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A decision-making methodology for selecting digital twin applications in the product service phase considering value and effort

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Abstract
The digital twin holds great potential for manufacturing using time series data in statistical models and simulations. Despite the recognised benefits of digital twins, many companies fail to achieve satisfactory value from their data due to a disconnect between data collection and its application in data-driven use cases. A "data-to-value" strategy is lacking, which would enable companies to select effective applications to achieve specific goals. This publication introduces a methodology that allows for the quantification of suitability and targeted selection of data-driven applications based on a value-effort analysis and the underlying time series data. This makes it easier for manufacturing companies to select the most suitable application for their individual needs. After identifying value aspects and their interactions, the value of each data-driven application is evaluated using the analytical network process. Subsequently, the implementation effort of each application is assessed from both a data and technological perspective. The results of the quantifications are then compared using the TOPSIS method. The methodology is demonstrated using a grinding process example before final discussions. Assuming that the economic value and effort are initially unknown, the methodology contributes to decision-making in selecting the most suitable digital twin application.

Keywords Data Assessment · Digital Twin · Value-Effort Analysis · Data Application · Data-to-Value Strategy · Decision Theory

1 Introduction

Within manufacturing, multivariate time series data is a very common level of data aggregation. They are recorded at the machine and collected by several sensors over time. [1] The concept of the digital twin results from the utilisation of this data in statistical models and simulations. It represents the properties and behaviour of the physical object and exhibits a bidirectional relationship between the physical and digital product. The use of time series data in models to create targeted added value for the process or product is referred to in this paper as a data-driven application. Such applications enable, for instance, to reduce material consumption or increase productivity within the production process. [2] Despite the potential of a digital twin, the collection of data and its application in data-driven applications diverge. Studies indicate that approximately 80% of companies fail to achieve satisfactory benefits from their data. Possible reasons for this include an insufficient in-house database and a lack of effective applications for utilising the data. To address these challenges, companies require a "data-to-value" strategy that supports the systematic selection of applications to achieve specific business objectives. [3] Such a decision model, which enables a quantification of the suitability and targeted selection of data-driven use cases, is currently lacking.

The scientific novelty of the presented work lies in its methodology that enables companies to systematically evaluate data-driven digital twin applications through a coherent value and effort framework. In contrast to existing approaches, this methodology facilitates, for the first time, a precise assessment of various application scenarios based on time series data without requiring prior monetary quantification. This is particularly valuable for small and

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medium-sized enterprises, providing a viable pathway for targeted digital twin implementation. The methodology forms the foundation of a data-to-value strategy, which, as a next step, enables value-based assessment and pricing of time series data (beyond the scope of this paper). This work acknowledges that companies typically cannot quantify economic values or costs in advance. The methodology consists of three core components, which will be introduced in Sect. 4. The practical application of the decision model is demonstrated using the example of grinding production technology.

2 Definition of the problem of evaluating data and data-driven applications

The evaluation of the value and suitability of data or digital technologies in the context of manufacturing technology has already been addressed in scientific work. Brandstätter and Brunlechner [4] developed a cost–benefit model for evaluating cyber-physical systems (CPS). They used a literature review to derive performance indicators to quantify the benefits and relevant cost types. However, the model neither considered interactions between the value aspects nor used measurement and evaluation indicators. [4] It is also disadvantageous that data and their specific applications are subject to marginal cost theory. As a result of the infinite reproducibility of data with almost constant costs, the costs would have to be continuously adjusted when comparing value and costs depending on the amount of data used in the application. Transferability to the evaluation of data-driven applications is therefore not possible. Stein et al. [5] described central requirements for models for the evaluation of data from production without presenting an evaluation approach. Among other things, they named the consideration of data quality, the determination of a value from a monetary and application-specific perspective and the inclusion of the industrial context. [5] Kreutzer [6] presented a methodology for determining the potential value of CPS field data in the production environment. Manufacturing process data represented a subset of the field data considered. Users of the methodology from Kreutzer [6] are enabled to identify the potential of field data in the form of value aspects. Kreutzer [6] pursued the ordinal benefit theory instead of the cardinal benefit theory, within which no quantification of the value is provided. The author did not consider the connection between value aspects and data in specific applications and therefore assumed that data itself generates value. [6] Mendizabel-Arrieta et al. [7] presented a mathematical model for pricing industrial data. The pricing model was based on the costs of data collection, storage and analysis and multiplied weighted factors of data quality, data entropy, data value and Customer Relevancy Index (CRI). The data value from the perspective of buyers and manufacturers was determined using a survey as a score. The CRI represents the importance of each customer for the industrial producer. The authors implied an understanding of the value of selected data and used the subjective judgement of the data provider and consumer in their model. However, this knowledge regarding the suitability of time series data for production technology is not given in the majority of cases. [7] It can be summarised that an approach for evaluating the value and effort of data-driven applications in relation to the underlying basis of time series data is lacking.

