentage reduction x of the learning rate to include induced-learning or training effects in the objective function ($f(\pi, x) = \sum_{i=1}^{n}(E_i + T_i) + k(x)$). Moreover, they provided a procedure to receive an optimal schedule and amount x of induced-learning in polynomial time ($\mathrm{O}(n^3)$). Note, that their model was based on a known common due date.

Multi-Machine Environments Anzanello and Fogliatto (2010) developed 12 heuristic algorithms to minimize the total weighted earliness and tardiness for workers with different skill endowments modeled as unrelated parallel machines. In their study, learning is not included explicitly in the model, but processing times are derived from hyperbolic learning curves related to job and machine characteristics, prior to optimization. Moreover, a common due date is already given in advance.

Table 10: Results on Multi-Criteria Objectives and Due Date Assignment Problems with Learning and Forgetting Effects

Problem	Solution Method	Paper
$1\|LE_p, d_j = d\|\sum(w_1E_j + w_2T_j + w_3C_j)$	ASGMT, $\mathrm{O}(n^3)$	Biskup (1999)
$1\|LE_p, d_j = d\|\sum(w_1E_j + w_2T_j + w_3d)$	ASGMT, $\mathrm{O}(n^3)$	Mosheiov (2001b)
$1\|LE_p, d_j = d\|f(d, \sigma) = \sum E_j + T_j$	ALGO, $\mathrm{O}(n \cdot \log(n))$ if $A < a < 0$	Chang et al. (2009)
$1\|LE_{p,j}, d_j = d\|\sum(w_1E_j + w_2T_j + w_3d)$	ASGMT $\mathrm{O}(n^3)$	Mosheiov and Sidney (2003)
$1\|LE_p\|BC$	ASGMT, $\mathrm{O}(n^3)$	Mosheiov (2001b)
$1\|LEC_p\|DDA(CON)$	ALGO, $\mathrm{O}(n \cdot \log(n))$	Wang and Wang (2015)
$1\|LEC_p\|DDA(DIF)$	ALGO, $\mathrm{O}(n \cdot \log(n))$	Wang and Wang (2015)
$1\|LEC_p\|DDA(SLK)$	ALGO, $\mathrm{O}(n \cdot \log(n))$	Wang and Wang (2015)
$1\|LEC_p, DDA(CON) \leq R\|\sum u_j$	ALGO, $\mathrm{O}(n \cdot log(n))$	Wang and Wang (2015)
$1\|LEC_p, DDA(DIF) \leq R\|\sum u_j$	ALGO, $\mathrm{O}(n \cdot log(n))$	Wang and Wang (2015)
$1\|LEC_p, DDA(SLK) \leq R\|\sum u_j$	ALGO, $\mathrm{O}(n \cdot log(n))$	Wang and Wang (2015)
$1\|LEC_{p,j}\|DDA(CON)$	ALGO, $\mathrm{O}(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j}\|DDA(DIF)$	ALGO, $\mathrm{O}(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j}\|DDA(SLK)$	ALGO, $\mathrm{O}(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j}, DDA(CON) \leq R\|\sum u_j$	ALGO, $\mathrm{O}(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j}, DDA(DIF) \leq R\|\sum u_j$	ALGO, $\mathrm{O}(n^3)$	Wang and Wang (2015)
$1\|LEC_{p,j}, DDA(SLK) \leq R\|\sum u_j$	ALGO, $\mathrm{O}(n^3)$	Wang and Wang (2015)
$1\|LE_p, a < 0\|f(d, \pi) = \sum(E_{[j]} + T_{[j]})$	ALGO, $O(n \cdot log(n))$ if $B^a < a < 0$	Chang et al. (2009)
$1\|LE_p, a > 0\|f(d, \pi) = \sum(E_{[j]} + T_{[j]})$	ALGO, $O(n \cdot log(n))$ if $A^a > a > 0$	Chang et al. (2009)
$1\|(LE + F)_g\|job\ penalty\ problem$	ALGO	Dondeti and Mohanty (1998)
$R_m\|d_j = d\|w_1 \cdot \sum 1_1 \cdot E_j + w_2 \cdot T_j$	12 heuristics	Anzanello and Fogliatto (2010)
$HF\|LEHF_{p,j,s}\|w_1 \cdot C_{\max} + w_2 \cdot \sum T_j$	*NP-hard*, Meta-heuristic	Pargar and Zandieh (2012)

A hybrid-flow-shop problem (HFS) with m_t identical parallel machines on each stage t and position-based setup time learning and job-dependent learning coefficient ($LE_{p,j,\mathrm{setup}}$) was proposed by Pargar and Zandieh (2012). For minimizing the weighted sum of the makespan and total completion time ($w_1 \cdot c_{\max} + w_2 \sum T_j$), they introduce a meta-heuristic (Water-Flow-Like Algorithm) and benchmark it against two other heuristics for hybrid flow-shop problems in a computational study. Shahvari and Logendran (2018) again considered a hybrid-flow-shop problem with position-based learning effects and past sequence-dependent setup times. In contrast to the described model, learning takes place during the production and does therefore affect the processing but not the setup times. Moreover, the authors considered a batch scheduling problem for group manufacturing. Here, groups of similar parts are split into dissimilar batches in order to account for the priority of different jobs. The learning effect is implemented for jobs belonging to one group with a common learning parameter for all groups of jobs. Shahvari and Logendran (2018) assumed that all prior experience gains are lost after switching from one batch to another. In order to minimize the sum of the Weighted Total Completion Times (WTC) and the total weighted tardiness of the NP-complete problem, two basic and hybrid meta-heuristics and lower-bounds were presented.

5.3 Relevance of Model Complexity

For different learning and forgetting effects polynomial time solution methods including exact algorithms, heuristics, meta-heuristics or approximation algorithms have been presented. These cover a number of different machine environments, learning and forgetting effects, and objective functions. When evaluating the complexity results it is noteworthy that the completion time-related objective functions 'makespan' and 'total completion time' are polynomially solvable by the SPT-rule or via reformulation as an assignment problem ASGMT for most learning effects. Only when including both actual processing times and job-dependent learning rates in time-based learning effects, these problems are not solvable. For multi-criteria objectives that refer to completion times, classical solution methods, i.e. the WSPT-rule for the weighted total completion time or the WDSPT for the weighted discounted total completion time, can only be used to obtain approximations. For these cases, lower bounds have been provided or additional conditions like aggregated weights or processing times have been considered in order to receive problems that can be solved efficiently, see for example Wang et al. (2008), Cheng et al. (2009) or Lai and Lee (2013). Similarly, due date-related objective encounter increased computational complexity for all learning and forgetting effects introduced. Therefore, efficient solution methods for these problems exist only if additional conditions are assumed. In contrast to the total tardiness which is already $NP-hard$ without learning and forgetting effects, the maximum lateness, the maximum tardiness and the number of tardy jobs could be solved in polynomial time. Table 11 lists the effect of including even basic learning effects in single-machine problem with respect to the different objective functions considered.

Table 11: Effects of introducing learning effects on computational complexity

Efficiently solvable	Makespan, Total Completion Time
Computational complexity increases	Total Weighted Completion Time, Maximum Lateness, Maximum Tardiness, Number of Tardy Jobs
Efficiency not influenced	Total Tardiness

Although including learning and forgetting effects generally increases the computational complexity, this is not true for all effects and objective functions presented. Especially when a plateau effect for both position- and time-based learning effects is included or when considering the actual processing times of jobs for the time-based effect, it does not impact the optimization of the makespan or the total completion time. Thus, a variety of learning effects can be supplemented by these effects which results in more precise objective function values. For plateau effects in position-based models in particular, to the best of our knowledge, no results on the makespan and total completion time are presented. However, for the single-machine effect $LE_{p,plat}$ the makespan and the total completion time can be solved by the SPT rule (Section A). Anzanello et al. (2014) avoided increasing the computational complexity by externalizing the learning effects by estimating processing times for different job and worker combinations by fitting hyperbolic learning curves. This approach differs strongly from the majority of effects presented. Nevertheless, it might be worth considering similar approaches for objective functions like that become intractable when learning is explicitly included.

6 Conclusion and Directions for Future Research

Machine scheduling problems are a key element of short-term production planning and decision making. The processing of jobs depends on human labor either for setting up and maintaining machines or for performing the jobs themselves. Hence, employee performance influences production processes and it is therefore be crucial to consider workforce development in production planning. Efficiency gains can be achieved by autonomous learning, due to experience gained on the job, or induced improvements by, for example, training measures. Forgetting effects and other losses can be a by-product of production planning or also be driven by managerial decisions, e.g., due to changes in the production process or the assignment of workers to work stations. To accurately estimate the actual processing times for scheduling, the impact of competencies and skills needs to be taken into account. The purpose of this article has been to present an overview of how concepts of competence management and employee skill development are embodied in models of machine scheduling. For this purpose, a structured literature review was conducted.

The skill development of employees has been researched by different disciplines, as for example, psychology and engineering, leading to conceptualizations not always applicable in mathematical modeling (Nembhard and Bentefouet, 2012). Likewise, research published in the fields of learning and competence development already covers a number of relevant aspects not always incorporated in existing models. Turning to avenues for further research, we found four outstanding matters.

First, forgetting effects, building the counterpart to learning are under-represented in the machine scheduling literature. Even though a few models include forgetting effects they mostly omit the most prominent factor that leads to forgetting: interruptions (Jaber et al., 2003). Therefore, the machine scheduling literature should propose models that include forgetting in at least a basic way as it has an tremendous influence on actual processing times.

Second, opposed to learning-by-doing, managers can influence the efficiency of their workforce due to training measures (Biskup, 2008). Here, the timing (Vits et al., 2007) and amount of training measures as well as the part of the workforce to be trained have to be carefully evaluated (Büke et al., 2016; Valeva et al., 2017; Sleptchenko et al., 2019). Since training sessions are normally connected with costs and consume time, that could otherwise be utilized for production, the relevant trade-offs and the timing of training measures should be considered in more detail (Xu et al., 2011; De Bruecker et al., 2015; Qin et al., 2015).

Third, future models should draw from the already elaborated empirical literature on learning and forgetting. Aspects such as cognitive load, feedback, information overload and spillover learning (Letmathe and Rößler, 2019) should be explicitly considered as they can be key to manage a company's learning curve and, hence, can substantially impact its overall competitiveness.

Fourth, the existing literature is surprisingly limited to (processing) time and cost effects of learning and forgetting. Considering other criteria such as product quality (Alamri et al., 2016), flexibility (Qin and Nembhard, 2010) and the resilience of production systems can also be intriguing additions to the existing body of literature.

Fifth, proposed models often neglect simple effects, e.g. plateau or actual processing times effects, which can be included in a number of models without impacting computational complexity. Furthermore, it might be worth to externalize effects of skill development to overcome the computational intractably arising due to learning and forgetting effects for some objective functions.

This article (1) focused on the ability of presented models to describe realistic skill development processes and, on the other hand, how those models are applicable in practice, (2) provides avenues for future research and (3) introduces a unified notation for different learning and forgetting models developed in this field. To the best of our knowledge, we cover all relevant publications including forgetting effects. In contrast to learning effects, forgetting has not been considered in reviews on the scheduling literature thus far.

Although digitization has automated a variety of jobs, production processes still depend highly on human labor. Considering the changing nature of employees skills is crucial to obtain lower costs and higher productivity. Thus, properly incorporating the underlying dynamics into production planning and scheduling models yields competitive advantage for companies.

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A Appendix

Scheduling with Plateau Learning Effect

Theorem A.1. *The problem $1|LE_{p,plat}|C_{\max}$ is minimized by the SPT-rule.*

Proof. Let π be an SPT schedule for $1|LE_{p,plat}|C_{\max}$. The processing time $p_{j,r} \equiv p_j \cdot \max\{r^a, \gamma\}$ of job $j \in J$ depends on its position r in the schedule π. Let $k, l \in J$ be two arbitrary jobs scheduled on position r and $r+1$ respectively. The objective function value is denoted by $C_{\max}(k,l)$.

The cases $\gamma < r+1^a < r^a$ and $r+1^a < r^a < \gamma$ are already covered by literature, as these relate to a normal position based learning effect Biskup (1999) and no learning effect respectively. Thus it remains to consider $r^a > \gamma$ and $(r+1)^a < \gamma$ with $p_{k,r} = p_k \cdot r^a$, $p_{l,r+1} = p_l \cdot \gamma$ and $p_{r+1} = p_r + b$ for $b \in \mathbb{R} > 0$ since $p_k < p_l$ holds as a consequence of the SPT-order assumed. For the shake of contradiction interchange the jobs position in the schedule.

$$\begin{aligned} C_{\max}(l,k) &= C_{\max}(k,l) + p_{r+1} \cdot r^a + p_r \cdot \gamma - p_r \cdot r^a + p_{r+1} \cdot \gamma \\ &= C_{\max}(k,l) + \underbrace{b \underbrace{(r^a - \gamma)}_{>0}}_{>0} > C_{\max}(k,l) \end{aligned}$$

□

Research Paper 3: Single Machine Scheduling with Product Category-based Learning and Forgetting Effects

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Abstract In today's constantly changing work environment, the dynamic nature of employee skills, and the underlying learning and forgetting effects that influence production efficiency become increasingly important. As a consequence, especially during a production ramp-up, processing times benefit from learning effects when workers repeatedly perform similar tasks. To account for these skill development processes and the fact that different types of products are often processed on a single production line, we introduce a new learning and forgetting effect for single-machine scheduling. The effect assumes different product categories and considers intra-category learning effects and inter-category forgetting effects. Near-optimal or optimal solution methods for minimizing either the makespan or the total completion time are presented. For computationally intractable cases, we show promising performance and processing time-saving results utilizing 337,500 example instances to benchmark the proposed near-optimal heuristics. Further, we provide guidance to help practitioners identify production settings that benefit most from using the categorized effect.

1 Introduction

In literature and likewise in practice, it is widely recognized that unit processing times vary over time (Yelle, 1979; Dutton and Thomas, 1984; Biskup, 2008; Anzanello and Fogliatto, 2011; De Bruecker et al., 2015; Grosse et al., 2015; Glock et al., 2019). Hereby, efficiency gains due to the improvement of employee skills can be realized. By repeatedly performing a task, employees develop know-how, i.e. a deeper understanding of the comprised operations. This knowledge can increase production speed, efficiency, and, quality, and can reduce production costs (De Bruecker et al., 2015). The underlying effect is referred to in the literature as 'the learning effect'. Since the discovery that unit processing times decrease at a uniform rate as production output doubles (Wright, 1936), employee development and learning emerged as an important field of research affecting production planning. Dutton and Thomas (1984) analyzed approximately 200 studies on production learning and found that these learning rates vary between 60-90%. The individual learning rates differ not only concerning different companies and production plants but, further, for employees and task types (Argote and Epple, 1990; Yelle, 1979). Here, for example, the distinction between cognitive and motor tasks can be made (Jaber et al., 2010) which leads to different learning slopes. Certainly, the underlying production environment affects the learning potential (Biskup, 2008). Human-paced productions, for example, record higher improvements compared to machine-paced environments (Hirsch, 1956). Moreover, the degree of similarity of different products plays a crucial role. While products with a high similarity yield full knowledge transfer from one unit to another, there might be no or very little spillover learning between dissimilar tasks (Jaber et al., 2003; Corominas et al., 2010).

Contrarily to learning effects, decreases in productivity as a consequence of forgetting the acquired knowledge are recorded. These may arise on the one hand as a consequence of a disruption of the production (Howick and Eden, 2007) e.g., due to the interruption of production processes (Jaber et al., 2003), changes in the production environment or equipment (Vits et al., 2006). Furthermore, the interruption may be caused by planned maintenance activities, unplanned machine failures (Marmier et al., 2009), or even suppliers (Wang et al., 2013). On the other hand, efficiency may be affected negatively by fatigue (Digiesi et al., 2009; Dode et al., 2016), employee boredom (Azizi et al., 2010), a lack of motivation, and ergonomic factors (Anzanello et al., 2014) caused by monotonous production.

Especially during the initial phase of production, learning and forgetting strongly influence processing times, since workers need to get accustomed to the production process (Hansen and Grunow, 2015). This ramp-up phase can be defined as the *'period between completion of development and full capacity utilization'* (Bohn and Terwiesch, 1999), or, more precisely the start of production since product and process improvements are still present (Surbier et al., 2014). Amongst others, Glock and Grosse (2015) considered learning as one of seven important characteristics of the ramp-up phase and emphasized the relevance of learning curve theory as a related field of research. Here, the authors named workflow management, which includes scheduling decisions, and worker assignment as relevant planning problems (Glock and Grosse, 2015). The importance of considering the dynamic nature of employee skills is further pronounced by high demand and premium prices paid for products at their market launch (Terwiesch and Bohn, 2001). Letmathe and Rößler (2019) found evidence for learning effects that are transferable between consecutive ramp-ups. Surbier et al. (2014) hinted that ramp-up literature lacks models and insights for low-volume industries with high product diversity. In practice, often several different products are processed or assembled on one shared production line.

Several studies, e.g. Surbier et al. (2014); Glock and Grosse (2015); Hansen and Grunow (2015) Letmathe and Rößler (2019), stress the growing importance of managing the ramp-up situation, as product life cycles - and thus the time to bring products to market - are decreasing. Moreover, the introduction phase was found to yield a competitive advantage for companies and products. Lastly, ramp-up situations are not only present during the introduction of a new product but also when establishing new plants or production lines for mature products or when changes occur in product design or production processes (Vits et al., 2006; Surbier et al., 2014; Glock and Grosse, 2015; Terwiesch and Bohn, 2001). Therefore, it is crucial to take not only the underlying learning and forgetting effects into account, when turning to production planning and scheduling, but also the similarities and differences of products produced.

This article presents a new model for incorporating different product types into single-machine scheduling problems. Hereto, a category-dependent learning effect is introduced. The *position-based* effect accounts for different product families or categories. Hereby, products from a certain category allow a full knowledge transfer from one unit to another, while we anticipate no spillover learning to products from other categories. We also extend the presented learning effect by introducing, to the best of our knowledge, the first *interruption-based* forgetting effect for single-machine scheduling. For both models, the makespan and the total completion time are minimized individually. Optimal solution methods for the learning effect and the makespan concerning learning and forgetting are presented. Moreover, the ability of the proposed sorting routines to deliver near-optimal solutions for minimizing the total completion time is assessed. Hereto, 63,000 example instances with up to nine jobs are considered. Additionally, computational examples for 50 and 100 jobs per instance are calculated and benchmarked against the *Shortest-Processing-Time-First (SPT)*-rule. This heuristic solves the underlying problems for *position-based* learning without categories and forgetting. Based on the results, we provide guidance to help practitioners identify production settings that benefit most from applying the proposed model and solution methods.

The remainder of the article is structured as follows: Section 2 reviews the literature of learning and forgetting effects for single-machine scheduling problems. Section 3 presents the technical details of the proposed learning and forgetting model. In Sections 4 and 5, results for the leaning and forgetting effects are presented respectively. We close with remarks and a conclusion in Section 6.

2 Related Work

Wright (1936) discovered that unit processing times decrease at a uniform rate, the learning rate l, as the output produced doubles. To formulate the first learning curve, he defined the learning coefficient $a := -\log_2(l)$ to obtain the processing time needed to produce the nth unit by $T_n := T_1 \cdot n^a$. Based on his observations, a vast body of literature on learning effects in production has emerged.

While some studies focused on providing insights on the nature of improvements in production environments (Dutton and Thomas, 1984; Argote and Epple, 1990), other publications presented refined learning curves to better describe the actual learning processes (Yelle, 1979; Grosse et al., 2015), or they provided help for estimating learning parameters (Uzumeri and Nembhard, 1998; Howick and Eden, 2007).

Nevertheless, in the context of machine-scheduling, these effects were first considered at the end of the 20th century by Biskup (1999). He proposed a *position-based* learning effect LE_p for single-machine problems considering the common due date assignment problem and minimizing the total completion time. Several publications used the same learning effect while considering different objective functions. These articles either presented optimal solution methods, heuristics, or complexity results for the problems considered (Mosheiov, 2001b; Wang, 2006; Wang and Cheng, 2007; Chang et al., 2009; Yang and Kuo, 2009; Koulamas, 2010; Lai and Lee, 2013; Qian and Steiner, 2013; Wang and Wang, 2015; Oron, 2016; Wang et al., 2017). Other articles extend the learning effect to be either job-dependent $LE_{p,j}$ in order to account for the differences in job complexities or dissimilarities (Mosheiov and Sidney, 2003, 2005; Lin, 2007; Koulamas, 2010; Qian and Steiner, 2013; Wang and Wang, 2015) or they included a plateau effect $LE_{t,plat}$ that prevents processing times from decreasing arbitrarily (Cheng et al., 2013).

Implicitly assuming that each job requires constant repetition of a single operation, the *time-based* learning effect LE_t does not only consider the number of jobs processed prior but also the total time spent on production thus far (Yang and Kuo, 2007). Therefore, this learning effect is also referred to as *sum-of-the-processing-times* learning effect (Biskup, 2008). As for the *position-based* learning effect, different objective functions (Dondeti and Mohanty, 1998; Kuo and Yang, 2006; Koulamas and Kyparisis, 2007; Yang and Kuo, 2007; Koulamas and Kyparisis, 2008; Wang et al., 2008; Cheng et al., 2009; Janiak and Rudek, 2009; Wang et al., 2009; Jiang et al., 2013; Lai and Lee, 2013) or extensions, including job dependence $LE_{t,j}$ (Jiang et al., 2013) and plateau effects $LE_{j,plat}$ (Cheng et al., 2011), have been considered.

Considering the minimisation of the makespan $C_{\max}$ and the Total Completion Time $TC := \sum C_j$ time, it is noteworthy, that the position-based learning effect ($p_{j,r} = p_j * r^a$) and the position-based learning effect extended by a constant deterioration rate is solved by ordering the jobs according to the Shortest-Processing-Time-First (SPT)-rule. This further applies to the time based learning effect ($p_{j,r} := p_j(1 + \sum_{k=1}^{r-1} p_{[k]})^a$) as well as the fractional, exponential and logarithmic formulation of the same, just like the extension based on actual processing times, and a time based learning effect included in set-up times. The position-based learning effect with individual learning rates for each job can be solved by reformulating as an assignment problem. Considering the actual processing times of jobs in combination with a time-based learning effect and individual learning rates for each job minimizing the makespan is NP-complete by reduction on *3-Partiotion*.

For in-depth reviews on learning effects for scheduling problems, see Biskup (2008); Anzanello and Fogliatto (2011); Janiak and Rudek (2009); Heuser et al. (2022).

Learning theory and research on employee skill development do not only consider efficiency gains but also forgetting as a counterpart to learning. Mainly two types of forgetting are distinguished based on consequences of extensive task repetition (Digiesi et al., 2009; Dode et al., 2016) or interruption of the production process (Jaber et al., 2003). The first effect can be seen as a special case of deterioration. Compared to common deteriorating processing times, here, processing times increase after a certain threshold, based on the number of receptions or the time spent in production. This *deterioration-based* forgetting effect accounts for fatigue (Dondeti and Mohanty, 1998), boredom (Azizi et al., 2010), as well as ergonomic factors (Anzanello et al., 2014) and can, for example, be mitigated by job rotation (Azizi et al., 2010). Note that this effect is outside the scope of this paper, as it has already been covered by single-machine scheduling literature.

Additionally, forgetting emerges if the production process is paused or disrupted (Globerson, 1987) since the information from the immediate memory gets lost (Delasay et al., 2019). This type of forgetting, further referred to as *interruption-based* forgetting, impacts especially procedural tasks, e.g. productions tasks (Bailey, 1989). Jaber et al. (2003) listed several properties of interruption-based forgetting curves, established in different studies, e.g. by Globerson et al. (1989); Bailey (1989); Dar-El et al. (1995) and Schultz et al. (2003). Hereby, the amount of knowledge forgotten can depend on (i) the number and (ii) the length of interruption, as well as (iii) the amount of knowledge accumulated earlier. Further, workers (iv) relearn at the same rate as their original learning rate, (v) forgetting and learning curves are mirror images of each other and (vi) both depend on the task's nature and, thus, complexity. Moreover, they stated (vii) power-based models to appropriately capture forgetting effects (Jaber et al., 2003).Schultz et al. (2003) emphasized that forgetting effects caused by interruption comprise not only memory-related components but are fostered by a break of rhythm. Thus, also short interruptions lead to penalty costs. Nembhard and Osothsilp (2001) presented a comparative review of different forgetting models.

Although forgetting effects are known to affect production efficiency, only a few publications for single-machine scheduling included these effects. Whereas *deterioration-based* forgetting effects are considered for single-machine scheduling problems with classical objective functions (Dondeti and Mohanty, 1998; Lai and Lee, 2013, 2014; Wu et al., 2015, 2016), *interruption-based* forgetting effects are, to the best of our knowledge, only considered for batch-sizing and batch-scheduling problems for single machines (Pan et al., 2014; Yang and Chand, 2008). The deterioration-based forgetting effects can, again, be solved by the SPT-rule when minimising the makespan and the total completion time.

Hence, we contribute to the literature of machine-scheduling by considering a *position-based* learning and an *interruption-based* forgetting effect for single-machine problems. The models account for different product categories with intra-category learning and inter-category forgetting effects.

3 Model

Consider a scheduling problem with a finite set of jobs $J := \{1, \dots, n\}$ that has to be processed on a single machine. Every job $j \in J$ is equipped with a standard processing time $p_j \in \mathbb{R}^+$ and associated to a category $c_j = c \in \mathcal{C}$, where $\mathcal{C} := \{1, \dots, k\}$. A fixed permutation π of J is denoted as schedule. The objective of this article is either to compute a schedule π that minimizes the makespan $C_{\max} := \max\{C_1, \dots, C_n\}$ or the total completion time $TC := \sum C_j$, where C_j denotes the completion time of job $j \in J$.

3.1 Learning

As a consequence of consecutive repetition of jobs belonging to the same category, efficiency gains due to learning-by-doing are realized. The abbreviation $LE_{p,cat}$ is used to denote the categorized learning effect.

Our research model generalizes the position-based learning effect introduced by (Biskup, 1999). Within this model, the processing time of a job j depends on the position r in a given schedule π, i.e.

$$p_{j,r} := p_j \cdot r^a. \tag{1}$$

The learning rate l, observable in production, is utilized to calculate the learning coefficient a, where $a := -\log_2(l)$. Without loss of generality, assume $a \in [-1, 0)$, which corresponds to learning rates ranging from 50% to 99.99% and, thus, covers all relevant learning effects (Dutton and Thomas, 1984). If not mentioned otherwise, the examples presented in this article consider a learning rate of 80%, corresponding to $a \approx -0.322$.

The position-dependent processing times are reformulated in such a way that the processing time of job j is only affected by the number of identically categorized jobs processed priorly. So, to determine the actual processing time of a job scheduled at position r it is sufficient to only consider the jobs scheduled prior and of those count the number of jobs r_c belonging to the same category c. Hereto, we define the number of jobs belonging to category c processed before a job at position r in the realization π as

$$r_c := \sum_{i=1,\ldots,r} \sum_{j \in J} \left(x_{j,i} \cdot \chi(c_j, c) \right), \tag{2}$$

where $x_{j,i}$ indicates whether job j is placed at position i in schedule π, and $\chi(c_j, c) = 1$ if $c_j = c$ or otherwise $\chi(c_j, c) = 0$. The learning coefficient of product category c, $a_c \in [-1, 0)$, allows to describe an individual learning rate for each category and, thus, accounts for different complexities of the tasks and product categories considered. Consequently, the actual processing times with position-based learning effect and different product categories are

$$p_{j,r} := p_j \cdot r_{c_j}^{a_c}, \tag{3}$$

where we define $r_{c_j}^{a_c} := \sum_{c \in \mathcal{C}} \left(\chi(c_j, c) \cdot r_c^{a_c} \right)$ to improve readability.

3.2 Forgetting

A further generalisation of the model introduced in Section 3.1 incorporates forgetting effects $LE_{p,cat} + F_{I,cat}$ based on the interruption of category production.

In order to introduce a proper forgetting effect, we rewrite the above formulated counter r_c as a recursive function $\hat{\gamma}_{r,c}$ for all $c \in \mathcal{C}$. Whenever a job of a certain category c is processed, the corresponding $\hat{\gamma}_c$ is increased by 1, i.e.

$$\hat{\gamma}_{i,c} := \hat{\gamma}_{i-1,c} + \sum_{j \in J} \chi(c_j, c) \cdot x_{j,i}, \qquad \forall i \in \{1, \ldots, r\}, \tag{4}$$

$$\hat{\gamma}_{0,c} := 1.$$

Hence, either $\hat{\gamma}_{i,c}$ increases by one, if the job scheduled at position i belongs to category c, otherwise it remains unchanged compared to the previous element of the sequence.
Now, equation (4) is modified to incorporate forgetting effects. The extension

$$\gamma_{r,c} := \max \left\{ 1, \gamma_{r-1,c} - 1 + 2 \cdot \sum_{j \in J} \left(\chi(c_j, c) \cdot x_{j,r} \right) \right\} \tag{5}$$

allows the counter γ_c to decrease with interruption of category production. That is, the value decreases by 1 for each job, belonging to another category and processed between two jobs of one category. Thus, the models account for the number and length of interruptions. The forgetting effect, hereby, is a mirror image of the learning curve introduced in Section 3.1.

A further generalisation of the above effect incorporates a forgetting-parameter $\delta \in \mathbb{R}^+$. This value moderates the relation between learning and forgetting and can easily be included in Equation (5), i.e.

$$\gamma_{r,c}(\delta) := \max \left\{ 1, \gamma_{r-1,c} - \delta + 2 \cdot \sum_{j \in J} \left(\chi(c_j, c) \cdot x_{j,r} \right) \right\}. \tag{6}$$

Consequently, the actual processing times with position-based learning and forgetting effects and different product categories are

$$p_{j,r} := p_j \cdot \gamma_{r,c_j}^{a_c}. \tag{7}$$

Note that Equations (5) and (6) ensure that $p_{j,r} \leq p_j$ for all r for all realisations π. See example 3.1 for a comparison of the considered learning rates.

Example 3.1. Consider the following scheduling instance: Let $J = \{1, \dots, 10\}$ and π correspond to a list sorted by the indexes. We visualise a certain category $c \in \mathcal{C}$ in Figure 1, i.e., the jobs associated with category c are scheduled at positions $2, 3, 5, 10$ and the learning rate for c is $a_c = -0.322$.

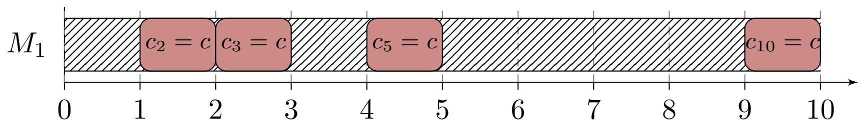

Figure 1: Positions of job associated to category c in schedule π.

Within Figure 2, the corresponding learning index influenced by different learning and forgetting effects is presented: The dashed black line corresponds to the learning factor of Equation (1). Note that this curve represents the special case where all jobs are associated with the same category and thus no forgetting effects will occur. Hence, this curve is a lower bound for the learning factors $\hat{\gamma}_{i,c}^{a_c}$ and $\gamma_{i,c}^{a_c}$ for all considered model variants.

The blue line represents the learning factor of Equation (4). Whenever a job of category c is produced, the learning factor decreases whereas it remains constant if a job of a different category is produced.
The red and the green line correspond to the learning and forgetting factor of Equation (6), where the forgetting slope of the red line mirrors its learning slope (thus $\delta = 1$, see Equation (5)), while

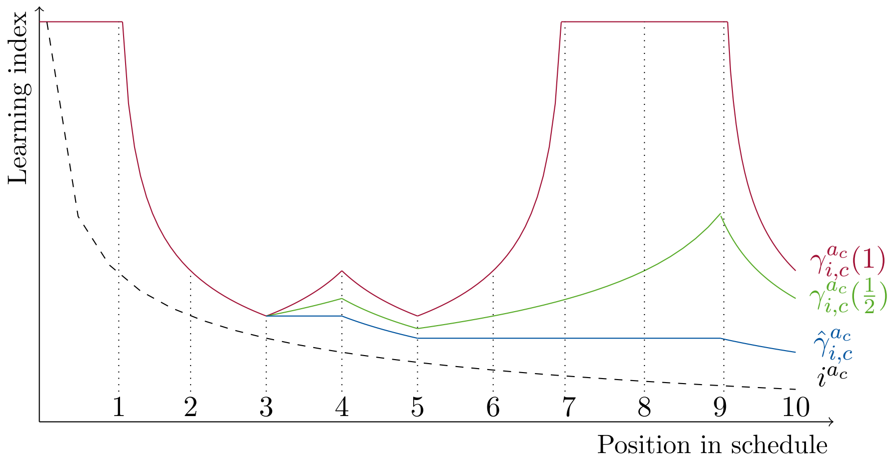

Figure 2: Comparison of the introduced learning and forgetting effects for the proposed example.

the forgetting slope of the green line is reduced by applying a forgetting-parameter of $\delta = \frac{1}{2}$. Note, that due to Equation (6) there is a fixed bound (depicted by e.g. the initial plateau before the first job of category c is produced), which corresponds to the maximum initial processing time of any job. Therefore, regardless of the extent of the forgetting effect, no condition with worse processing times than in the initial setup can be achieved, as can be seen from the second plateau of the red curve.

4 Learning

In this section, we consider the learning effect ($LE_{p,cat}$) introduced in Equation (4). First, a solution method minimising the makespan makespan $\mathrm{C}_{\max}$ is presented. Second, the total completion time TC is analyzed.

4.1 Makespan

Since no forgetting effects occur, classical scheduling heuristics for scheduling problems with learning effects can be applied to minimize the makespan. Here a common heuristic minimizing the makespan for most problems is the SPT-rule

Corollary 4.1. *The Shortest Processing Time First (SPT)-rule solves the problem* $1 \mid LE_{p,cat} \mid C_{\max}$ *in* $\mathcal{O}(|J| \log(|J|))$ *time.*

Proof. The argumentation presented in Mosheiov (2001a) for the position-based learning effect without categories can be transferred to each category $c \in \mathcal{C}$ separately. Consequently, the processing times of jobs from category c are minimized by the SPT-rule. Due to the absence of forgetting effects, jobs from a different category can be inserted between two jobs from category c without affecting the processing times. Hereby, the jobs associated with one category c are independent of jobs of other categories $\hat{c} \in \mathcal{C} \setminus \{c\}$. Thus, if the order of the jobs within each category is held constant, jobs belonging to different categories can be merged arbitrarily. Please note, that the SPT-rule fulfills these structural requirements. It represents a merge of categories each sorted according to the SPT-rule. Hence, the optimality of the subsets is not affected. $\square$

To profit from learning, only the intra-category order of jobs is relevant. Hence, the makespan is equally minimized by a category-SPT-rule. Hereto, all jobs of one category are scheduled coherently in one batch according to the SPT-rule. Subsequently, this heuristic is named *batch-wise shortest processing time first (BSPT)*. For a detailed definition of the algorithm, refer to the formal description in Section 5, i.e., Algorithm 2 which also accounts for forgetting effects.

Corollary 4.2. *The Batch-Wise Shortest Processing Time First (BSPT)-rule solves the problem* $1 \mid LE_{p,cat} \mid C_{\max}$ *in* $\mathcal{O}(|\mathcal{C}|\log(|\mathcal{C}|) + \sum_{c\in\mathcal{C}} n_c \log(n_c))$ *time, where* $n_c = |\{j \in J : c_j = c\}|$.

Proof. The argumentation follows the structural properties used to prove Corollary 4.1. Since the obtained schedule contains SPT-sub-schedules for each category, a BSPT-schedule equals an SPT-merge. Thus, the schedule obtained yields an optimal solution. The runtime is determined by initially sorting all jobs associated with a category, and then sorting all resulting batches again. □

The following numerical example illustrates the SPT- and the BSPT-rule when minimizing the makespan for different categories of tasks.