3 Fundamentals of this work

This study builds upon both methodological foundations and the definition of the data-driven applications considered. To establish a solid basis, this chapter first introduces the Analytic Network Process (ANP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) as the methodological framework for decision-making. Subsequently, the relevant data-driven applications are defined, outlining their role in the context of this research.

3.1 Theoretical foundations regarding decision-making

The choice of an application that appears to be suitable based on the available time series data is a multi-criteria decision problem. Such a problem requires a decision to be made regarding several alternatives, considering different, often competing criteria and weightings. In real-life decision-making situations, alternatives and criteria can influence each other, which is why a network structure is suitable for modelling these situations. To select an appropriate method for solving the multi-criteria decision problem, the standardized framework by Wątróbski et al. [8] was applied [8]. This framework reduces the risk of poor decision quality by systematically evaluating decision characteristics. Given the nature of this problem, a two-stage decision process is required: First, applications are evaluated based on their value-effort ratio and ranked accordingly. Second, the value aspects are assessed in relation to the company's strategic objectives. Since these assessments are subject to individual preferences and uncertainties, relative weightings are needed for both applications and value aspects. As the value aspects influence each other and exhibit a network structure rather than a strict hierarchy, the framework recommends Fuzzy analytical network process (ANP) + Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) as the most suitable method combination. ANP captures interdependencies between value aspects, while TOPSIS provides a structured ranking of applications based on their weighted value-effort scores.

To implement this methodology, the ANP is applied, as it is specifically designed for network-based decision problems. The process begins with the identification of all components of the network structure, alternatives, criteria, so-called clusters and their interdependencies. Clusters summarise decision criteria with a high degree of interaction. In most cases using pairwise comparisons, the influence of all components on the objective of the decision problem is analysed and mapped in evaluation matrices a_{ij} with i rows and j columns. The rows and columns depend on the criteria or options to be compared. The scale of relative importance from 1–9 can be used for pairwise comparisons. If there is an indifference between two options, a rating of"1"is assigned. If option A has maximum importance compared to option B, the assessment score is "9". For each evaluation matrix m, a vector r_m is calculated using the geometric mean, which represents the importance of the alternatives and criteria of the decision problem. The entries of a matrix are multiplied column by column and raised to the power of the reciprocal value of the number of columns s of the corresponding evaluation matrix a_{ij} [9]:

$$r_m = \left(\prod_{j=1}^{s} a_{ij} \right)^{\frac{1}{s}} \tag{3.1}$$

From the n vectors r_m, weights w_m are formed by normalisation (each vector entry is divided by the sum of the column values of the vector), which are combined into priority vectors W for the x elements and clusters of the decision problem [10].

$$w_m = \frac{r_m}{\sum_{m=1}^{n} r_m} \tag{3.2}$$

$$W = (w_1, \ldots, w_m)^T \tag{3.3}$$

Based on the priority vectors, the square supermatrix S of dimension NxN is formed, where N represents the total number of all model elements from the various clusters. This supermatrix, which is organised as a so-called block matrix, represents the direct influences of all model elements on each other, but not the indirect influences along various impact chains of the network on the objective of the ANP. To map the indirect influences on the objective of a decision situation, a so-called limit matrix L is developed by multiplying the supermatrix by itself until the values of a row converge to one value. This matrix indicates the weights of all clusters and elements of a network in relation to the objective of the ANP and represents the preferences of a decision-maker. [9] Repeated exponentiation is used to capture the long-term effects of direct and indirect influences in the network. When convergence occurs, the values per row of the matrix have stabilised.

The *Technique for Order Preference by Similarity to Ideal Solution* (*TOPSIS*) is another method for solving decision problems. The method recommends the option that has the shortest distance to the positive ideal solution (best possible solution) and the greatest distance to the negative ideal solution (worst possible solution) of a decision problem. The Euclidean distance of an alternative to the positive ideal solution (D_i^+) and the distance to the negative ideal solution (D_i^-) results from the best possible ($v_j{}^+$) and worst possible values ($v_j{}^-$) of the weights of the j-th criterion and the weighted normalised values of the decision matrix v_{ij} [11]:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j{}^+\right)^2} \tag{3.4}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j{}^-\right)^2} \tag{3.5}$$