Example 4.3. Consider an instance with $|J| = 6$ and $|\mathcal{C}| = 2$, where the jobs $j \in \{1, 2, 3\}$ with $p_1 = 6$, $p_2 = 3$ and $p_3 = 2$ are associated with category A and jobs $j \in \{4, 5, 6\}$ with $p_4 = 6$, $p_5 = 3$ and $p_6 = 2$ are associated with B. The Gantt Chart in Figure 3 shows the jobs ordered according to the SPT- and BSPT-rule. Both, yielding the same actual processing times $p_1 = 6 \cdot 3^{-0.322} = 4.2123$, $p_2 = 2.3999$, $p_3 = 2$, $p_4 = 4.2123$, $p_5 = 2.3999$ and $p_6 = 2$. Thus, both rules result in the same optimal makespan $C_{\max} = 17.2243$.

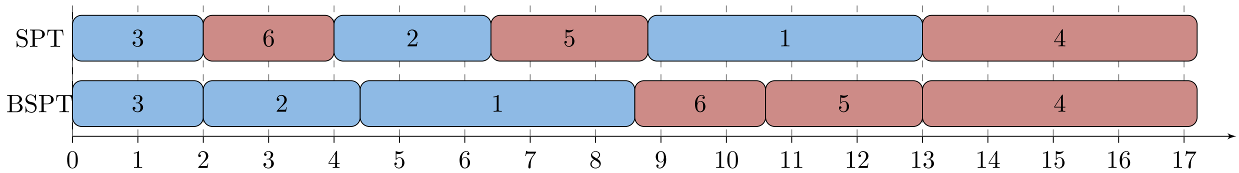

Figure 3: Visualisation of the schedules of Example 4.3. The colours highlight the affiliation of jobs to a certain category.

4.2 Sum of Completion Times

More sophisticated is the objective to minimize the sum of completion times. Again, a variation of the classical SPT-heuristic approach delivers an optimal solution. Hereto, the learning effects have to be considered when building the SPT-sequence. In this sense, the shortest processing time $p_{j,r}$, as defined in Equation (3), has to be selected instead of the processing time p_j. Following the need to calculate the actual processing times at each iteration, the heuristic variation described in Algorithm 1 is called *dynamic shortest processing time first (DSPT)*.

Theorem 4.4. *The Dynamic Shortest Processing Time First (DSPT)-rule solves the problem* $1 \mid LE_{p,cat} \mid \sum C_j$ *in* $\mathcal{O}(|J|^2)$ *time.*

Proof. The proof relies on pairwise job interchange arguments distinguishing, additionally, if the considered consecutively scheduled jobs $i, j \in J$ belong to the same category. For the sake of

Algorithm 1: Dynamic-Shortest-Processing-Time-First (DSPT) heuristic

1 $r \leftarrow 1$, $C \leftarrow 0$, $C_j \leftarrow 0$, $x_{r,j} \leftarrow 0$, $\bar{J} \leftarrow J$, $j^* \leftarrow 0$
2 **for** $r < |J|$ **do**
3     $j^* \leftarrow \arg\min_{j \in \bar{J}} p_{j,r}$
4     $C \leftarrow C + p_{j^*,r}$
5     $C_{j^*} \leftarrow C$
6     $x_{r,j^*} \leftarrow 1$
7     $\bar{J} \leftarrow \bar{J} \setminus j^*$
8     $\gamma_r(\chi(j^*)) \leftarrow \gamma_r(\chi(j^*)) + 1$
9     $r \leftarrow r + 1$
10 **end**
11 **return** $x_{r,j}$,C_j

contradiction, we assume $p_{i,r} \leq p_{j,r}$, job j is scheduled at position r and job i is scheduled at position $r+1$.

The case $\chi(i,c) = \chi(j,c) = 1$ for any $c \in \mathcal{C}$, corresponds to the single category case as described in Biskup (1999). With TC_{ji} denoting the sum of the completion times if j is scheduled before i and TC_{ij} vice versa, we obtain

$$TC_{ji} - TC_{ij} \geq (p_j - p_i)(r_k^{a^k} - (r+1)_k^{a^k}) \geq 0.$$

Since both jobs are associated with the same category, the processing times of all remaining jobs are not affected in case of an i-j swap. It remains to consider the case where $1 \neq \chi(i,c) \cdot \chi(j,c)$ for all $c \in \mathcal{C}$. As no forgetting effects occur, the learning effects of all remaining jobs are independent of the order of i, j. Moreover, $p_j r_k^{a^k}$ and $p_i r_\ell^{a^\ell}$, $k \neq \ell \in \mathcal{C}$, are independent of the job positions with respect to each other, since they are contained in different categories. Hence, once again, we apply a standard swapping argumentation. Within this comparison $p_j r_k^{a^k} = p_j(r-1)_k^{a^k}$ and $p_i r_\ell^{a^\ell} = p_i(r-1)_\ell^{a^\ell}$ holds. Thus this case corresponds to the classic situation with fixed processing times without learning effects. Repeating this argumentation for all jobs which are not in DSPT-order yields the Theorem. □

Hence, an optimal schedule that reduces the sum of completion times can be obtained by a sorting algorithm (Algorithm 1, line 3) being applied to each position in the schedule. Thus, DSPT runs in $\mathcal{O}(|J|^2 \log(|J|))$ time. Observe that in each iteration the learning factor of a single category only is affected. Moreover, since the realized processing times are monotonously decreasing, the order of all jobs of the changed category stays the same. Thus, instead of sorting from scratch, a sub-list of all unchanged processing times can be merged with the list of the newly computed processing times. So, the temporary list of jobs $\bar{J}$ that still has to be scheduled in each run of the for-loop is already sorted after a single merge step. This improved algorithm takes $\mathcal{O}(|J|^2)$ time.

5 Learning and Forgetting

The problems considered in Section 4 are extended to comprise an *interruption-* and *category-based* forgetting effect $F_{I,cat}$. Hereto, the learn-forget index introduced in Equation (5) is utilised hereinafter. Following the previous structure, we first turn to minimize the makespan $C_{\max}$ and later the total completion time TC.

5.1 Makespan

For a single-machine scheduling problem with the compound learn-forget effect $LE_{p,cat} + F_{I,cat}$, a minimal schedule with respect to the makespan is obtained by the BSPT-rule.

Theorem 5.1. *The Batch-Wise Shortest Processing Time First (BSPT)-rule solves the problem* $1 \mid LE_{p,cat} + F_{I,cat} \mid C_{\max}$ *in* $\mathcal{O}(|\mathcal{C}| \log(|\mathcal{C}|) + \sum_{c\in\mathcal{C}} n_c \log(n_c))$ *time, where* $n_c = |\{j \in J : c_j = c\}|$.

Proof. As seen in Corollary 4.2, the BSPT-rule minimises the makespan for the setup without forgetting. Moreover, since BSPT processes one category after another, in no category $c \in \mathcal{C}$ do any forgetting effects occur before all jobs of this category are finished. Hence, BSPT is optimal for the learn-forget setup as well. □

Example 5.2. Consider the instance from Example 4.3 in order to compare BSPT and SPT. The processing times received by the BSPT-rule stay unchanged since no forgetting effects occur as all jobs of one product group are processed consecutively. Hence, the processing times are, again, $p_1 = 6 \cdot 3^{-0.322} = 4.2123$, $p_2 = 2.3999$, $p_3 = 2$, $p_4 = 4.2123$, $p_5 = 2.3999$ and $p_6 = 2$. When applying the SPT-rule, we receive a solution alternating jobs from both categories throughout the whole schedule. Therefore, the jobs record no efficiency gains, as the forgetting effect counteracts the positive effect of learning. Thus, the actual processing times correspond to the standard processing times: $p_1 = 6 \cdot 1^{-0.322} = 6$, $p_2 = 3$, $p_3 = 2$, $p_4 = 6$, $p_5 = 3$ and $p_6 = 2$. The Gantt Chart 4 shows the jobs ordered according to the SPT- and the BSPT-rule with makespan $C_{\max} = 22$ and $C_{\max} = 17.2243$ respectively.

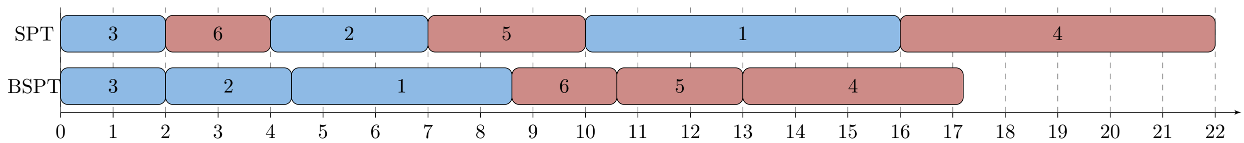

Figure 4: Visualisation of the schedules of Example 5.2. The colors highlight the affiliation of jobs to a certain category.

5.2 Minimise the Sum of Completion Times

As soon as the completion times C_j of all jobs are relevant, i.e., while minimizing the sum of completion times, none of the so far considered heuristics can guarantee an optimal solution.

Observation 5.3. *The total completion time is not minimised by the SPT-, BSPT- or DSPT-rule if forgetting effects are included.*

Example 5.4. In this example, neither BSPT nor DSPT yield an optimal solution for minimising the total completion time, even if only two categories and a mirrored forgetting pattern, i.e. $\delta = 1$, are considered. The processing times of category $A = \{1, 2, 3, 4\}$ are $p_1 = p_2 = p_3 = 1$ and $p_4 = 8$ while the processing times of category $B = \{5, 6, 7\}$ are $p_5 = 0.9$, $p_6 = 1.1$ and $p_7 = 5$. The Gantt Chart in Figure 5 visualizes the performance of the considered heuristics in contrast to the optimal solution. The total completion time of the optimal solution OPT is approximately 36.572, while BSPT results in a value of 42.057 and DSPT in a value of 37.503. Note, that the optimal solution omits the initial benefit of scheduling the shortest job 5, with $p_5 = 0.9$ first to ensure a higher reduction due to learning for job 7 with $p_7 = 5$ later on. Hence, the SPT-rule is not optimal either.

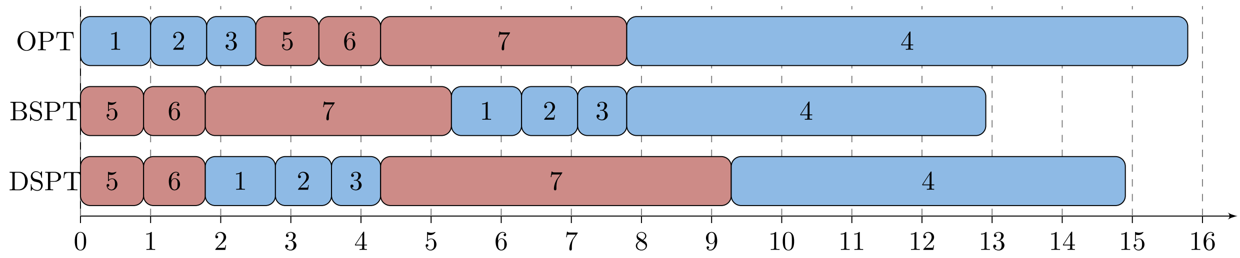

Figure 5: Visualization of the schedules of Example 5.4. The colors highlight the affiliation of jobs to a certain category.

Algorithm 2: Batch-wise shortest processing time (BSPT) heuristic

$C_j \leftarrow 0$, $x_{r,j} \leftarrow 0$, $M_c \leftarrow \emptyset$, $\bar{C} \leftarrow C$, $\bar{J} \leftarrow J$
for $c \in \bar{C}$ **do**
  $M_c \leftarrow \{j \in \bar{J}, c = c_j\}$
  $\bar{J} \leftarrow \bar{J} \setminus M_c$
  $C_{max_c} \leftarrow 0$
  $r \leftarrow 1$
  for $m \in M_c$ **do**
    $m^* \leftarrow \arg\min_{m \in M_c} p_m$
    $C_{\max_c} \leftarrow C_{\max_c} + p_{m^*} \cdot r^{a_c}$
    $M_c \leftarrow M_c \setminus m^*$
    $r \leftarrow r + 1$
  end
  $AC_c \leftarrow \frac{C_{\max_c}}{r-1}$
  $\bar{C} \leftarrow \bar{C} \setminus c,$
end
apply SPT for $J = \mathcal{C}$ with $p_c = AC_c$
return $x_{r,j}$,C_j

To assure receiving the optimal order of the batches, in the case that the BSPT-rule optimizes the underlying problem, we formulate the following Lemma 5.5. Based on the ordering criterion in Lemma 5.5 we formally define the BSPT (Algorithm 2) already utilised in the section before.

Lemma 5.5. *For the BSPT-heuristic, the smallest total completion time is realized by ordering the batches according to increasing actual average processing times AC_c for each category c.*

Proof. Let A and B be two batches with $\frac{C_{\max SPT}(A)}{a} > \frac{C_{\max SPT}(B)}{b}$ and $a = |A|$, $b = |B|$. Consider the schedule $\pi = \{A, B\}$ and the total completion time TC_{AB}. By switching the batches A and B, a new schedule with smaller total completion time will be obtained. The switch yields costs as follows:

$$TC_{BA} := TC_{AB} + a \cdot C_{\max SPT}(B) - b \cdot C_{\max SPT}(A).$$

For the switch to be beneficial the costs need to decrease and we get the following condition

$$a \cdot C_{\max SPT}(B) - b \cdot C_{\max SPT}(A) < 0$$

that gives us the property:

$$\frac{C_{\max SPT}(B)}{b} < \frac{C_{\max SPT}(A)}{a}.$$

The so retrieved coefficients are referred to as the actual average processing times.

□

Analyzing the results from the DSPT-rule we find an avenue for improvement. By considering a situation containing equally small values in each category at a time, the result can be improved, as the following example shows.

Example 5.6. Independent of the above example, an optimal schedule might still be a DSPT-structure. Nevertheless, due to uncertainties in tie-breaking situations, the DSPT-algorithms might not return an optimal solution. Gantt Chart 6 shows two DSPT-solutions for the following instance: The processing times of category $A = \{1, 2, 3\}$ are $p_1 = p_2 = 1$ and $p_3 = 8$, while the processing times of category $B = \{4, 5, 6\}$ are $p_4 = 1$, $p_5 = 3$, and $p_6 = 7$. The differences in the two schedules arise due to different decisions in a tie-situation. In Schedule i), the optimal solution, job 1 is selected first, while in schedule ii) initial job 4 is scheduled, which results in a higher total completion time. Thus, the DSPT-heuristic could be improved utilizing a decent rule for handling the tie-breaking.
Due to the fact that there exist instances in which the optimal solution does not provide a DSPT-structure, see Example 5.4, we omit further investigations on the tie-breaking rule and choose a job randomly in the case of a tie as described in Algorithm 1.

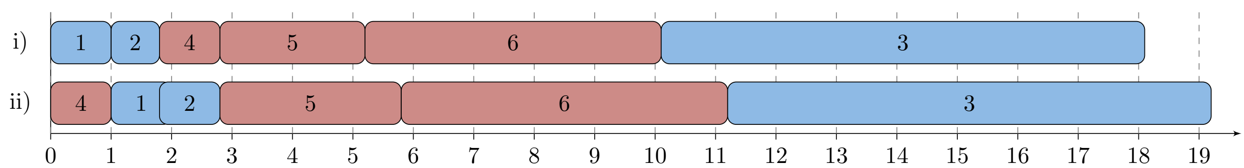

Figure 6: Tie-breaking impacts the performance of DSPT. The colours highlight the affiliation of jobs to a certain category.

5.2.1 Computational Study

Although we presume that the above-presented problem is NP-hard, we would like to provide insights on the efficiency of the proposed heuristics in order to give practitioners a solution method at hand. To assess the benefits of the BSPT- and the DSPT-rule for minimizing the total completion time when learning and forgetting effects are present, two computational studies are conducted.

Based on the computational effort required to solve the problem to optimality, we present results for small problem sizes with up to $n = 9$ jobs in Section 5.2.2. Building on the observed results a second simulation is conducted, benchmarking the upper envelope of the two heuristics to results obtained by the SPT-rule in Section 5.2.3. This decision is based on the fact that the SPT-rule is commonly used to minimize the total completion time when omitting forgetting effects. All heuristics and methods are implemented in Python and executed using a Python 3.6 interpreter.

Parameters Throughout, different values for the parameters *number of jobs*, *number of categories*, *maximum processing time,* and *learning rate* are utilised to derive different scenarios. To analyse the impact of the number of categories for a fixed *number of jobs* n, examples for each *number of categories* $c \in \{2, \ldots, n-1\}$ are calculated. In order to respect different job sizes, three ranges $\{[1, 10], [1, 100], [1, 1000]\}$ for the job processing times p_j are established, based on distinct *maximum processing times*. Hereto, the function *random.randint()* is utilised to generate random integer processing times within the given boundaries. According to a study by Dutton and Thomas (1984), learning rates l, observable in practice, vary between $60 - 90\%$ whereas 80% is the most common value. Confirming with this result, *learning coefficients* $a \in \{-0.73696559416, -0.32192809488, -0.07400058144\}$ corresponding to learning rates of 60%, 80% and 90%, respectively are considered. Finally, for each set of parameter combinations, 250 examples are calculated. This leads to $250 \cdot 3 \cdot 3 \cdot (n-2) = 2250 \cdot (n-2)$ results for each size of jobs n.

Heuristics For small problem sizes, a permutation method is implemented to find an optimal solution OPT for a given instance of the proposed problem. Hereto, all possible schedules are created and the total completion time is calculated in order to retrieve a minimal solution. Since we hypothesize the optimal solution to be a merge from SPT-sequences of the different categories, we further analyze the structure of the optimal solution with regard to that characteristic. Therefore, the Boolean value (*IS_SPTMERGE*) is computed for all minimal schedules. The optimal solution is, further, used to assess the performance of the heuristics SPT, BSPT, and DSPT.

Lastly, the upper envelope of the heuristics is considered to improve the accuracy of the results obtained. First, including the DSPT- and BSPT-rules only and second further including the SPT-rule. Hereto, the minimal solution for each instance of the problem is extracted to calculate $ENVELOPE = \max\{BSPT,\ DSPT\}$, and $ENVELOPE_{SPT} = \max\{SPT,\ BSPT,\ DSPT\}$.

5.2.2 Small Problem Sizes

Based on the computational effort needed to retrieve optimal solutions, problem instances with $n \in \{3, ..., 9\}$ jobs are considered in this section only. Concerning the parameters mentioned, we receive 63,000 example instances. To compare the influence of different parameters, we first calculate the deviation from the optimal solution in percentage for each heuristic (HE) using the following expression: $Gap(HE) := \frac{HE-OPT}{OPT} \cdot 100$. For each parameter combination, we calculate the mean for the GAP to obtain a performance indicator for each scenario. Note that each of those values is based on 250 random example instances. In addition, we further consider the worst-case performance for each scenario. Hereto, we extract the problem instance leading to the highest GAP value for the $ENVELOPE_{SPT}$.

Evaluating the results we find that the *maximum processing time*, and thereby the range of processing times, does not influence the performance of the heuristics. Figure 7 shows the deviation from the optimal solution for the three heuristics and the upper envelopes. The curves depict the behavior with respect to the number of jobs n and the number of categories k. Results for different example sizes, that is, different values of n, are separated by a vertical dashed line. Considering the red graph describing the SPT-rule, the performance is especially poor for small numbers of different categories and increases with the *number of categories*. This effect is not surprising, since for a growing number of categories only a few jobs are in one category and can potentially profit from learning and, thus, be affected by forgetting. Comparing the results to the BSPT (blue curve) and the DSPT (green curve), we find a similar effect resulting in a lower accuracy for smaller *numbers of categories*.

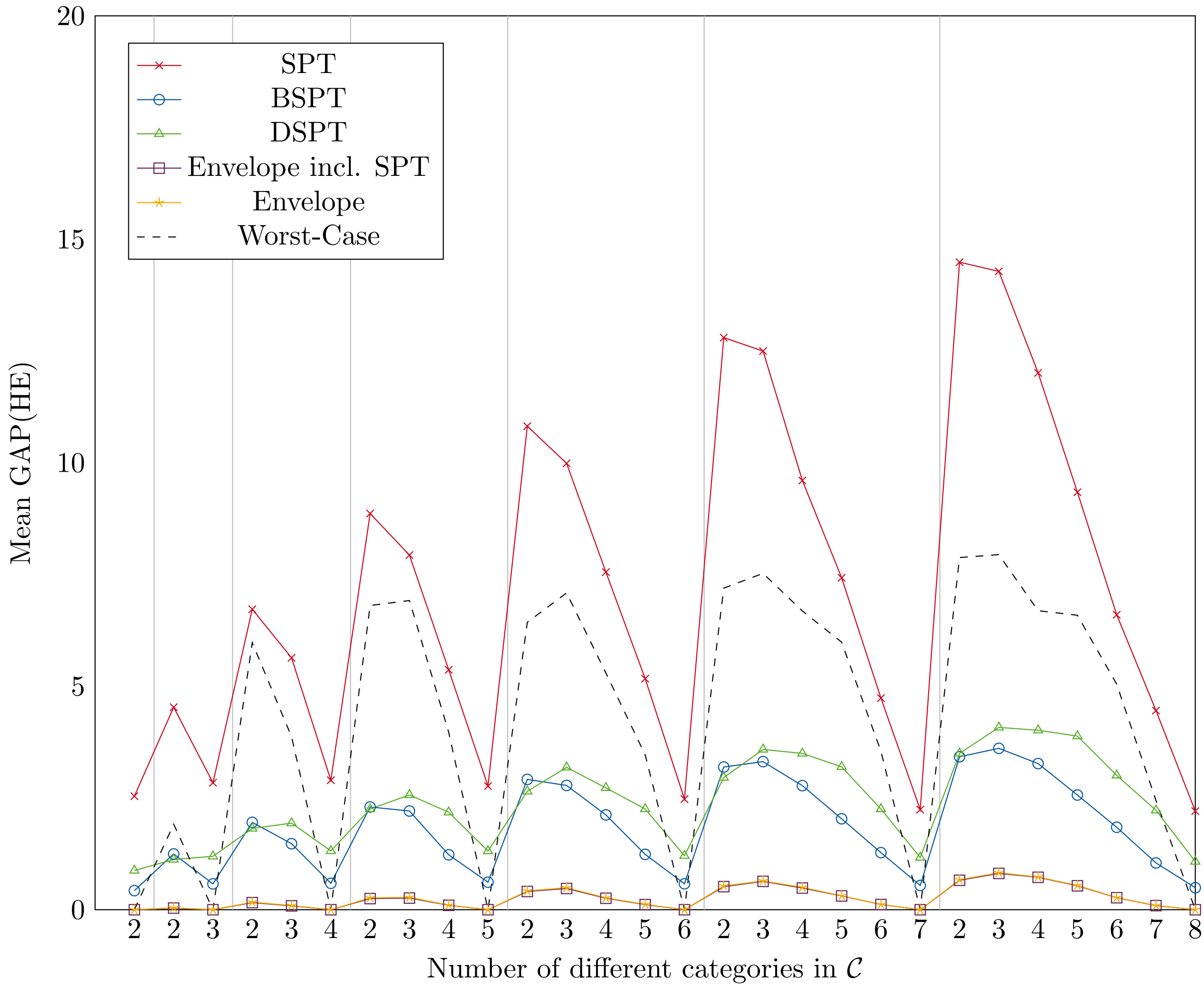

Figure 7: GAP of the heuristics SPT, BSPT, and DSPT as well as the two envelops with respect to the optimal solution.

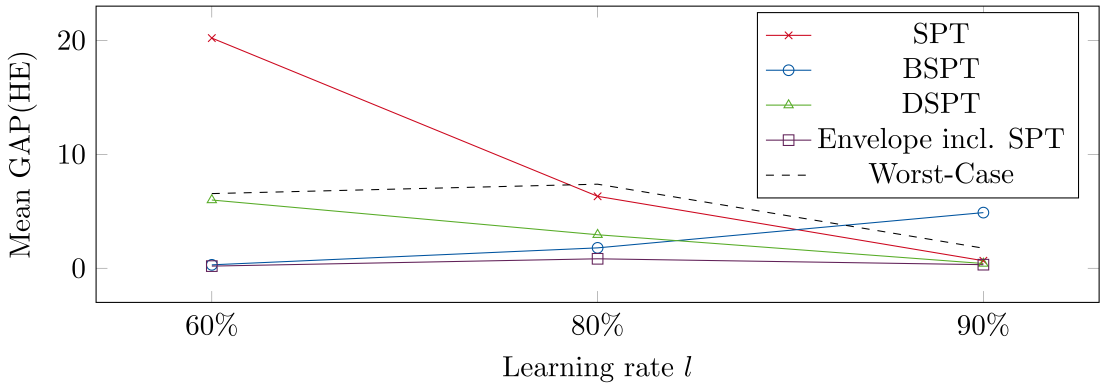

Figure 8: Performance of the heuristics for different learning rates (example: $n = 9$).

Nevertheless, both heuristics clearly outperform the SPT-rule. Turning to the envelope curves (orange, purple) we again receive a performance improvement. Note that the two envelope curves only record small differences, since the SPT-rule only seldom delivers superior results compared to the other heuristics. We find further support when looking at the worst-case performance. The dashed black line shows that the $ENVELOPE_{SPT}$ still clearly outperforms the SPT-rule in every scenario. Turning to the influence of the learning rates, we find that the overall observed effects are strongest for a 60% learning rate, persist for 80%, but harshly decrease for 90%. Still, we find differences considering the individual heuristics which are depicted in Figure 8. For production environments with high learning potentials ($l = 60\%$), the BSPT-rule (0.30% deviation from the optimum) outperforms the DSPT-rule (GAP=20.20). A reverted effect is visible for environments with low learning rates ($l = 90\%$). Here the DSPT- and the SPT-rule deliver similar results with an accuracy of 99.59% and 0.66% respectively.

Independent of the underlying learning rate the upper envelope of the three heuristics delivers near-optimal solutions with a GAP of 0.18%, 0.83% and 0.31% for 60%, 80% and 90% respectively. Considering the worst-case performance, described by the dashed black line, we still find an improvement of approximately 13 % compared to the SPT-rule for the 60% learning rate ($GAP = 6.55\%$, $GAP = 20.20\%$) and slightly inferior results for the other learning rates. Note that the worst-case curve is based only on the instance with the poorest performance out of the 250 cases per scenario. Thus, the mean curves of the envelope (purple) must be utilized for an adequate comparison to the SPT-rule.

Note that independent from the underlying setting, all 63,000 examples are a SPT-merge. This strengthens our belief that a pseudo-polynomial time algorithm could be developed to solve the problem to optimality.

5.2.3 Larger Problem Sizes

Figure 7 shows that the performance reduction is reinforced by rising problem sizes, that is, an increasing *number of jobs*. To analyze whether this effect persists larger problem sizes, with $n = 50$ and $n = 100$ jobs, are considered. Calculating all permutations of the underlying problem instances to obtain an optimal solution is not possible due to the computational effort. Therefore, the results from the SPT-rule are used to benchmark the performance of the upper envelope of the heuristics.

In order to provide the best possible solution for practitioners, we choose the envelope containing all three heuristics. Again we calculate for both problem sizes the results for the SPT, the DSPT, and the BSPT-heuristic for all parameter combinations receiving $112,500$ and $225,000$ records for $n = 50$, 100 respectively. For each example, we calculate the upper envelope and the performance improvement compared to the SPT-rule as follows $\Delta TC_{Envelope_{SPT}} := \frac{SPT - Envelope_{SPT}}{SPT} \cdot 100$. Figure 9 shows the mean performance improvement and thereby, the total completion time reduction when using the upper envelope when considering $n = 50$ (dashed) and 100 jobs. For each learning rate and the whole data set, a separate curve is established. Again, we see that for small *numbers of categories* the combination of the proposed heuristics delivers large cost reductions compared to the SPT-rule. When considering the topmost (red) curve for the 60% learning rate, reductions of 78.60% ($n = 100$) and 66.81% ($n = 50$) are realised in the case that three product categories are present. For an 80% and 90% learning rate and the whole data set, a reduction of 42.78% (31.18%), 4.89%, (2.60%) and 42.09% (33.53%) is achieved for $n = 100$ ($n = 50$) respectively. Again, the effects observable diminish with a larger number of categories. This in turn is not surprising, as lower overall learning benefits are possible for smaller category sizes.

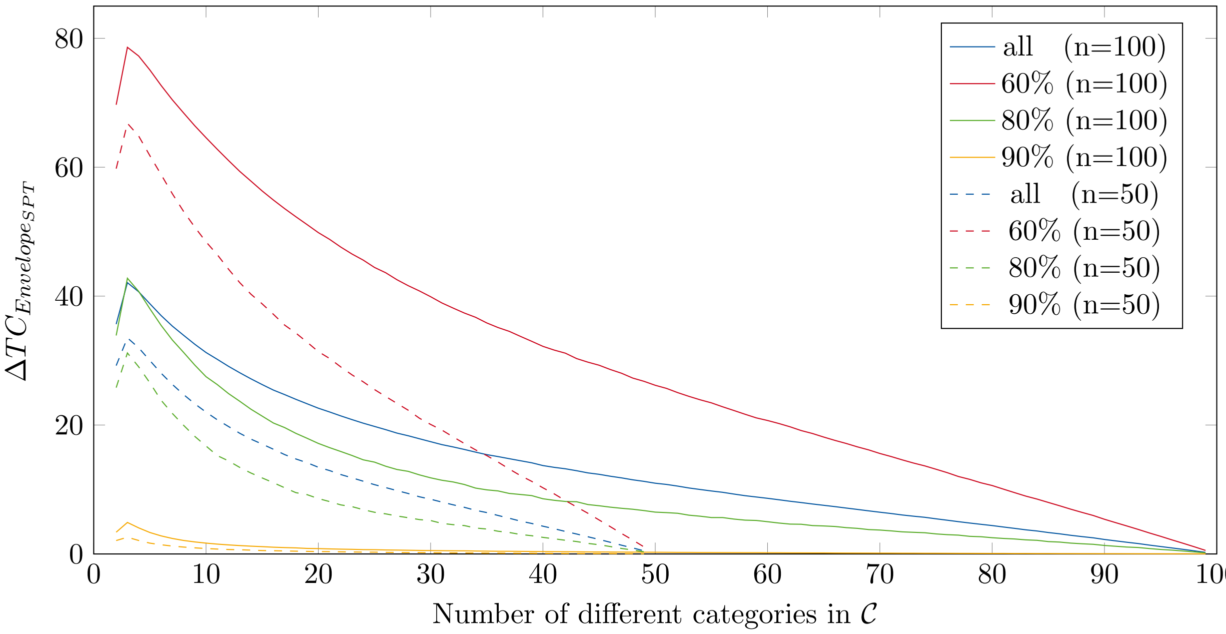

Figure 9: Improvements of the performance of the upper envelope compared to the SPT-rule for 50 (dashed) and 100 jobs and different number of categories.

6 Conclusion

A new effect of worker learning and forgetting for single-machine scheduling problems is presented. Firms often need to process different products on one production line during the ramp-up phase of production, when learning rates are high and consumers pay premium prices for newly introduced products. Based on that requirement, our model accounts for different product types, referred to as 'categories of jobs'. Processing jobs from a single category leads to position-based learning effects for inherent jobs. Moreover, a forgetting effect is introduced. Although a wide range of different learning effects for single-machine problems exist, only little research has been conducted on forgetting effects decreasing worker efficiency. To our knowledge, this is the first article considering an interruption-based forgetting effect for single-machine scheduling problems.

For both the learning and learn-forget effect, we aim to minimize the makespan and total completion time individually. Hereto, two heuristics, the Batchwise-Shortest-Processing-Time-First (BSPT) and the Dynamic-Shortest-Processing-Time-First (DSPT), are developed. Whereas the BSPT-rule delivers optimal solutions for the learning effect considering both objectives, the DSPT-rule minimizes the makespan when considering the learn-forget effect. Turning to the sum of completion times, no optimal solution method could be derived when learning and forgetting effects are present. Therefore, the performance of the heuristics and the upper envelope of these are calculated in a computational study. Hereto, 63,000 example instances are utilized to benchmark the heuristics to the optimal solution. Results indicate that the developed methods deliver near-optimal solutions in a reasonable time. Moreover, we focus on the performance differences with regard to the SPT-rule, since this is the standard method to solve single-machine scheduling problems for most learning effects. Therefore, we compare the performance of the upper envelope against the solutions obtained by the SPT-rule. As the reduction in the total completion time concerning the SPT-rule, is reinforced by an increasing example size, a second computational study is conducted. Hereto, 337,500 example instances for larger problem sizes are considered. In cases of medium to high learning rates, especially for a small number of different categories, savings of up to 78% could be realized. This scenario, again, matches the production ramp-up with fast learning and shared production lines of a few product types. Hence, utilizing our learn-forget effect and the presented solution methods is especially beneficial for production ramp-ups or mature production lines with high learning rates, producing different product types at a time. Nevertheless, also production lines with lower learning effects or a higher product variety can realize performance gains. For the latter scenario, the DSPT-rule performs particularly well, while the BSPT-rule should be implemented when higher learning effects are present. In all scenarios, but especially for intermediate learning behavior, utilizing the envelope (including all three heuristics) for production planning yields the best results.

We contribute to the literature of learning theory and single-machine scheduling by providing a category- and position-based learning effect as well as the first interruption-based forgetting effect. Moreover, we close the research gap in the ramp-up literature, identified by Surbier et al. (2014), by considering the ramp-up of - often low-volume - industries with high product variety. Furthermore, we give practitioners efficient methods to derive optimal and near-optimal solutions at hand.

Although we presume that the problem of minimizing the total completion time when utilizing the learn-forget effect is *NP-hard*, assessing the complexity remains open for further research. Another avenue for further work could be developing a pseudo-polynomial algorithm that makes use of the finding that all optimal solutions obtained in our study are SPT-merges. Moreover, the influence of individual learning rates for different categories could be considered as well as the impact of manipulating the forgetting-parameter δ and analyze the effect of task similarities. The consideration of forgetting effects could be extended in a twofold way. Firstly, recent studies included deterioration of knowledge during production based on interference into refined learning-curves (Jaber et al., 2021; Peltokorpi and Jaber, 2022). Secondly, not only switching between different product categories but the scheduling of production breaks might provide interesting insights. Next to the simulation data set chosen in this study, shop floor data could be used to evaluated if the observed effects sizes persist in a practical manufacturing setting.

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Research Paper 4: Workforce Planning in Production with Flexible or Budgeted Employee Training and Volatile Demand

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Abstract Companies have to adapt their product portfolio to rapidly changing markets and high demand volatility. As a result, they need to invest in workforce learning and training measures to gain flexibility. Especially during ramp-up phases employees have to adjust their skill set to new production requirements. While traditional employee training models focus on a condensed period of training at the beginning of a production ramp-up, we aim to shed light on the effectiveness of more flexible concepts of training with a general availability of training measures during a product's life cycle. We budget training in two dimensions, (1) training capacity per period and (2) periods that do not allow training. To analyze the impact of different training scenarios, a multi-period workforce scheduling problem with workers who learn through learning-by-doing and training is considered. The model further incorporates forgetting. We distinguish a flexible and a budgeted training environment. In the budgeted setting, training measures are only available in the first periods of a production ramp-up to a limited extent. Data from a computational study with 600 scenarios and near-optimal solutions are analyzed statistically to derive insights into an employee's skill development. Overall, we investigate different training strategies under demand volatility and capacity scenarios and analyze the specific outcomes in order to provide managerial implications. Our results indicate that traditional budgeting of training measures has a negative effect on employee learning. The negative impact of budgeting is stronger when production capacity is scarce and demand cannot be fully satisfied.

1 Introduction

Due to digitization and demographic changes, a variety of new challenges are arising for organizations (Wisner, 1996; Surbier et al., 2014). Customers require updated products within shorter periods of time and, because of technological advances, production processes have often become more complex (Surbier et al., 2014). Since the 1990s, development times and product life cycles have been reduced substantially (Terwiesch and Bohn, 2001). The Companies often have to develop new products and bring them to market in less than a year, which equals the market time window for selling many products. A famous example is the cell phone industry where new models are introduced every year. To address rapid changes in customer preferences and technology, companies have to be able to adapt to new market requirements if they are to keep up with the constant rate of change (Qin et al., 2015). Hence, to meet the challenges of fast-changing markets with high demand volatility, companies have to adjust not only their product portfolio and services, they also have to invest in the fast ramp-up of new production processes (Hansen and Grunow, 2015). As these production processes are becoming increasingly interconnected, required employee skills are changing and existing skills might decrease in value over time (Letmathe and Schinner, 2017).