The weighting vector v_{ij} represents the value of the j-th criterion for the i-th alternative. The positive v_j^+ and negative ideal solution v_j^- are the maximum and minimum value of criterion j across all alternatives i. After calculating the Euclidean distance, alternatives are ranked by their relative proximity to the positive ideal solution C_i^*. The best alternative of a decision problem is given the highest value C_i^*.

$$C_i^* = \frac{\boldsymbol{D_i^-}}{\boldsymbol{D_i^+} + \boldsymbol{D_i^-}} \tag{3.6}$$

In multi-criteria decision problems, imprecise statements are often made by the user due to the complexity. Fuzzy logic is used for the mathematical modelling of fuzziness and colloquial descriptions. With the help of fuzzy numbers, it is possible to convert linguistic judgements of decision-makers into a mathematical form. Triangular fuzzy numbers in the form of the triple $\widetilde{a}=(a,b,c)$ can be used, for example, to expand the scale of relative importance. By assigning the triangular fuzzy numbers to a linguistic assessment of the decision maker, the inherent fuzziness of such an assessment can be compensated for, since a range of three assessments is considered for each assessment. Special rules apply to fuzzy numbers regarding arithmetic operations. The so-called fuzzy addition (⊕) and fuzzy multiplication (⊗) of two fuzzy numbers $\widetilde{a}=(a,b,c)$ and $\widetilde{b}=(d,e,f)$ are defined as follows: [12]

$$\widetilde{a} \oplus \widetilde{b} = (a+d, b+e, c+f) \tag{3.7}$$

$$\widetilde{a} \otimes \widetilde{b} = (a \bullet d, b \bullet e, c \bullet f) \tag{3.8}$$

After fuzzifying a number and performing arithmetic operations, it is often necessary to convert a fuzzy number back into a"sharp"value. The centre of area method (COA) can be used for such defuzzification [13].

3.2 Definition of relevant data-driven applications in the context of the digital twin

In addition to selecting appropriate methods for the decision-making methodology, it is essential to define the data-driven digital twin applications in manufacturing that will be considered in this study. Data-driven applications in the context of digital twins utilise time series data and analytical methods to optimise manufacturing processes and product performance. These methods can be based on machine learning, statistical modelling, or rule-based approaches such as Life Cycle Assessment (LCA) according to ISO 14044. Unlike purely static decision models, data-driven applications enable the continuous processing of sensor data, the identification of patterns, and the data-driven assessment of environmental and process factors. They are applied across various stages of manufacturing, including design, production, service, and recycling [14]. This study focuses on applications in the service phase, which leverage time series data to create value in distribution, usage, repair, and maintenance of workpieces. In contrast, applications related to the production phase focus on resource allocation, production planning, and order management [15]. However, time series data recorded by sensors on machines, such as force, temperature or acoustic emission data, are not suitable for such applications.

In the service phase, Tao et al. define nine potential applications [15], which were also analysed for their suitability for time series data. The applications *"Service of user management and behaviour analysis"*, *"Service of user operation guide"* and *"Service of intelligent optimisation and update"* are excluded from this work due to the use of user data. The services *"Product virtual maintenance"* and *"Product virtual operation"* are also not considered in more detail, as no virtual applications that can be used, for example, for learning and training purposes are intended to be part of this work. Instead, the focus is on digital twin applications that utilise data and models to characterise the property profile of a physical object and generate added value. Following a refinement of the application descriptions of Tao et al. for improved clarity [15], the following five applications (Service 1–5) are identified (Table 1):

4 A decision-making methodology for selecting digital twin applications

This paper presents a three-step decision-making methodology that enables a structured selection of suitable data-driven digital twin applications by considering both their potential value and implementation effort (Fig. 1). In the first step, the value of digital twin applications is quantified by identifying and assessing relevant value aspects and their interdependencies. These aspects fall into three value categories: product quality, process quality, and fulfilment of regulatory requirements. To systematically evaluate the value, the ANP method is applied. ANP facilitates pairwise comparisons to determine the relative importance of value aspects while accounting for their interdependencies, resulting in a quantitative value score for each application.

In the second step, the effort required is assessed from two perspectives. The data-related effort reflects the availability of the required time series data and key performance indicators for a given application. The technological effort evaluates a company's methodological competence as well as its willingness to engage in cross-company data sharing.