Thus, project portfolio decisions should be based on the employees' competencies and take their targeted development into consideration (Gutjahr et al., 2010). If the proficiency of different products is known up-front or assessable during production, it is worthwhile for companies to focus on a specialized workforce when selecting project (Gutjahr, 2011). However, especially during a product's ramp-up phase, which involves low production capacity and high demand, employees have to adjust their skill set to new requirements. Therefore, it is crucial for firms to invest in workforce learning and training measures (Terwiesch and Bohn, 2001). Hence, employee skill development and competence management alongside concepts of learning and forgetting as well as different concepts of training should become an integral part of workforce management practices. Traditional employee training models focus on a condensed period of training at the beginning of employment or during the implementation of a new production process (Ally, 2009). Such approaches limit training measures often by determining the available training budget and capacity and do not allow for training during the whole life cycle of a product. In this sense, companies have often a fixed budget of training measures that they can distribute among the work force. We aim to shed light on the effects of more flexible concepts of training which incorporate a general availability of training measures at all times. In order to compare traditional concepts of employee development with more flexible ones, we limit training measures in two dimensions. The training budget is defined by the available training capacity per period and periods which allow for training compared to those that prohibit training. Considering traditional, budgeted training, companies cannot react sufficiently flexibly to any demand oscillations. Thus, they are not able to use times of low demand for training in order to increase their skill levels. Moreover, high demand reduces the amount of time that can be used for training; thus, training opportunities are forgone. Since budgeting often only allows for training measures in the first periods, employees cannot recover the missed training opportunities in later periods. As a consequence of production ramp-ups incorporating high and unknown demand (Terwiesch and Bohn, 2001), the effect of budgeting training measures might increase with rising demand volatility and lower employee capacities.

Consequently, the question arises: What impact do demand volatility and the application of budgeted training measures have on the learning and training outcomes of employees in production systems? To analyze the impact of different training scenarios, a multi-period workforce scheduling model is considered with workers who gain experience by learning-by-doing and due to training or lose skill units through forgetting. Data from a computational study with near-optimal solutions obtained via GAMS and a Gurobi 7.5.2 solver are analyzed with General Estimation Equations (GEE) to derive insights on the production system's overall performance and skill outcomes depending on different training environments and demand volatility.

The remainder of the paper is structured as follows: section 2 provides the theoretical background on production ramp-ups, learning theory, and types of training. In section 3, we derive hypotheses for the main relationships of training and production outcomes with specific regard to employee training. We test these hypotheses with a set of simulated data generated through a mixed-integer optimization model that is presented in section 4. The last sections 5 and 6 present the results of our analysis and discuss our findings.

2 Theoretical Foundation

The implementation of new production processes, which can take up to a quarter of a product's life cycle, is known as the ramp-up phase and defined as the period '*between completion of development and full capacity utilization*' by Terwiesch and Bohn (2001, p.1). They described three different kinds of ramp-up scenarios: plant ramp-up, product ramp-up, and process ramp-up. These are influenced by the same characteristics: uncertainty, high complexity (Surbier et al., 2014), interruptions, defects (Glock and Grosse, 2015), low production capacity, and high demand volatility (Terwiesch and Bohn, 2001). Hence the ramp-up phase is characterized by a trade-off between normal production and learning, which increases yields and decreases production times, which, vice versa, stimulates production output (Schultz et al., 2003). Since high demand oscillations are one of the main dynamic cost drivers, organizations have to build up safety stocks to cope with volatile demand patterns (Holweg et al., 2011). During ramp-ups, building these safety stocks is often impossible, as the productivity of the newly introduced production processes is low, and full capacity utilization is not possible in this phase (Schultz et al., 2003). However, the ramp-up phase is often also characterized by high demand for new products with customers willing to pay premium prices (Terwiesch and Bohn, 2001). Research on demand volatility has especially been carried out in the field of forecasting to enable more precise predictions (e.g. Abolghasemi et al. (2020)). Although demand volatility is of great importance for production scheduling and workforce planning, forecasting models require historical data on which to base calculations. Such data are often absent in production ramp-up situations (Huang et al., 2008). Since the combination of demand volatility and unstable production processes is challenging to control in ramp-up scenarios, companies need to invest in the factor ' human resource' in order to increase production output and workforce flexibility and thus be able to meet the customer demand and achieve long-term stability (Qin and Nembhard, 2010). In this regard the production or project duration benefits from an even allocation of flexibility measures among available resources, i.e. workers or machines (Vairaktarakis, 2003) However, employees' time capacities are limited and cannot be extended flexibly to meet a given demand, thus these capacities limit production output per period. Hence, a trade-off between more efficient production by investing time into training and meeting customer wishes arises, especially when high demand volatility is present (Anderson, 2001). Compared to capacity limits, capacity utilization can be increased due to learning and training when employees become more productive over time (Terwiesch and Bohn, 2001; Qin and Nembhard, 2010). High learning rates of workers in manufacturing production can lead to an increase in production quality as well as to a reduction in production costs and processing times (Yelle, 1979; Dutton and Thomas, 1984; Biskup, 2008; Anzanello and Fogliatto, 2011). These in turn enable workers to produce larger product quantities within the same time span (Argote and Ingram, 2000). Therefore, in today's changing production environments, a redesign of workforce planning, scheduling, and training approaches is indispensable and can help companies to maintain their competitive advantages (Qin and Nembhard, 2015).

In 1936, Wright (1936) described the interdependency of the quantity produced and the time needed to execute a production task. By discovering that the amount of time workers need to produce one unit decreases in a log-linear relation to the cumulative number of goods produced, he developed the first learning curve model with a constant learning rate. Since this discovery, extensive research has been carried out on different types of learning curves (Yelle, 1979; Dutton and Thomas, 1984; Jaber et al., 2003; Biskup, 2008; Anzanello and Fogliatto, 2011; Hansen and Grunow, 2015). Anzanello and Fogliatto (2011) compared univariate learning curve models, e.g. log-linear, exponential and hyperbolic learning curves, with multivariate approaches. Globerson (1987), Globerson and Gold (1997) and Grosse et al. (2015) discovered that the log-linear model with a non-complex mathematical structure nevertheless estimates production based on manual tasks with sufficient precision. Consequently, the log-linear model is the most widely used learning curve in production-based scenarios (Yelle, 1979; Dar-El et al., 1995). In their review article, De Bruecker et al. (2015, p.2) described the development of skills, as having a positive impact on an employee's '*ability to perform certain tasks well*'. They identified the following factors as being positively affected by employee skills: processing time, production efficiency, product quality, and labor costs. Not only does the performance with respect to a single task increase, experienced workers at high skill levels are further able to adapt to changes in the production process more efficiently (Wright, 1936).
In contrast to learning, forgetting has a negative influence on employee performance (Jaber et al., 2003; Digiesi et al., 2009; Dode et al., 2016). Thus, it decreases the skill levels of a worker and therefore production efficiency. Teyarachakul et al. (2011) provide an overview of ways in which forgetting has been modeled in manufacturing settings, e.g. depending on the number of interruptions, experience or skill level gained previously, or the duration of an interruption. Moreover, forgetting curves were found to be mirror images of learning curves and to be dependent on the respective production task (Globerson et al., 1989). Jaber et al. (2003) presume that training measures cannot only foster learning but can also help to maintain achieved skill levels by counteracting any loss of skills by preventing forgetting.

In addition to learning-by-doing, skill enhancements and better capacity utilization can be generated by the training of employees (Carrillo and Gaimon, 2000). According to Chen et al. (2010), training decisions entail at which point in time (i.e. when) which skills or production tasks (i.e. what) should be trained by which worker (i.e. who). Thus, in the context of training decisions, workers are assigned to training sessions. In order to develop employee skills, training measures are typically affected by two dimensions of costs: direct costs for the training sessions and opportunity costs, as workers cannot use the training time for production (Büke et al., 2016). To reduce overall costs, achieve shorter lead times, create higher product quality, and increase workforce flexibility, employees can be cross-trained (Inman et al., 2004; Yang and Kuo, 2007). Cross-training enables workers to process different production activities which require distinct skills (Hopp and Van Oyen, 2004). Compared to purely relying on the specialization of employee skills, a broader set of skills allows companies to better cope with demand volatility, which influences the mix and quantities of tasks to be performed. Although the resulting high level of workforce flexibility enables a company to meet stochastic demand by re-assigning employees to a variety of tasks, further costs for cross-training may arise: e.g., additional training costs and wage payments, decreased efficiency and productivity of an employee, as well as transfer costs (Qin et al., 2015).

Traditional training approaches aim to build knowledge in a condensed learning period at the beginning of the employment or a new production process (Ally, 2009). Such budgeting approaches follow the rationale that learning should take place in the early phases of ramping up a new task and that follow-up learning does not need to be managed but happens somewhat automatically. In the same vein, sophisticated management of learning processes does not seem to be required, as initial learning takes place in the early phases of a ramp-up process and does not have to be planned in the later stages. However, in ramp-up scenarios, training and knowledge transfer can lead to a deceleration of the production process if not timed properly, as employees need to use their time for training instead of production (Szabó, 2018). Therefore, it is of special interest to investigate the influence of more flexible training concepts, allowing workers to time training suitably under consideration of different markets and demand or capacity environments. Hence, the traditional budgeting approaches should be refined and potentially extended to the entire planning horizon of a product's life cycle.

Valeva et al. (2017) analyzed the extend to which employee learning and forgetting can be used to cope with demand volatility. They took three different demand variation scenarios into account to model the influence on production and capacity utilization, but they did not distinguish between different approaches to employee training. Heimerl and Kolisch (2010) examined company skill targets at the end of the production phase to ensure sufficient skill development and to broaden a company's skill portfolio. Letmathe and Schinner (2022) analyzed how training measures can help to overcome the negative influence of demand volatility during production ramp-ups by showing that training measures can reduce the impact of demand volatility on skill development and productivity. These relationships are moderated by the available employee capacity. Their results show that if the time endowment of employees is sufficiently large, most of the training measures are used in the first periods of the ramp-up phase. In contrast to this, in scenarios with low employee time capacities, the number of training sessions undertaken appears to be rather constant in all periods.

Although the influence of novel training measures, which arise due to technological advances, has been investigated in the literature of Human Resource Development (Chalofsky et al., 2014; Noe, 2010; Beardwell and Thompson, 2017), to the best of our knowledge no such research has been carried out on the influence of the timing of training measures on workforce flexibility and workforce scheduling. We aim to contribute to the literature on workforce planning and ramp-up management by providing insights into the interaction between demand volatility and flexible training concepts compared to time-budgeted training. Furthermore, we focus on the interaction of training approaches and demand volatility in different employee capacity scenarios. We simulate demand volatility and different employee time capacity settings based on the approach of Letmathe and Schinner (2022). In contrast to the work of Letmathe and Schinner (2022) we include two scenarios to investigate the difference between flexible and traditional concepts of employee training. In the first setting, training measures are time-budgeted and training is only available in the first periods of production. This setting mirrors traditional concepts of employee skill development. In contrast, the second setting does not rely on a budgeted approach, i.e. employees can undergo training sessions in each period. Hence, workforce planning can react more flexibly to demand volatility.

3 Hypotheses

Considering the budgeted scenario, training measures are only available in the first periods of the planning horizon. Additionally, not only are the periods which allow for training limited but also the number of training sessions available per period. In consequence, we expect the number of training sessions undertaken by all employees in all periods to be significantly lower if the access to training measures is budgeted, compared to the scenario with flexible training. This assumption aligns with the results of Letmathe and Schinner (2022), who found the number of training measures to be close to constant during all periods with scarce employee capacities. The results of Valeva et al. (2020), who expect workers to train especially in periods of low demand, also support this finding. During the introduction phase of a new product, customers often pay premium prices with high demand. Thus, shortage costs are especially high during the ramp-up phase (Terwiesch and Bohn, 2001). Such scenarios are especially relevant for industries with innovative products, e.g. electronics, where initial demand is often unpredictable when a new product is launched (Fisher, 1997). Henceforth, depending on the shortage costs, companies might forgo training opportunities rather than not meeting the given demand, even if employee training would not be available in later periods. Resulting from these expectations, the total learning output, which is the sum of learning-by-doing and learning through training, is expected to be significantly lower in the budgeted training scenario. As it is not possible to use training measures to prevent forgetting in the periods following the initial ramp-up and and as production as well as learning depend on volatile demand, we expect forgetting to be higher in the budgeted scenario compared to the more flexible non-budgeted setting.

This expectation is in line with Jaber and Guiffrida (2008), who argued that training can prevent employees from forgetting and enables employees to maintain skill levels. Consequently, budgeting can lead to higher levels of forgetting and, thus skill units might decrease over time.

Throughout this paper, skill development is defined as the total learning output reduced by forgetting. Driven by the trade-off between learning-by-doing and training in the first periods of a production ramp-up and the lack of training measures to prevent forgetting and to foster employee skills in later periods, we assume the total skill development to be significant negatively impacted by budgeted training measures. Summarizing, we formulate the following hypothesis:

H1: The budgeting of training measures has a negative impact on skill development.

We model the amount of time needed to gain additional skills during a training session to be lower than gaining the same skill enhancement during production. Thus, a decision for learning-by-doing during production and against training sessions results in lower skill enhancement. Considering the trade-off between production and training measures, especially in the budgeted scenario, we expect the production quantity to decrease marginally because companies will use a minimum amount of time for training to profit from lower production costs and decreasing production time requirements in later periods.

Characteristic of scenarios with high demand volatility are oscillations between successive periods and uncertainty concerning the demanded amount (Huang et al., 2008). When companies have to face high volatility, they have to find a trade-off between meeting the given demand and investing in training opportunities in the respective periods. We expect companies to prefer to meet customer demand than to accept shortage costs. Thus, we predict a decrease in skill development regarding scenarios with high demand volatility. As training can also prevent forgetting, less training in high volatility scenarios might not only result in fewer newly adopted skill levels but might also lead to forgetting when workers are not assigned to a task for a longer period of time. Combining these factors, we derive the following hypothesis:

H2: Demand volatility has a negative impact on skill development.

Prior to the market introduction of a new product, not only is the actual demand per period unknown but also the general interest in the product itself. Therefore, companies face different intensities of demand volatility. We model the impact of different levels of demand volatility relative to the workforce capacity. Hence, employees have a limited amount of time units per period, which can be used either for training or production. In each capacity scenario, all employees work the same number of hours per period, i.e. they have the same capacity in every period. In a low-capacity scenario, the initial time endowments of employees barely suffice to meet a given demand. Thus, the trade-off situation between production and training intensifies, as workers need to increase their skill levels to be able to meet the demand in the following periods. At the same time, scarce capacity makes it more difficult to buffer production against demand volatility, as there is no slack for additional production. Considering a medium-capacity scenario, workers can satisfy the demand using their initial skill endowment but do not have any time remaining for training or production if the demand substantially exceeds the average demand. Hence, demand volatility still plays a limiting role but to a lesser degree than in low-capacity scenarios. High-capacity scenarios enable workers to produce goods and undergo training measures simultaneously in most periods. Moreover, they enable employees to obtain higher skill levels due to training. This results in improvements in production time and costs. At the same time, it is possible to buffer production against demand volatility.

According to the settings described above, we aim to shed light on the effects of budgeted training measures in the different employee capacity scenarios. We expect the impact of budgeted training measures on the amount of training to be negative in the low- and medium-capacity scenarios but to vanish regarding the high-capacity scenario due to better buffering opportunities. Thereby, employees develop more skills through training in the first periods in the high-capacity scenario to prepare for any forgetting effects in later periods. Hence, we expect the interaction effect of employee capacity and budgeting on skill development to be positive regarding increasing capacity endowments. To put it another way: Traditional budgeting approaches are less detrimental if a production system has sufficient capacity buffers. The mentioned expectations result in the following hypothesis:

H3: Employees' skill development is affected positively by the interaction effect of budgeting and employee capacity.

Budgeting for training measures reduces the ability to respond to skewed or low demand when employees are not enabled to achieve higher skill levels through targeted on-the-job learning. In times of high demand volatility, periods with high demand that deviates from the average demand are typical. Considering that periods of high demand are also possible in the first periods of observation, we expect a decrease in undertaken training measures that is caused by shortage costs. This will, in turn, lead to fewer opportunities to increase production efficiency through training. In the later periods, there will be fewer opportunities for employees to undergo training sessions, even when demand is low and surplus time capacities are available. Consequently, efficiency gains that are necessary to meet the demand in periods with higher demand are forgone if budgeting and high demand volatility are present. Fewer opportunities for training in combination with unmet demand can therefore lead to a negative impact on employee skill development. Following this line of reasoning, we expect:

H4: Employees' skill development is affected negatively by the interaction effect of budgeting and demand volatility.

4 Methodology

To test the hypotheses concerning the influence of the budgeting of training measures and demand volatility, we use a mixed-integer optimization model based on Letmathe and Schinner (2022). This model contains the possibility of non-budgeted training and autonomous learning. Here, an extension of this model has been developed and then utilized to answer the formulated research questions. First, the model is introduced in section 4.1; second, in 4.2, the parameters used for the simulation are depicted.

4.1 Model Description

Let $i \in \{1, ..., m\}$ denote the set of shop floor employees who can conduct a production activity $l \in \{1, ..., L\}$ to produce products $j \in \{1, .., n\}$ in each period $t \in \{1, ..., T\}$. Executing production activity l results in an output of l_j units of product j. Whereas each worker can theoretically perform each activity, each production activity allows the production of exactly one of the products relevant to meeting customer demand. Each employee i is characterized by a skill level for every production activity l in every period t, denoted by $z_{ilt} \geq 0$. Note, that this skill level can change over time due to training, learning-by-doing, or forgetting.

4.1.1 Skill development

To obtain a linear program we use a linear approximation for our learning curve by introducing discrete skill levels $k \in \{1, ..., K\}$. Depending on the skill level k achieved due to skill units $z_{ilt} \geq 0$, the time required for processing production activity l, denoted by p_{kl}, and the production costs per unit, denoted by c_{kl}, differ. The required amount of skill units for processing production activity l at the skill level k is defined by $z_{kl}^{min} \geq 0$. In line with the learning curve theory, we assume production time and costs to decrease due to learning, i.e. with increasing skill levels. Forgetting and the two dimensions of learning are incorporated in the following ways:

First, we model learning-by-doing which occurs while executing production activity l in period t with skill level k, with $y_{iklt} \geq 0$ denoting the amount of product l produced in period t by employee i with skill level k. Employee i gains experience based on an individual linearized skill development or learning factor v_i . Second, we consider training measures with costs per training measure c_l and time units tr_l needed for one training unit. Both parameters depend on the production activity l. Further, $u_{ilt} \geq 0$ denotes the total amount of training measures for production activity l of employee i in period t. The training effects, i.e. the gains in skill levels, occur proportionally to the time spent on training for each activity. In each period, worker i is equipped with a constant time capacity $\overline{CAP_i}$ which can either be used for training or production, i.e. $\sum_{l=1}^{L} \sum_{k=1}^{K} p_{kl} \cdot y_{iklt} + tr_l \cdot u_{ilt} \leq \overline{CAP_i}$ $\forall i \in \{1, ..., m\}, t \in \{1, ..., T\}$.

As a counterpart to learning, we incorporate forgetting in our model. An employee i loses w_i skill units for a certain production activity l, according to his or her individual linearized forgetting factor, if she or he gains fewer than $fl_l > 0$ skill units for this production activity in the respective period. Thus, the amount of skill units forgotten depends on the length of the interruption, as it is possible that forgetting occurs in several successive periods, and on the experience gained so far due to the discrete skill level k. To display forgetting, we incorporate the binary variable fg_{ilt} with $fg_{ilt} = 1$ if employee i earns less than fl_l skill units due to training or processing of production activity l in period t, and $fg_{ilt} = 0$ if he does not lose skill units. Hence, we add the two constraints (1) and (2) to the model to determine if a worker i experiences forgetting effects for production activity l in period t measured by the binary variable fg_{ilt}. Constraint (1) ensures that forgetting effects are calculated if the threshold of fl_l produced units of product l is not reached by forcing $fg_{ilt} = 1$. The second constraint prevents forgetting effects to occur in case the sum of the unit production and the training sessions undertaken exceed the threshold fl_l. For this purpose, we chose the big M constant $M > 0$ to be a sufficiently large number in both inequalities. Note that we assume the forgetting threshold to be greater or equal to 1 to assure that forgetting effects are present if an activity is skipped in both, training or production.

$$yt_{ilt} + u_{ilt} + M \cdot fg_{ilt} \geq fl_l \qquad \forall i \in \{1, ..., m\}, l \in \{1, ..., L\}, t \in \{1, ..., T\} \tag{1}$$

$$yt_{ilt} + u_{ilt} + M \cdot fg_{ilt} < (M + fl_l) \qquad \forall i \in \{1, ..., m\}, l \in \{1, ..., L\}, t \in \{1, ..., T\} \tag{2}$$

Combining learning-by-doing, training, and forgetting, we derive the following constraint:

$$z_{ilt} = z_{il(t-1)} + yt_{ilt} \cdot v_i + u_{ilt} - w_i \cdot fg_{ilt} \qquad \forall i \in \{1, ..., m\}, l \in \{1, ..., L\}, t \in \{1, ..., T\}, \tag{3}$$

with $fg_{ilt} \in \{0, 1\}$ and $yt_{ilt} = \sum_{k=1}^{K} y_{iklt}$. The following constraints assure that workers only carry out production activities on those skill levels k that they have already achieved, with $r_{iklt} \in \{0, 1\}$.

$$z_{kl}^{min} - z_{ilt} \leq M \cdot (1 - r_{iklt}) \qquad \forall i \in \{1, ..., m\}, k \in \{1, ..., K\}, l \in \{1, ..., L\}, t \in \{1, ..., T\} \tag{4}$$

$$y_{iklt} \leq M \cdot r_{iklt} \qquad \forall i \in \{1, ..., m\}, k \in \{1, ..., K\}, l \in \{1, ..., L\}, t \in \{1, ..., T\} \tag{5}$$

A company skill level target $\phi_i < \sum_{l=1}^{L} z_{ilT}$ needs to be satisfied by every employee i. The target is embodied in the model to assure that the skill development does not drop in the last period T and that company skill levels are sufficiently developed by the end of the planning horizon (Heimerl and Kolisch, 2010).

4.1.2 Budgeted training measures

To budget training measures, we introduce a training sessions limit $\overline{ucap_t}$ which restrains the total number of all training sessions for all production activities l and all employees i. We incorporate the following constraints into our model to analyze the effect of budgeted training and we omit these in the model not incorporating budgeting.

$$\sum_{i=1}^{m} \sum_{l=1}^{L} u_{ilt} \leq \overline{ucap_t} \qquad \forall t \in \{1, ..., T\} \tag{6}$$

In order to prohibit training in certain periods t, the capacity $\overline{ucap_t} = 0$ can be chosen, resulting in $u_{ilt} = 0$ for the respective periods.

4.1.3 Demand

In every period t, a demand D_{jt} for product j has to be satisfied. As storage is not possible, a shortage of product j, defined as $sh_{jt} = D_{jt} - \sum_{l=1}^{L}(a_{jl} \cdot ys_{lt})$, may arise and is penalized with shortage costs sc_j per unit (with $ys_{lt} = \sum_{i=1}^{m} \sum_{k=1}^{K} y_{iklt}$). The variable a_{jl} defines the number of products j produced by production activity l.

To simulate demand volatility, a randomization function is implemented in GAMS to create demand values for all periods and products depending on a given volatility level. The level of volatility determines an upper and lower boundary within which the demand can vary. Starting with a fixed demand D and a volatility level $dv \in \{1, ..., D\}$, the set of possible demand values is given by $D_{jt} \in \{D - dv, D - dv + 1, ..., D + dv\}$.

4.1.4 Objective Function

We implement our Mixed-Integer-Program as a minimization problem, optimizing the total production costs over all periods $t \in \{1, ..., T\}$. The total costs consist of production costs, training costs, and shortage costs.

$$\underbrace{\sum_{i=1}^{m}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} c_{kl} \cdot y_{iklt}}_{production\ costs} + \underbrace{\sum_{i=1}^{m}\sum_{l=1}^{L}\sum_{t=1}^{T} c_l \cdot u_{ilt}}_{training\ costs} + \underbrace{\sum_{j=1}^{n}\sum_{t=1}^{T} sc_j * sh_{jt}}_{shortage\ costs} \rightarrow \min \tag{7}$$

This model is developed to simulate the interplay of training measures, learning-by-doing, forgetting, and volatile demand. Therefore, it is not suited for operative workforce assignment in its current version.

4.2 Numerical Example

In our simulation, $m = 4$ employees can process $L = 3$ production activities each to produce one of the $n = 3$ products during $T = 18$ periods. During the ramp-up phase, the new production processes are introduced. For the sake of simplicity, we assume that all workers i start with the same competence level $z_{il0} = 30$ with respect to all production activities l. Employees can increase their competence level through learning-by-doing with an underlying learning rate $v_i = 1$ or through training. As described above, each training measure increases the skill units. A continuous scale of skill units is combined with $K = 4$ discrete skill levels which enable workers to perform production activities on a higher efficiency level, meaning that their production costs c_{kl} and time p_{kl} will decrease with a higher skill level k according to the following values:

$$p_{kl} = \begin{Bmatrix} 5 & 5 & 5 \\ 4.5 & 4.5 & 4.5 \\ 4.2 & 4.2 & 4.2 \\ 4 & 4 & 4 \end{Bmatrix}, c_{kl} = \begin{Bmatrix} 10 & 20 & 40 \\ 9 & 20 & 30 \\ 8 & 18 & 20 \\ 7 & 17 & 10 \end{Bmatrix}, sc_j = \begin{Bmatrix} 40 \\ 70 \\ 40 \end{Bmatrix}$$

The skill levels are set as follows: Level one starts at one skill unit, level two at 50 skill units, level three at 200 skill units, and level four, the highest skill level, starts at 500 skill units. Workers with skill level four cannot improve their performance in the respective production activity any further. However, higher skill levels also prevent forgetting. It is not possible, though, for workers to exceed 2500 skill units in any production activity, i.e. $z_{ilt} \leq 2500$. The values for c_{kl} were chosen to allow for different learning patterns which might be driven by different levels of task complexity (Shafiei-Monfared and Jenab, 2011). For this purpose, a product produced with high efficiency gains due to learning ($l = 3$), an s-shaped model ($l = 2$) with slow learning at the beginning (Baloff, 1971), and a moderate log-linear learning curve ($l = 1$), e.g. accounting for cognitive or manual tasks with high complexity (Dar-El et al., 1995; Shafiei-Monfared and Jenab, 2011), are employed in terms of production costs. Note that cost learning effects include effects from employee learning, such as material handling and waste reduction (Lapré et al., 2000), as well as effects from reengineering and incremental changes of production processes which are prominent in the s-curve model (Baloff, 1971).

While learning-by-doing takes place during the production process and does not result in any further costs, two distinct kinds of training costs arise for training: on the one hand, the needed time $tr_l = 5$ and on the other hand, the monetary costs $c_l = 2$. The time utilized for training reduces the capacity available for production. Therefore, opportunity costs of lost production (shortage costs) arise. Forgetting occurs if an employee pursues a production activity or undergoes training fewer than $fl_l = 10$ times in a period. In the case of forgetting, the workers' competence units decrease by $w_i = 10$ units. The company skill target for the end of the planning horizon is $\phi_i = 500$ skill units per worker.

Three features of the modeled production system factors are manipulated: the demand, employee capacities, and training availability. To simulate a stochastic demand, a random distribution of period demands is applied. After choosing a stochasticity (demand volatility) level dv from 1 to 100, a random algorithm sets demands D_{jt} for all products j so that they sum up to 5400 over all 18 periods per product. Different time capacity levels of employees are applied in order to analyze the intensity of the demand volatility relative to the workforce capacity. The aforementioned three scenarios use the following time capacity $\overline{CAP}_i$ per period: $low = 200$, $medium = 375$, and $high = 550$. These limits are chosen to simulate different impacts of demand volatility on production. In the low-capacity scenario, workers cannot meet the average demand of 100 units per period per product with their initial skill endowment. The medium-capacity scenario enables workers to meet the average demand exactly, while employees in the high-capacity scenario can meet the given demand and have additional capacity to be trained in each period.

The third manipulated factor is the budgeted training access. In the budgeted scenario, the training capacity limit for all employees together is set to $\overline{ucap} = 180$ per period in the first five periods. The following periods 6 to 18 do not allow for training measures.

Combining those factors, we receive 100 datasets based on the volatility simulation for each capacity level and each scenario, with and without budgeted training measures, resulting in 600 datasets in total with 10,800 data points due to the 18 periods of observation. To solve the above-described model we utilize the Gurobi 7.5.2. solver in GAMS. We terminate the runs when a gap of 4% is reached. The dataset obtained serves as the basis for the analysis which is performed in the following section.

5 Results and Discussion

In the following a description of the applied analysis method in Section 5.1 and a descriptive analysis in Section 5.2 is presented. The section is hereinafter structured according to the hypothesis derived in Section 3. The influence of budgeting training measures on skill development is analyzed in Section 5.3. Further, we aim to shed light on the effects of demand volatility in Section 5.4 and, lastly, we analyze the interplay of budgeted training measures and the intensity of demand volatility and employee capacity in Section 5.5.

5.1 Analysis Methodology

Throughout our analyses, *Linear Generalized Estimating Equations* (*GEE*) are employed in order to investigate the effects of the above explained factors on the dependent variables and to test the previously formulated hypotheses. To do so, we used the open-source platform *R* (version 3.6.1) and the package *geepack* (Halekoh et al., 2006). Regression analyses with GEE are appropriate for the analysis of longitudinal data. Because of the normal distribution of the variables, we employ a *gaussian* family and use an *identitylink*. Due to the time-dependent nature of our variables, we use an AR(1) structure (Ballinger, 2004). With regard to our previously formulated hypotheses, we use six dependent variables: *Training* (Table 1), *Forgetting* (Table 3) and *Learning-By-Doing* (Table 2), as well as *Learning Output* = *Training* + *Learning-By-Doing* (Table 4), *Total Skill Development* = *Training* + *Learning-By-Doing* −*Forgetting* per period (Table 5) and, lastly, *Achieved Skill Units*, which equal the sum of the achieved skill units over all activities for each period (Table 6). The expression ' employees' skill development' utilized in the hypothesis focuses mainly on the variables *Total Skill Development* which combine *Training*, *Learning-By-Doing* and *Forgetting*. Table 7 in the appendix links the six dependent variables to the simulation model.

The main explanatory variables are *Budget*, displaying whether training is budgeted $Budget = 1$ or whether unconstrained training is available $Budget = 0$, *Volatility* ranging from 1 to 100 in discrete steps, and *Capacity* taking values for the three capacity scenarios of 200 (low), 375 (medium), or 550 (high). Further, we include *Time* which reflects the periods during the planning horizon. For each dependent variable we conducted six GEE regressions displayed in Tables 1 to 6. The first three columns show models depicting the main effects only, i.e. on all 10,800 data points per variable and all capacity scenarios. The model in column 1 assumes a linear relationship between the employees' capacities. Similarly to Letmathe and Schinner (2022), we find a non-linear relationship when analyzing the influence of employee capacity on training. For this purpose, the significance of the model for quadratic correlations is usually determined by the *P*-value (Twisk, 2013). Here, the *P*-value is consistently highly significant for the quadratic variable *Capacity*. We model this non-linear relationship by using a quadratic term for *Capacity* and extend the models in columns two and three by the quadratic term $Capacity^2$ to better fit the quadratic u-shaped effects that we see in the data. Further, we compute the interaction variables $Volatility * Capacity$, $Volatility * Budget$, and $Budget * Capacity$ to analyze the interplay of the manipulated variables and the capacity scenarios in more detail. The latter three models (columns 4-6) comprise the main effects for the different capacity scenarios separately. Throughout our analysis, we focus on significant effects only. The quadratic term $Capacity^2$ is significant in all models. Therefore we analyze the effects displayed in the second columns and omit analyzing the results in the first columns, where a linear relationship is assumed. For the sake of completeness we display the models without $Capacity^2$ in the first columns.

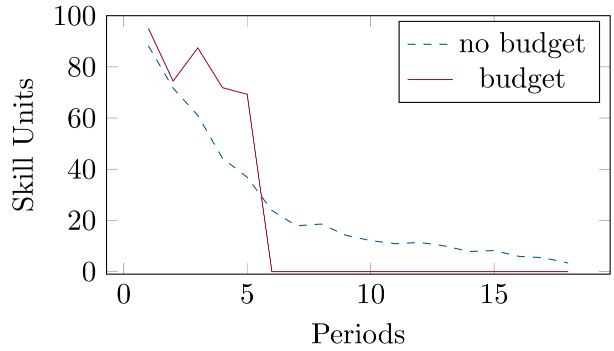

Figure 1: Average Training per Period

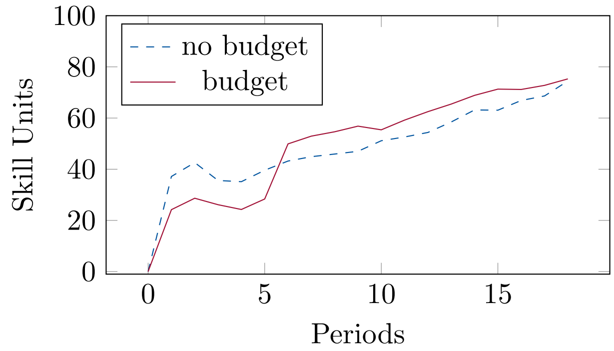

Figure 2: Average Forgetting per Period

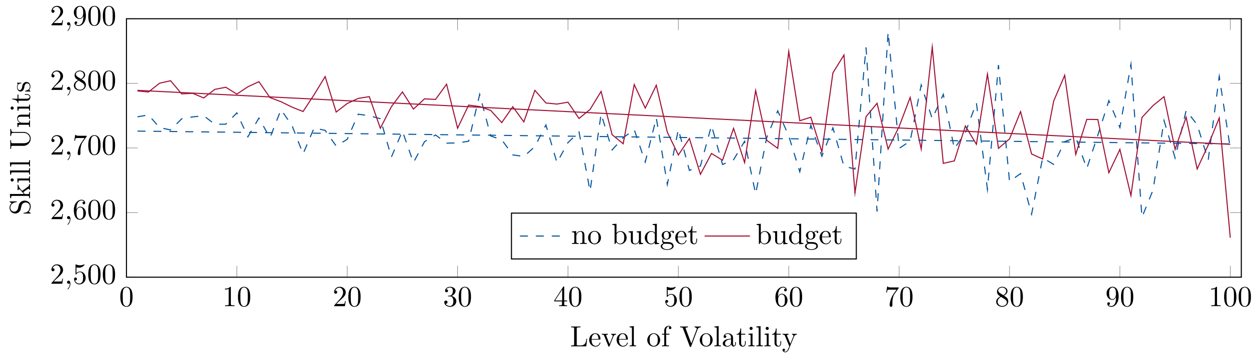

Figure 3: Average Achieved Skill Level vs Volatility

5.2 Descriptive Analyses

Before turning to the results of the multivariate statistics and the tests of the hypotheses, we first report some descriptive results for a better understanding of the underlying strategies for how companies can most efficiently cope with learning and training requirements in the different scenarios. In Figure 1, the average training measures undertaken by all workers per period are displayed. The number of training sessions decreases over time in both scenarios; nevertheless, training measures are initially used more frequently in the budgeted scenario than in the flexible scenario, where they decrease continuously. Due to the model's assumption, workers in the budgeted scenario cannot train later than in period 5, whereas workers in the flexible scenario can be trained in all periods.