In the third step, the TOPSIS method is applied to establish a ranking of applications based on their value-effort ratio. TOPSIS enables a structured comparison by

Table 1 Selected application of the digital twin in the service phase referring to Tao et al. [15]

Name of the applications	Explanation
Service of product quality monitoring and prediction (Service 1)	Data-driven identification of product defects and their causes, as well as real-time monitoring and prediction of product quality
Service of process monitoring and improvement (Service 2)	Data-driven real-time process monitoring and optimisation of machine settings for preventive process adjustments and increased productivity and resource efficiency
Service of energy consumption analysis and forecast (Service 3)	Data-driven measurement and optimisation of energy consumption by identifying savings potential and consumption patterns
Service of measuring ecological footprint (Service 4)	Data-driven analysis of greenhouse gas emissions for assessing and improving environmental sustainability
Service of condition-based and predictive maintenance strategy (Service 5)	Data-driven maintenance and restoration of tool and machine availability, as well as monitoring of remaining service life

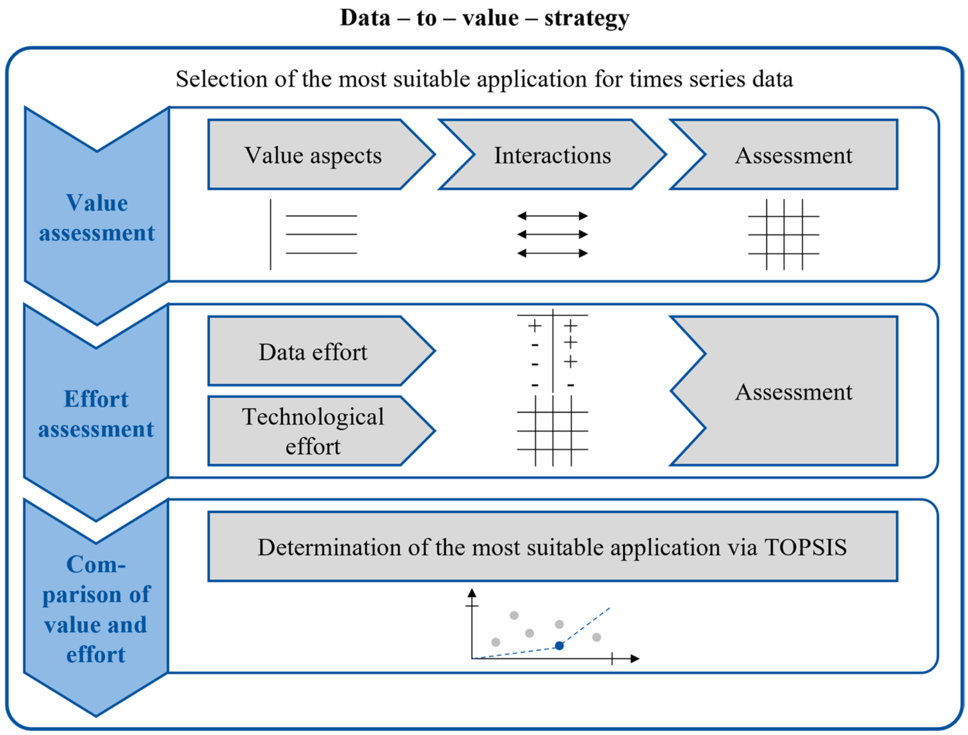

Fig. 1 Methodology for determining the potential of applications of the digital twin based on value and effort

calculating the relative distance of each application, based on its value and effort scores, to a positive-ideal and a negative-ideal solution. This approach allows for a prioritised selection of applications, ensuring that the most promising use cases are identified while considering practical constraints such as data availability and technological feasibility. The highest score C_i^* represents the most suitable application. The methodology provides concrete recommendations for selecting digital twin applications based on a structured and reproducible evaluation process.

4.1 Identification and assessment of the value for data-driven applications

The quantification of value requires the prior definition of value categories depending on their scope, the derivation of so-called value aspects and their allocation to the defined data-driven applications as well as the identification of dependencies between the value aspects. A value aspect (*VA*) is the specific way in which a stakeholder generates value by satisfying needs (e.g. increased productivity, improved customer experience, positive impact on the environment) [6].

4.1.1 Definition of relevant value categories and value aspects of time series data-driven applications

The previously identified applications can generate value in three categories. Time series data collected in the manufacturing process generates value in corresponding applications, including within *process quality* by reducing throughput times and resource consumption and increasing process utilisation [16]. Another value-related area of impact of data-driven applications is *product quality*. Product-specific quality parameters can be identified and evaluated in a data-driven manner during ongoing operations [17]. There is a relationship between the two value categories. *Process quality* is the prerequisite to produce high-quality products. However, as the quality of a manufacturing process is not the only factor influencing *product quality*, the two categories are listed separately below and are not represented by a single category. In addition to improving process and product quality, data-driven applications also serve to *fulfil regulatory requirements*. They support compliance with legal regulations relating to environmental protection, plant safety and product liability. Financial penalties for a company under the Product Liability Act can be prevented by ensuring a continuous level of product quality. [18] This results in a relationship between product quality and the *fulfilment of regulatory requirements*.

The identification of VA for the three value categories was conducted through a comprehensive literature review using Scopus, Web of Science, and Google Scholar. As existing literature does not explicitly categorise the value of data-driven applications into distinct aspects, relevant studies on production improvements through time series data were analysed. The extracted VA were then systematically assigned to the corresponding data-driven applications based on their functional characteristics and impact on value dimensions. The final mapping is presented in Tables 1.

At the beginning, the value aspects of the product quality category were identified. The improvement of (macro- and micro-) geometric and mechanical product properties characterise the goal of optimised product quality [19]. The *improvement of product quality* (*VA1*) is therefore defined as the first value aspect of the product quality category. The recording of measured variables provides information about potential shape deviations on the workpiece itself or about their underlying causes and quality defects. These include deviations in shape, position or length (macro-geometric properties) as well as waviness, roughness and microstructural composition of the workpiece surface (micro-geometric properties). [20] In addition to optimised product quality, the *minimisation of quality fluctuations* (*VA2*) by reducing the probability of a defect in a product is a further value aspect. Product quality is subject to a variety of influences. Process anomalies in the form of unknown non-linear effects are responsible for quality fluctuations in manufacturing processes and cause rejects. [21] Data-driven quality monitoring (e.g. in the form of recording and adapting vibration information and machine performance [22]) enables flexible, proactive and automated control of the manufacturing process regarding quality parameters in real time. The value aspects *VA1* and *VA2* are based on quality control. By recording process parameters during the ongoing process, it is possible to recognise deviations in the production process without the need to measure the machined component [23]. This results in time savings and fewer rejects [24]. *Improved quality control* is the third value aspect *VA3* to be defined. The identified value aspects *VA1* to *VA3* are generated by the *"Service 1"*. Product quality monitoring is used for the early detection of defects in products and components to detect and reduce product quality fluctuations during the process (*VA2*) and to improve quality control (*VA3*). The use of time series data in machine learning models, for example, allows the prediction of component properties even before the start of the production process based on the planned machine parameters and available historical process signals. Adjusting these parameters ensures that the desired component properties are available (*VA1*).

The category of process quality encompasses two value aspects. The increasing automation of manufacturing processes results in heightened demands for process reliability. Reliable processes are characterised by a production flow with minimal disruptions and little to no downtime. [25] In the present context, process reliability refers to the stability and dependability of a process rather than to a risk-free manufacturing process. Monitoring production parameters (e.g. a machine's acoustic emissions) enables the control of a manufacturing process's stability. [26] The analysis of process data and monitoring of machine conditions allow for the avoidance of unplanned machine failures, thus contributing to high process reliability. Consequently, the fourth value aspect is defined as the *enhancement of process reliability* (*VA4*). A financial value aspect resulting from the use of manufacturing process data concerns the *reduction of process costs* (*VA5*). The analysis of process data supports the reduction of production process costs. [27] Cost drivers such as scrap rates or energy consumption can be reduced by evaluating time series data [28]. The identified value aspects *VA4* and *VA5* are triggered by three different data-driven applications. The recording of time series data for the *"Service 2"* contributes to the monitoring and control of process reliability (*VA4*). When process parameters are identified as being outside of a defined range, they can be adjusted to prevent instability and ensure a reliable process. Furthermore, the application enables a reduction in cost-driving process indicators such as processing time (*VA5*). [29] *"Service 5"* also fulfils the value aspects of enhancing process reliability (*VA4*) and reducing process costs (*VA5*). Continuous monitoring of tool wear promotes early detection of process deviations, prevents unplanned downtime, and improves process reliability. Predicted maintenance intervals also prevent damage to machines and tools before a failure occurs, thereby impacting process costs. *"Service 3"* also fulfils the economic value aspect *VA5*, as the reduced consumption lowers energy costs per product.