Considering the development of forgetting, displayed in Figure 2, we see contradictory behavior, which aligns with the findings from the average training measures. Overall, forgetting increases over time in both scenarios. However, in the budgeted scenario, workers forget less knowledge in the first five periods of observation compared to the flexible scenario. In period six, this effect changes, as workers forget more acquired knowledge in the budgeted scenario. The effect of more training and fewer forgetting in the first five periods results in a generally higher level of average achieved skills in the budgeted scenario. In both scenarios, but more pronounced in the flexible scenario, employees can use their time endowment in periods of low demand for training and prepare for periods with higher demand. The effect that workers achieve higher average skill levels in the budgeted setting is especially strong in the settings with low to medium volatility ($Volatility \leq 60$), shown in Figure

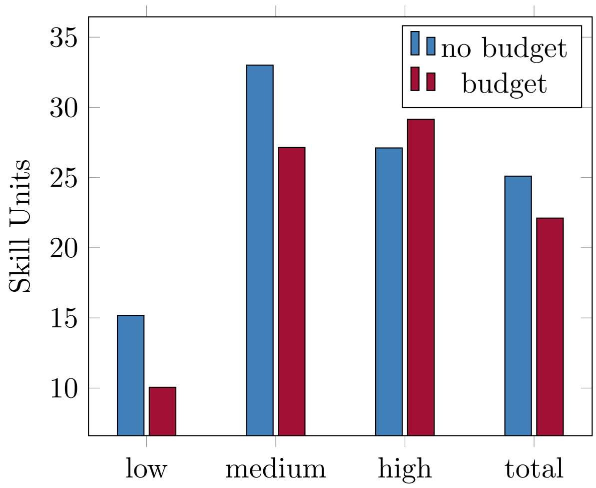

Figure 4: Average Training per Capacity Scenario

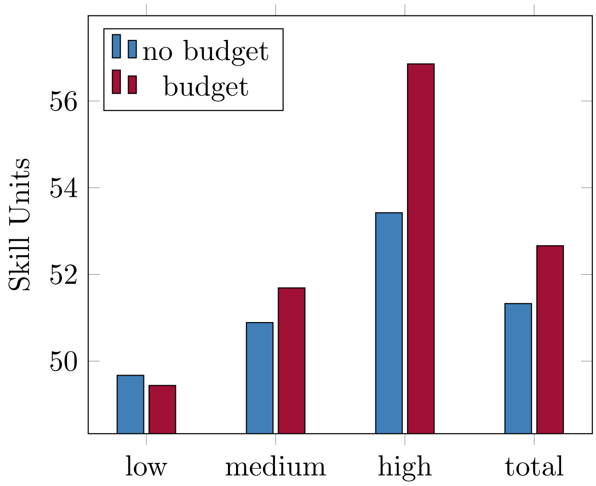

Figure 5: Average Forgetting per Capacity Scenario

3, and diminishes with higher volatility ($Volatility > 60$). Considering a volatility level of 100, the underlying trend lines of budgeting and flexible training merge. Thus, if volatility and capacity allow for training, workers are trained more intensively in the first five periods in the budgeted scenario compared to the flexible scenario. Hereby, the forgetting caused by missing training opportunities in the later periods is counterbalanced Since our model does not allow to build up inventory, the excess employee capacity during low demand can solely be used for training. In the budgeted scenario, this is only possible in the first five periods. In later periods the capacity cannot be used to counteract forgetting by training measures. Consequently, in times of low demand and budgeting, the available capacity cannot be used for neither training nor production. This results in excess unused capacity due to the fluctuations in demand. This results in excess, unused capacity due to fluctuations in demand. However, excess capacity must still be maintained for periods of high demand. The dynamics are visualized in Figures 6, 7 and 8 in the appendix.

When turning to the three capacity scenarios, we find a difference in the absolute number of training measures (Figure 4). By indicating an inverse u-shape curve, training is higher in the medium-capacity scenario and somewhat lower in both other scenarios. The lowest amount of training measures is undertaken in the low-capacity scenario. Based on the u-shaped influence of the capacity endowments employed, we modeled capacity as a quadratic term $Capacity^2$ in our GEEs to test whether this relationship has a significant impact. Surprisingly, we find the number of average training sessions to be larger in the budgeted than in the flexible scenario, considering the high-capacity setting. Figure 5 reveals that forgetting increases with higher capacity. This relation can be explained through more intensive training in the first periods due to the higher time capacities available. More initial training leads to more forgetting in later periods. Not surprisingly, this effect is more pronounced in the budgeted scenarios, where training is squeezed into the first periods of the planning horizon. Each of the following sections evaluates the individual effects of learning, training and forgetting first and turns later to the compound variables learning output, skill development and achieved skill levels.

Table 1: Coefficients from GEE Regression Training

Variables	All Capacity Levels			Different Capacities		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	$N = 10800$	$N = 10800$	$N = 10800$	$N = 3600$	$N = 3600$	$N = 3600$
Intercept	50.866***	14.460***	28.992***	35.056***	90.424***	87.990***
Budget	- 2.713***	- 2.733***	- 6.653***	- 4.889***	- 5.580***	1.053
Volatility	0.044***	0.042***	- 0.182***	- 0.069***	0.019	0.175***
Time	- 4.858***	- 4.852***	- 4.850***	- 1.729***	- 6.130***	- 6.906***
Capacity	0.052***	0.279***	0.237***			
Capacity2		-0.0003***	-0.0003***			
Volatility*Capacity			0.001***			
Volatility*Budget			- 0.049**			
Budget*Capacity			0.017***			

* weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

Table 2: Coefficients from GEE Regression Learning-By-Doing

Variables	All Capacity Levels			Different Capacities		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	$N = 10800$	$N = 10800$	$N = 10800$	$N = 3600$	$N = 3600$	$N = 3600$
Intercept	127.368***	- 88.072***	- 87.746***	163.071***	300.047***	301.447***
Budget	0.196	0.572**	2.409***	1.474***	0.172	- 0.035
Volatility	- 0.067*	- 0.062***	- 0.086***	- 0.023***	- 0.163***	- 0.0003
Time	0.773***	0.727***	0.727***	1.944***	0.374**	- 0.149
Capacity	0.339***	1.684***	1.683***			
$Capacity^2$		- 0.002***	- 0.002***			
Volatility∗Capacity			0.00007**			
Volatility∗Budget			- 0.002			
Budget∗Capacity			- 0.005***			

* weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

Table 3: Coefficients from GEE Regression Forgetting

Variables	All Capacity Levels			Different Capacities		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	$N = 10800$	$N = 10800$	$N = 10800$	$N = 3600$	$N = 3600$	$N = 3600$
Intercept	18.183***	22.040***	20.717***	16.403***	33.647***	22.425***
Budget	1.209***	1.211***	- 2.100**	- 0.324	0.669	3.390***
Volatility	0.026***	0.026***	0.091***	0.085***	- 0.038***	0.031***
Time	2.726***	2.726***	2.726***	3.050***	2.027***	3.101***
Capacity	0.016***	- 0.008	- 0.005			
$Capacity^2$		0.00003***	0.00003***			
Volatility∗Capacity			-0.0002***			
Volatility∗Budget			- 0.012			
Budget∗Capacity			0.011***			

* weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

5.3 Influence of Budgeted Training Measures

Focusing on the effect of budgeted training measures (*Budget*), we find evidence for the assumption that budgeting has a significant negative effect on $Training$ ($p < 0.001$, column 2, Table 1). In contrast to $Training$, $Learning - By - Doing$ is positively affected by budgeting training measures ($p = 0.018$, column 2, Table 2.) This effect can only be observed when including capacity as a quadratic term $Capacity^2$, as it is only significant in the low-capacity scenario ($p < 0.001$, column 4, Table 2) and vanishes with more employee capacity (columns 5 and 6, Table 2). This might be driven by possible efficiency gains due to training which reduce shortage costs in later periods to an

Table 4: Coefficients from GEE Regression Learning Output

Variables	All Capacity Levels			Different Capacities		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	$N = 10800$	$N = 10800$	$N = 10800$	$N = 3600$	$N = 3600$	$N = 3600$
Intercept	175.035***	- 73.847***	- 59.310***	198.155***	390.298***	383.761***
Budget	- 2.515	- 2.447***	- 5.627***	- 3.448***	- 5.635***	1.842**
Volatility	0.001	- 0.029**	- 0.262***	- 0.092***	- 0.145***	0.142***
Time	- 4.164***	- 4.068***	- 4.068***	0.211***	- 5.723***	- 6.645***
Capacity	0.404***	1.966**	1.924***			
Capacity^2		- 0.002***	- 0.002***			
Volatility$*$Capacity			0.001***			
Volatility$*$Budget			- 0.045**			
Budget$*$Capacity			0.015***			

* weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

Table 5: Coefficients from GEE Regression Total Skill Development

Variables	All Capacity Levels			Different Capacities		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	$N = 10800$	$N = 10800$	$N = 10800$	$N = 3600$	$N = 3600$	$N = 3600$
Intercept	157.039***	- 95.782***	- 79.911***	181.691***	356.584***	361.274***
Budget	- 2.841	- 3.595***	- 3.570**	- 3.099***	- 6.255***	- 1.515*
Volatility	- 0.030	- 0.055***	- 0.354***	- 0.178***	- 0.107***	0.111***
Time	- 6.831***	- 6.787***	- 6.787***	- 2.832***	- 7.748***	- 9.745***
Capacity	0.384***	1.973***	1.928***			
Capacity^2		- 0.002***	- 0.002***			
Volatility$*$Capacity			0.001***			
Volatility$*$Budget			- 0.032*			
Budget$*$Capacity			0.004			

* weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

Table 6: Coefficients from GEE Regression Achieved Skill Units

Variables	All Capacity Levels			Different Capacities		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	*N=10800*	*N=10800*	*N=10800*	*N=3600*	*N=3600*	*N=3600*
Intercept	- 896.802***	-3454.479***	-3222.401***	534.215***	642.943***	521.129***
Budget	5.111	17.789**	0.802	5.875	- 17.664	37.930**
Volatility	- 0.456	- 0.488***	- 4.627***	- 2.102***	- 1.213***	1.842***
Time	224.959***	223.649***	223.553***	142.324***	268.171***	263.153***
Capacity	3.861***	19.959***	19.312***			
Capacity^2		- 0.021***	- 0.021***			
Volatility$*$Capacity			0.012***			
Volatility$*$Budget			- 0.626**			
Budget$*$Capacity			0.131**			

* weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

extend that allows missing the demand and paying shortage costs in earlier periods. The missing effect in the higher capacity scenarios might be driven by the fact that there is sufficient capacity endowment to meet the given demand and to allow for the amount of training needed for preventing higher shortage costs in later periods. Consequently, companies produce equally in both scenarios to meet the given demand, which further fosters comparable results for learning-by-doing. The contradictory effects of $Training$ and $Learning - By - Doing$ result in an overall negative effect of *Budget* on the compound variable *Learning Output*, again with a non-linear and significant influence of the capacity endowments $Capacity^2$ ($p < 0.001$, column 2, Table 4). Turning to the three capacity levels, we find that in the low and medium scenarios the missing opportunities for training lead to a negative influence of *Budget* on the *Learning output* ($p < 0.001$, column 4 and 5, Table 4) whereas the budgeting leads to a positive effect in the high-capacity scenario ($p < 0.001$, column 6, Table 4). This effect aligns with the findings of the descriptive analyses which show that employees undertake more training measures in the first periods in the budgeted scenario compared to the flexible scenario (Figure 1). The amount of extra training sessions is high enough to exceed the training measures utilized in the flexible scenario in the whole planning horizon, and thus, lead to a significant positive learning output for budgeting in the high-capacity scenario as well as in the whole dataset. Analyzing the effect of *Budget* on $Forgetting$ (Table 3), we find that the absence of an all-time availability of training measures fosters the loss of workers' skill units significantly ($p < 0.001$, column 2 and 6 Table 3). The change of sign of the effects of the variable *Budget* throughout the different capacities illustrates the non-linear and significant impact of the capacity variable $Capacity^2$ ($p < 0.001$, column 2, Table 3). These findings are consistent with the assumption made by Jaber et al. (2003) that training measures might be used to keep skill units high and thus prevent forgetting.

When looking at the overall effect on the $Total\ Skill\ Development$ (Table 5), which includes $Training$, $Learning-By-Doing$ and $Forgetting$, we find a significant negative impact of budgeted training measures (*Budget*) with a non-linear and significant impact of the capacity endowment $Capacity^2$ ($p < 0.001$, column 2, Table 5). This negative impact persists in all scenarios while being only weakly significant in the high-capacity scenario ($p < 0.001$, column 4,5 and 6, Table 5). This shows that extensive training in the first periods allows compensating the effect of forgetting in the later periods. Consequently, the results support H1, as the budgeting of training measures has a negative impact on skill development.

Surprisingly, the data reveal a positive effect of *Budget* on the overall *Achieved Skill Units* ($p < 0.001$, column 2, Table 6). This effect depends on the non-linear influence of the capacity and can only be observed in the high-capacity scenario. However, this effect is no longer significant when the relevant interaction effects are considered ($p = 0.9667$, column 3, Table 6). Thus, H1 is supported. Therefore, we now turn to the hypotheses to investigate the relevant effects triggered by our two manipulated variables – demand $Volatility$ and employee *Capacity*.

5.4 Influence of Volatility

Hypothesis H2 proposes that demand volatility has a negative impact on employees' skill development. Again, we look at the individual effects of $Training$, $Learning-by-doing$, and $Forgetting$ first, and then consider the total effect on employee skill development. Surprisingly, we find that demand $Volatility$ has a small but significant ($p < 0.001$, column 2, Table 1) positive impact on workforce $Training$. Analyzing the capacity scenarios, we find contradictory results. The impact of $Volatility$ in the scenario with high demand intensity (low-capacity) is significant negative ($p < 0.001$, column 4, Table 1), not significant in the medium scenario, and significant positive ($p < 0.001$, column 6, Table 1) in the scenario with low demand impact (high-capacity). This effect is probably driven by the fact that high volatility at low capacity leads to high shortage costs, as the corresponding demand cannot be met when employees are trained extensively. At high capacity, the volatility can be absorbed and it is further possible to invest excess time in the training of the workers. Again, this effect on $Training$ is accompanied by a non-linear and significant influence of $Capacity^2$ ($p < 0.001$, column 2, Table 1). $Learning-by-doing$ is affected negatively by demand $Volatility$ ($p < 0.001$, column 2, Table 2). This effect persists in the low- and medium-capacity scenarios ($p < 0.001$, column 4 and 5, Table 2). Employees are not able to meet the high demand which is strongly deviating from the average if high demand volatility is employed. This might affect especially the first periods, where no experience gains are present, caused by their time capacity restrictions. Additionally, we do not include storage in our model and it is impossible to produce goods in advance to meet later demand. Thus, production opportunities are forgone and learning-by-doing decreases with respect to a scenario with lower demand volatility. Moreover, an explanation for this might be, for example, that volatility leads to workers frequently having to change tasks, which means that specialization potential cannot be fully exploited. As a result, increases in skill levels through learning-by-doing are lower when volatility is high and can only be buffered by excess capacity in the high-capacity scenario in which $Volatility$ has no effect (column 6, Table 2). Considering the combined variable *Learning Output* (Table 4), $Volatility$ has a negative influence. In the low- and medium-capacity scenarios, the effect is significant negative. In the high-capacity scenario, again, training measures can be used in times of low demand to prepare for times with higher demand. Thus, a positive effect occurs ($p < 0.001$, columns 4,5 and 6, Table 4).

Similarly, we find significant positive effects on $Forgetting$ due to $Volatility$ ($p < 0.001$, column 2, Table 3), as workers miss opportunities for learning-by-doing and training, which both of which may prevent forgetting. Interestingly we find a significant non-linear effect of $Capacity^2$ ($p < 0.001$, column 2, Table 3) which is reflected by a u-shaped effect in the different capacity scenarios, since the effect of $Volatility$ on $Forgetting$ is positive in the scenarios with low- and high-capacity ($p < 0.001$, columns 4 and 6, Table 3), whereas $Forgetting$ decreases with higher volatility in the medium scenario ($p < 0.001$, column 5, Table 3). This at first glance contradictory result can be interpreted by looking at various influence factors. Volatility at low capacity leads to frequent changes of tasks among the employees and thus to less specialization and more forgetting. The increase in forgetting at high capacity on the other hand can be explained by the fact that more knowledge is built up and thus the possibilities of forgetting increase. The medium-capacity scenario, on the other hand, might use a good mix of specialization and training. Therefore, more volatility does possibly not lead to more forgetting here, but on the contrary to significant higher retention of the skills once they have been acquired.

For *Total Skill Development* (column 2 Table 5) and *Achieved Skill Units* (column 2, Table 6), we observe negative effects with increasing demand $Volatility$, similarly to the individual effects described above. This effect is visualized in Figure 3. Hence, we find support for our second Hypothesis H2 in the whole data set ($p < 0.001$, column 2, Tables 5 6), as well as in the low- and medium-capacity scenario ($p < 0.001$, column 4 and 5, in Tables 5 and 6). Nevertheless, in the high-capacity scenario, we find a significant positive effect of increasing demand $Volatility$ on the *Total Skill Development* ($p < 0.001$, column 5, Table 5) and the *Achieved Skill Units* ($p < 0.001$, column 5, 6). After discussing the results for the individual effects, this result should no longer be surprising.

5.5 Interaction Effects with Budgeting

First, we present the interaction effect between budgeting training measures and employee capacity. Second, we analyze the interaction between demand volatility and budgeting.

Since employees' time capacity is used for training and production, the effect of budgeting on skill development depends on employees' capacity endowment. The importance and effect of the capacity scenarios have already emerged from the presented analyses, which further emphasized the importance of the non-linear effect. These effects are underlined by a significant influence of the quadratic term $Capacity^2$ on all variables. In order to gain further insight on the influence of the moderating variable *Capacity* in combination with budgeting, we compute the interaction effect of $Budget * Capacity$ on the variables describing employees' skill development. Analyzing the effect of the interaction variable on $Training$ measures, we find a significant positive effect ($p < 0.001$, column 3, Table 1). The effect supports H3 and indicates that employees practice more during the initial periods if excess capacity (high-capacity scenario) is available and shortage costs can be kept at their minimum. These extra training measures might be connected to costs for the company, at least in terms of employee capacity.

For *Learning-By-Doing*, we do not find a significant negative effect for the interaction of budgeting and capacity $Budget * Capacity$ ($p < 0.001$, column 3, Table 2). Interestingly, we find a positive interaction effect of $Budget * Capacity$ on $Forgetting$ ($p < 0.001$, column 3 Table 3), indicating that excess capacity leads to more forgetting. In this vein, Figure 4 reveals that workers lose relatively and absolutely more skill units due to forgetting in the high-capacity scenario. On the one hand, the high employee capacity endowment allows for tactical training, in order to prevent forgetting in the flexible scenario. On the other hand, the plot in Figure 5 shows that in the budgeted high-capacity scenario, absolutely more training measures are used, compared to the flexible setting. This is noteworthy, as training is only possible in the first five periods. Thus, employees are initially trained to a higher skill level in the high-capacity scenario, which consequently results in more forgetting and is driven by the aim to avoid shortage costs in later periods.