In the category of fulfilment of regulatory requirements, there are three value aspects for applications of manufacturing time series data. Since the introduction of the Energy Efficiency Act, manufacturing companies have been obliged to implement measures to reduce their resource and energy consumption to avoid the emission of harmful substances. Consequently, the analysis of time series data helps to maintain the resource efficiency of production processes to ensure legally compliant operations. [30] The *fulfilment of sustainability standards* represents an additional value aspect (*VA6*). *VA7* refers to *traceability*, particularly of consumed raw materials and resources, to comply with regulations such as the EU-Ecodesign-Directive, which aims to ensure transparency regarding the impact of business activities on people and the environment. Additionally, traceability concerning the ecological impacts of a product supports the fulfilment of sustainability requirements for business operations. [30] Time series data is necessary to capture and assess sustainability information from processes. Finally, the *assurance of product conformity* (*VA8*) is defined as a value aspect. Product conformity includes all legal requirements (e.g. those under EU directives) that a product must meet before entering the market [31]. Sensor data-based process monitoring indirectly ensures product conformity by monitoring product quality [32]. The identified value aspects *VA6* to *VA8* result from the use of time series data in the following four applications of a digital twin during the service phase. *"Service 2"* contributes to traceability (*VA7*) by collecting time series data related to resource consumption (e.g. coolant). When this data is used by machine learning methods to optimise consumption, the application supports the fulfilment of sustainability standards (*VA6*). *"Service 3"* maps process-related environmental impacts and drives their optimisation. Due to its interaction with greenhouse gas emissions, this application is relevant to a company's non-financial reporting (*VA6*). *"Service 4"* also serves *VA6*, as CO2 emissions are part of the reporting under the Corporate Sustainability Reporting Directive (CSRD). *"Service 1"* contributes to product conformity (*VA8*) by identifying and detecting component defects early, thus reducing the delivery of defective or substandard products. The allocation of all value aspects to the corresponding applications can be seen in Table 2 below.

The identified value aspects form the basis for quantifying the value of a data-driven application. Due to the relationships between the value categories, there are dependencies among the value aspects, despite their application-specific allocation, which will be examined below. The interdependencies between the value aspects are significant for the evaluation methodology, as the interaction involved in realising one value aspect may result in the (partial) fulfilment of another. The overall value of a data-driven application can be enhanced by such interdependencies. The identification of the interdependencies was also conducted through a comprehensive literature review using Scopus, Web of Science, and Google Scholar.

Within the value categories of *process quality* and *product quality*, the *minimisation of quality variations* (*VA2*) and the *enhancement of process reliability* (*VA4*) are interrelated, as high process reliability is characterised, among other things, by consistent product quality [33]. The second value aspect also influences *VA5* (*reduction of process costs*), as lower variability in product quality reduces scrap rates, material costs, and consequently, process costs [34]. Furthermore, process costs (*VA5*) are affected by process reliability (*VA4*). A key aspect of a stable process is a lower failure rate of machines and a production free from unplanned downtime. As a result of reduced downtime, the productive time of a process is increased, and the production costs for a product are lowered [35].

Within the value category of product quality, *improved quality control* (*VA3*) influences the value aspects of *product quality improvement* (*VA1*) and *minimisation of quality variations* (*VA2*). Optimised quality control enables the reliable assessment of a product's characteristic features and the successful identification of quality variations during the production process [36].

There is a relationship between the value categories of *fulfilment of regulatory requirements* and *product quality*, particularly between *ensuring product conformity* (*VA8*) and *improving quality control* (*VA3*). Comprehensive quality control identifies defects and ensures compliance with regulatory requirements [32]. *VA8* and the *improvement of product quality* (*VA1*) also influence each other. Adequate product quality is often the basis for meeting regulatory requirements regarding product conformity [37]. *Minimising quality variations* (*VA2*) results in less scrap and rework, as well as reduced material and energy consumption. This form of sustainability enhancement affects *VA6* [38].

The value aspect of enabling *traceability* (*VA7*) interacts with two value aspects. Traceability aids in the quick and efficient identification of affected products in the event of a product recall for regulatory or safety reasons. To identify the products, quality parameters must be consistently recorded and stored [23]. Consequently, the value aspect of *improved quality control* (*VA3*) underpins *VA7*. A central element of traceability is the assessment of a product's sustainability balance, for which the collection of sensor data is particularly relevant. The described influence on political

Table 2 Application-specific allocation of the identified value aspects within the value category of fulfilment of regulatory requirements

		Data-driven applications of a digital twin in the product service phase				
		Service of product quality monitoring and prediction (Service 1)	Service of process monitoring and improvement (Service 2)	Service of energy consumption analysis and forecast (Service 3)	Service of measuring ecological footprint (Service 4)	Service of condition-based and predictive maintenance strategy (Service 5)
Value category *product quality*	VA1	x				
	VA2	x				
	VA3	x				
Value category *process quality*	VA4		x	x		x
	VA5		x			x
Value category *fulfilment of requirements*	VA6		x	x	x	
	VA7		x			
	VA8	x				

requirements, such as the Non-Financial Reporting Directive, highlights the impact of *VA7* on the *fulfilment of sustainability standards* (*VA6*). Table 3 presents the identified interdependencies between the value aspects.