Considering the compound variable *Learning Output*, the interaction variable $Budget{*}Capacity$ has a significant positive effect ($p < 0.001$, column 3, Table 4), driven by the effect on $Training$ ($p < 0.001$, column 3, Table 1). However, the data do not reveal a significant effect on the $Total\ Skill\ Development$, which incorporates $Forgetting$ and thus a complementary effect to $Training$. Relating to the $Achieved\ Skill\ Units$ of employees, we observe a significant positive interaction of *Budget* and *Capacity* ($p = 0.0022$, column 3, Table 6). These results provide partial support for H3. The achieved skill units are positively affected, as employees are initially trained to a higher skill level in the budgeted scenario in order to use the initial productivity gains as a buffer against future volatility and forgetting. Therefore, the total skill development per period is not positively affected as the higher achieved skill units decrease over time due to an increase in forgetting compared to scenarios without volatility. In this vein, employees do gain more skill units in absolute terms which are lost in the consecutive periods.

Turning to the effect of the interaction variable $Volatility * Budget$, which combines budgeting

and volatility, we find a negative and significant impact on $Training$ ($p = 0.003$, column 3, Table 1). On the one hand, this result might again be driven by the shortage costs which arise if production does not meet demand. Thus, production (reflected by the variable $Learning-by-doing$) is prioritized over $Training$ and is not further affected by the combination of budgeting and volatility (column 3, Table 2). On the other hand, higher demand in the first periods does not only lead to unmet demand for the budgeted and flexible scenarios but moreover to foregone training opportunities in the budgeted scenario which cannot be offset in later periods. Thus, $Volatility * Budget$ amplifies the negative influence on $Training$. Since it is not possible in the budgeted scenario to compensate for forgetting through training measures in the budgeted scenario any later than in period five, demand volatility in combination with budgeting does not have any further significant effect on $Forgetting$ (column 3, Table 3). As a result, we receive a negative and significant impact on $Learning\ Output$ ($p = 0.014$, column 3, Table 4), $Total\ Skill\ Development$ ($p = 0.082$, column 3, Table 5) and $Achieved\ Skill\ Units$ ($p = 0.0065$, column 3, Table 6). Therefore, hypothesis H4 is supported and we do find a negative influence of the interaction variable $Volatility * Budget$ on the employees' skill development.
Due to the fact that the interaction variable $Volatility * Capacity$ has extensively been studied by Letmathe and Schinner (2022), we omit analyzing this relation. Since the effects were significant in their study, we included the variable for the sake of completeness so that we could analyze the remaining effects in a more differentiated manner.

6 Conclusion

Summarizing our analyses of traditional (budgeted) versus flexible training approaches on production ramp-up under the influence of demand volatility and different employee capacity endowments, we find that the budgeting of training measures has a negative influence on the skill development of employees. In detail, employees are trained less frequently and lose more skill units due to forgetting when training measures are budgeted. This is reflected by an overall lower average skill development of the workforce compared to flexible training approaches. Moreover, employees achieve higher skill units in the budgeted scenario, as excess training measures in the first periods can be used to compensate for forgetting in later periods. Thus, additional costs for initial training arise. To simulate different intensities of demand volatility, three scenarios with different time capacity endowments of workers are employed. In the low scenario, workers cannot meet the average demand per period using their initial time endowment. Thus, skill improvements through training and learning-by-doing are necessary for workers to meet the demand in later periods and to prevent shortages. The time endowment in the medium scenario is sufficient to meet the average demand but does not leave much time for training. In the high-capacity scenario, training and production are simultaneously possible. These three scenarios allow for an extensive analysis of the training impact on employees' skill development, depending on the products' demand and its volatility. When looking at the interplay of budgeted training measures and capacity, we find distinctive effects, which can be explained by different influence factors. Considering employees with a small capacity endowment, respective to demand, assignments to training or production are mainly driven by the need to fulfill a given demand and to prevent shortage costs. In the high-capacity scenario, on the other hand, the buffer effect predominates, i.e. the negative effects of demand volatility can largely be offset by the available overcapacity.

Therefore, the influence of budgeting is strongest in the low-capacity scenario, as employee training has to be squeezed into the few available time windows, and initial training in the first periods is often not possible. Consequently, the impact diminishes with higher capacity. Thus, the skill development and the achieved skill levels, increase with capacity. If employee capacities suffice, workers are trained extensively in the first periods to reach higher average skill levels allowing for lower costs and higher productivity in subsequent periods. Overall, the amount of training in the first five periods in the budgeted scenario is much higher than the number of training sessions in the flexible scenario, where workers can be trained at all times.

As a consequence, decisions on employee training need to be based on the employees' time capacity in relation to product demand. In times of high demand pressure, flexible training measures contribute to the skill development of employees, they prevent forgetting, and they offer higher efficiency gains. With enough employee capacities, it is possible to reduce negative effects by training employees to a higher extent than is needed in the first periods. Therefore, an investment in flexible training measures that can be used in times of low demand, e.g. e-learning or mobile learning, can potentially contribute to a company's productivity if employee capacities are fully utilized for meeting a given demand. Moreover, it can prevent costs for excess training measures undertaken in the first period which would not be necessary if employees have access to training when it is needed in order to prevent forgetting during all periods.

In summary, our research provides interesting insights into the interplay of employee learning, budgeting training measures, capacity restrictions, and demand volatility, which are also highly relevant in practice. The selected simulation scenarios make it possible to predict relevant interactions as a consequence of induced changes in the variables without making claiming general transferability of the results. Like any research, this article therefore has its limitations. Considering the results of our study, it should be noted that the used parameters were set by the researchers. Although these are derived using empirical results from the field and a former study by the authors, future research might validate the results using real shop floor data. Moreover, future research might include a setting that incorporates more employees and more tasks, or analyze the impact of flexible capacities to include overtime hours. The model considers categorical skills but assumes that each worker is able to perform any of the activities with her or his initial skill set. An extension to the study could model categorical skills in a way that demands employees to gain initial experience on the production task in order to be able to perform it. In this vein, effects of budgeted training measures on specialization and cross-training of workers could be evaluated. The production environment considered is a parallel production setting yielding multiple products. Analyzing the effects for serial production lines, i.e. assembly lines, provides further avenues for research.

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A Appendix

A.1 Mathematical Model

$i \in \{1, ..., m\}$ denote the set of shop floor employees
$j \in \{1, .., n\}$ products
$t \in \{1, ..., T\}$ period of the observation
$k \in \{1, ..., K\}$ discrete skill levels
$l \in \{1, ..., L\}$ production activities
a_{lj} number of units of product j produced after pursuing production activity l
$\overline{CAP_i}$ time capacity of employee i in every period
c_{kl} production costs per unit for activity l at skill level k
c_l costs per training measure for production activity l
D_{jt} demand for product j in period t
fg_{lit} binary variable displaying if forgetting occurs for employee i and production activity l in period t
fl_l minimum amount of newly gained skill units in a period needed to prevent forgetting for activity l
M big M
p_{kl} processing time per unit for activity l at skill level k
r_{iklt} binary variable displaying if employee i is able to pursue production activity l at skill level k in period t
sc_j shortage costs of product j
sh_{jt} amount of shortage of product j in period t
tr_l time needed for one unit of training for production activity l
$u_{ilt} \geq 0$ total amount of training measures of employee i in period t for production activity l
v_i individual linear learning or skill development factor of employee i
w_i individual factor for forgetting of employee i
$y_{iklt} \geq 0$ amount of product l produced by production activity k by worker i in period t
yt_{ilt} amount of all production activity l performed by employee i in period t
ys_{lt} amount of all production activity l in period t
$z_{ilt} \geq 0$ skill units of employee i for production activity l in period t
$z_{kl}^{min} \geq 0$ required skill minimum
ϕ_i company skill target for employee i in period $t = T$

$$\underbrace{\sum_{i=1}^{m}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} c_{kl}\cdot y_{iklt}}_{production\ costs}+\underbrace{\sum_{i=1}^{m}\sum_{l=1}^{L}\sum_{t=1}^{T} c_{l}\cdot u_{ilt}}_{training\ costs}+\underbrace{\sum_{j=1}^{n}\sum_{t=1}^{T} sc_{j}\cdot sh_{jt}}_{shortage\ costs}\rightarrow \min \tag{8}$$

$$yt_{ilt}+u_{ilt}+M\cdot fg_{ilt}\geq fl_{l} \qquad \forall i\in\{1,...,m\}, l\in\{1,...,L\}, t\in\{1,...,T\} \tag{9}$$

$$yt_{ilt}+u_{ilt}+M\cdot fg_{ilt}<(M+fl_{l}) \qquad \forall i\in\{1,...,m\}, l\in\{1,...,L\}, t\in\{1,...,T\} \tag{10}$$

$$z_{ilt}=z_{il(t-1)}+yt_{ilt}\cdot v_{i}+u_{ilt}-w_{i}\cdot fg_{ilt} \qquad \forall i\in\{1,...,m\}, l\in\{1,...,L\}, t\in\{1,...,T\}, \tag{11}$$

$$\sum_{k=1}^{K}\sum_{l=1}^{L} p_{kl}\cdot y_{iklt}+\sum_{l=1}^{L} tr_{l}\cdot u_{ilt}\leq \overline{CAP_{i}} \qquad \forall i\in\{1,...,m\}, t\in\{1,...,T\} \tag{12}$$

$$z_{kl}^{min}-z_{ilt}\leq M\cdot(1-r_{iklt}) \qquad \forall i\in\{1,...,m\}, k\in\{1,...,K\}, l\in\{1,...,L\}, t\in\{1,...,T\} \tag{13}$$

$$y_{iklt}\leq M\cdot r_{iklt} \qquad \forall i\in\{1,...,m\}, k\in\{1,...,K\}, l\in\{1,...,L\}, t\in\{1,...,T\} \tag{14}$$

$$\phi_{i}\leq \sum_{l=1}^{L} z_{ilT} \qquad \forall i\in\{1,...,m\} \tag{15}$$

$$\sum_{i=1}^{m}\sum_{l=1}^{L} u_{ilt}\leq \overline{ucap_{t}} \qquad \forall t\in\{1,...,T\} \tag{16}$$

$$sh_{jt}=D_{jt}-\sum_{l=1}^{L} a_{jl}\cdot ys_{lt} \qquad \forall j\in\{1,...,m\}, t\in\{1,...,T\} \tag{17}$$

$$ys_{lt}=\sum_{i=1}^{m}\sum_{k=1}^{K} y_{iklt} \qquad \forall l\in\{1,...,L\}, t\in\{1,...,T\} \tag{18}$$

$$yt_{ilt}=\sum_{k=1}^{K} y_{iklt} \qquad \forall i\in\{1,...,m\}, l\in\{1,...,L\}, t\in\{1,...,T\} \tag{19}$$

$$fg_{ilt}\in\{0,1\} \qquad \forall i\in\{1,...,m\}, l\in\{1,...,L\}, t\in\{1,...,T\} \tag{20}$$

$$r_{iklt}\in\{0,1\} \qquad \forall i\in\{1,...,m\}, k\in\{1,...,K\}, l\in\{1,...,L\}, t\in\{1,...,T\} \tag{21}$$

$$sh_{jt} \geq 0 \qquad \forall j \in \{1,...,n\}, t \in \{1,...,T\} \tag{22}$$

$$u_{ilt} \geq 0 \qquad \forall i \in \{1,...,m\}, l \in \{1,...,L\}, t \in \{1,...,T\} \tag{23}$$

$$y_{iklt} \geq 0 \qquad \forall i \in \{1,...,m\}, k \in \{1,...,K\}, l \in \{1,...,L\}, t \in \{1,...,T\} \tag{24}$$

$$yt_{ilt} \geq 0 \qquad \forall i \in \{1,...,m\}, l \in \{1,...,L\}, t \in \{1,...,T\} \tag{25}$$

$$ys_{lt} \geq 0 \qquad \forall l \in \{1,...,L\}, t \in \{1,...,T\} \tag{26}$$

$$z_{ilt} \geq 0 \qquad \forall i \in \{1,...,m\}, l \in \{1,...,L\}, t \in \{1,...,T\} \tag{27}$$

On request, the GAMS code and the data will be provided by the authors.

Table 7: Mathematical Formulation of the Dependent Variables

Variable	Definition	
Learning-by-doing	$\sum_{i=1}^{m}\sum_{l=1}^{L} yt_{ilt} \cdot v_i$	$t \in \{1, ..., T\}$
Training	$\sum_{i=1}^{m}\sum_{l=1}^{L} u_{ilt}$	$t \in \{1, ..., T\}$
Learning-Output	$\sum_{i=1}^{m}\sum_{l=1}^{L} yt_{ilt} \cdot v_i + \sum_{i=1}^{m}\sum_{l=1}^{L} u_{ilt}$	$t \in \{1, ..., T\}$
Forgetting	$\sum_{i=1}^{m}\sum_{l=1}^{L} w_i \cdot fg_{ilt}$	$t \in \{1, ..., T\}$
Total Skill Development	$\sum_{i=1}^{m}\sum_{l=1}^{L} yt_{ilt} \cdot v_i - \sum_{i=1}^{m}\sum_{l=1}^{L} w_i \cdot fg_{ilt} + \sum_{i=1}^{m}\sum_{l=1}^{L} u_{ilt}$	$t \in \{1, ..., T\}$
Achieved Skill Units	$\sum_{i=1}^{m}\sum_{l=1}^{L}\sum_{t=1}^{T} z_{ilt}$	

A.2 Unused Capacity

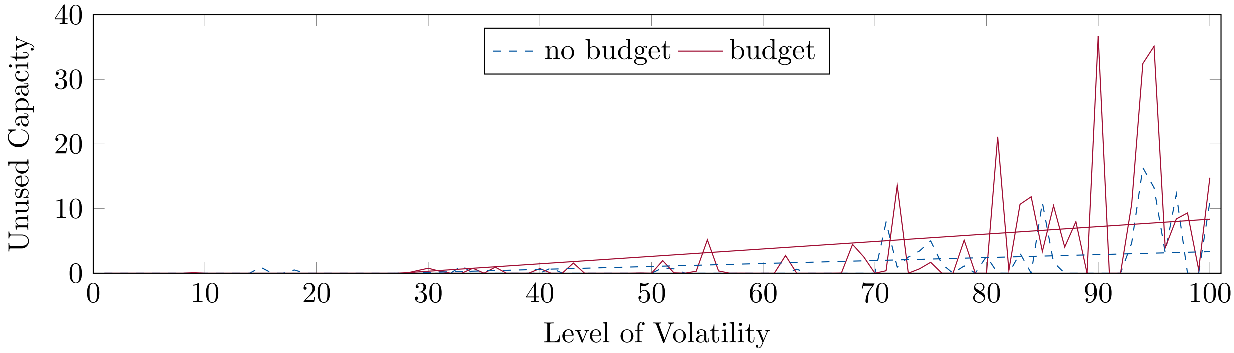

Figure 6: Unused Capacity - *Capacity* 200

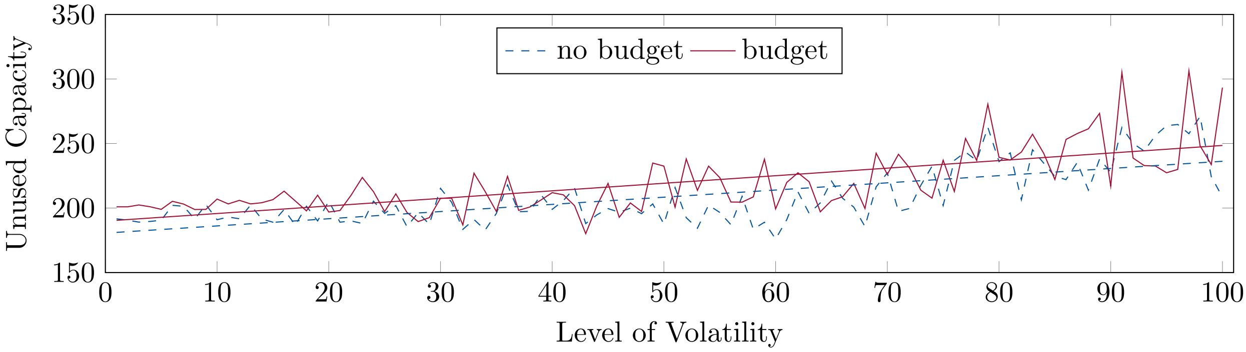

Figure 7: Unused Capacity - *Capacity* 375

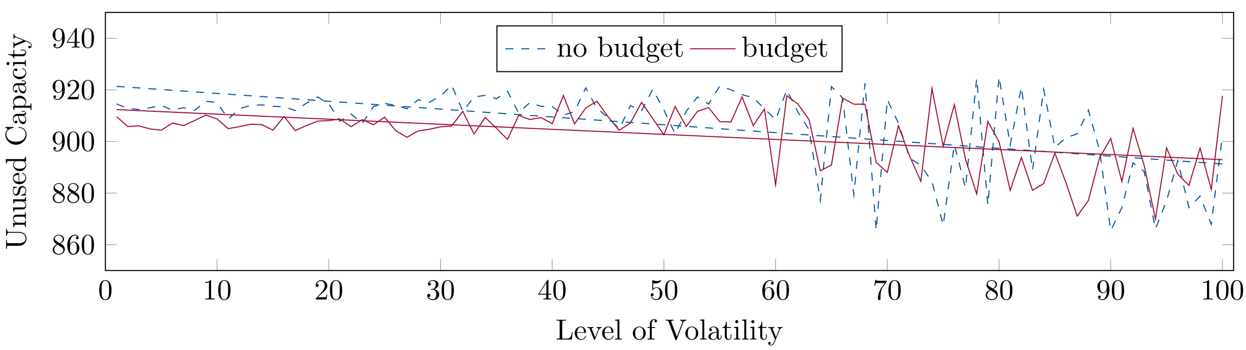

Figure 8: Unused Capacity - *Capacity* 550