4.1.2 Quantification of the value

The quantification of the value of the identified data-driven applications represents a decision problem with a network-like structure due to the dependencies of the value aspects that need to be considered. For this reason, the ANP method is chosen to solve the problem. The overarching goal is to maximise the value for the manufacturing company. The applications represent the alternatives to be selected in the decision problem, while the value aspects represent the underlying criteria (Chapter 3).

The quantification of the value of applications depends on the individual assessment of a decision-maker, as value is defined as a subjective measure of need satisfaction [6]. Consequently, the value of a data-driven application is individual for each company. This subjectivity is reflected by a pairwise comparison of the value categories and aspects, based on the fuzzified scale of relative importance (Table 4). The comparison creates transparency regarding a company's needs and maps these through the scale values or their reciprocal values. As described in the fundamentals section, fuzzy logic is suitable for considering potential grey areas in decision-making situations when human preferences are evaluated. The comparisons of the categories result in the evaluation matrix C, and the comparisons of the value aspects within each category lead to the evaluation matrices U1, U2, and U3. The values are assigned by the user of the methodology according to their individual preferences, ensuring that the specific requirements and priorities of their company are accurately represented.

For each of the matrices, a vector $\mathrm{r_m}$ is calculated using the geometric mean, which represents the importance of the value categories and aspects in a simple and compact form through numerical values. To do this, the fuzzy numbers (l_j, m_j, n_j) are multiplied column-wise and raised to the power of the reciprocal of the column count s of the corresponding evaluation matrix:

$$\mathrm{r_m} = \left(\left(\prod_{j=1}^{s} \mathrm{l_j} \right)^{\frac{1}{s}}, \left(\prod_{j=1}^{s} \mathrm{m_j} \right)^{\frac{1}{s}}, \left(\prod_{j=1}^{s} \mathrm{n_j} \right)^{\frac{1}{s}} \right) \tag{4.1}$$

After a normalisation, defuzzification of the results is performed using the COA method. The defuzzied weight $\mathrm{w_i}$ is derived from the division of the weighting vector $\mathrm{fw_i}$ by the value "3", which represents the three entries of a triangular fuzzy number:

$$w_i = \frac{fw_i}{3} \tag{4.2}$$

After accounting for subjectivity, the already identified interdependencies between the value aspects are quantified by a numerical scoring system to capture the rarity of an interaction. For this purpose, pairwise comparison is not used, as the interactions between the value aspects do not depend on individual subjective perception. Instead, an alternative evaluation approach is developed in this study. It is evaluated whether an interdependency exists

Table 3 Interdependencies between the identified value aspects

	VA1	VA2	VA3	VA4	VA5	VA6	VA7	VA8
VA1	-	x	x					x
VA2	x	-	x	x	x	x		
VA3	x	x	-				x	x
VA4		x		-	x			
VA5		x		x	-			
VA6		x				-	x	
VA7			x			x	-	
VA8	x		x					-

Table 4 Scale of relative importance

	Indifference between options	One option is slightly prioritised	One option is prioritised	One option is clearly prioritised	The importance of one option dominates	Intermediate values
Values	(1,1,1)	(2,3,4)	(4,5,6)	(6,7,8)	(9,9,9)	(1,2,3), (3,4,5), (5,6,7), (7,8,9)

between two value aspects and a third aspect. An aspect is considered highly significant and receives a value of "2" if only this aspect influences the third value aspect (e.g., Table 3: VA2 affects VA1, but VA4 does not, so VA2-VA4 is set to "2"). If there is an interaction with the third element for both aspects, a value of "1" is assigned to both (e.g., Table 3: VA2 and VA3 both affect VA1, so VA2-VA3 is set to "1"). No interaction corresponds to a rating of "0". Diagonal values are set to "1", representing self-interaction, while inverse values are mirrored to maintain symmetry. This systematic approach ensures a transparent and consistent quantification of interdependencies, forming a reliable basis for further analysis. The quantified interdependencies are derived from the relationships identified in Table 3. Table 5 shows all quantified interdependencies for VA1.

Eight evaluation matrices are generated for eight value aspects, for which weighting vectors are calculated after column-wise normalisation using the arithmetic mean. Unlike pairwise comparison using the fuzzified scale of relative importance, the evaluation approach for dependencies between VA can result in zero values. Therefore, the evaluation matrices are not constructed using the geometric mean. In the case of using the geometric mean, the overall result could potentially be "0" despite existing interdependencies, which would contradict an actual interaction. Instead, the arithmetic mean is applied column-wise to calculate the entries of the evaluation matrices for each individual VA. Consequently, the evaluation matrix for the first value aspect is denoted as VA_1.

$$\overline{\mathrm{VA}}_1 = \begin{pmatrix} - & - & - & - & - & - & - & - \\ - & 0.2 & 0.2 & 0.286 & 0.286 & 0.286 & 0.286 & 0.2 \\ - & 0.2 & 0.2 & 0.286 & 0.286 & 0.286 & 0.286 & 0.2 \\ - & 0.1 & 0.1 & 0.143 & 0 & 0 & 0 & 0.1 \\ - & 0.1 & 0.1 & 0 & 0.143 & 0 & 0 & 0.1 \\ - & 0.1 & 0.1 & 0 & 0 & 0.143 & 0 & 0.1 \\ - & 0.1 & 0.1 & 0 & 0 & 0 & 0.143 & 0.1 \\ - & 0.2 & 0.2 & 0.286 & 0.286 & 0.286 & 0.286 & 0.2 \end{pmatrix} \tag{4.3}$$

The first entry of the evaluation matrix $\mathrm{r}_{\mathrm{m},1}$ is determined as follows:

$$\mathrm{r}_{\mathrm{m},1} = \frac{1}{1+1+\frac{1}{2}+\frac{1}{2}+\frac{1}{2}+\frac{1}{2}+1} = 0.2 \tag{4.4}$$

This is followed by the normalisation of the evaluation matrices to determine the priority vectors. For this purpose, the matrix entries in each row of an evaluation matrix are summed and divided by the number of potentially available interaction partners (in this case, seven additional VA). For the first VA, the priority vector W_{VA1} is:

$$W_{VA1} = \begin{pmatrix} 0 \\ 0.249 \\ 0.249 \\ 0.063 \\ 0.063 \\ 0.063 \\ 0.063 \\ 0.249 \end{pmatrix} \tag{4.5}$$

The vector W_{VA1} indicates how important or influential the individual value aspects are for VA1, helping companies in their decision-making process to determine which application is the most suitable. The higher the entry within the vector, the greater the relative significance of each VA for VA1. As a result of the normalisation, a comparison of the importance between the VA is now possible. Since the evaluation matrices representing the dependencies between the value aspects are of an objective nature, they can be applied to each use case without the need for recalculation. To solve the decision problem of selecting the most appropriate application based on available time series data, the supermatrix (Table 6) is constructed. It integrates subjective preferences, interdependencies, and feedback loops between VA and applications, consolidating pairwise comparisons into a stable priority structure through matrix exponentiation. The goal is to maximise the value generated by the selected application, with evaluation results for value categories K_n and value aspects VA_n incorporated accordingly.

Table 5 Influences on VA1

	VA1	VA2	VA3	VA4	VA5	VA6	VA7	VA8
VA1	-	-	-	-	-	-	-	-
VA2	-	1	1	2	2	2	2	1
VA3	-	1	1	2	2	2	2	1
VA4	-	1/2	1/2	1	0	0	0	1/2
VA5	-	1/2	1/2	0	1	0	0	1/2
VA6	-	1/2	1/2	0	0	1	0	1/2
VA7	-	1/2	1/2	0	0	0	1	1/2
VA8	-	1	1	2	2	2	2	1

Table 6 Supermatrix in current context

	Goal	K1	K2	K3	VA1	VA2	VA3	VA4	VA5	VA6	VA7	VA8
Goal	0	0	0	0	0	0	0	0	0	0	0	0
K1	w_{C1}	0	0	0	0	0	0	0	0	0	0	0
K2	w_{C2}	0	0	0	0	0	0	0	0	0	0	0
K3	w_{C3}	0	0	0	0	0	0	0	0	0	0	0
VA1	0	w_{U11}	0	0	$W_{VA1,1}$	$W_{VA2,1}$	$W_{VA3,1}$	$W_{VA4,1}$	$W_{VA5,1}$	$W_{VA6,1}$	$W_{VA7,1}$	$W_{VA8,1}$
VA2	0	w_{U12}	0	0	$W_{VA1,2}$	$W_{VA2,2}$	$W_{VA3,2}$	$W_{VA4,2}$	$W_{VA5,2}$	$W_{VA6,2}$	$W_{VA7,2}$	$W_{VA8,2}$
VA3	0	w_{U13}	0	0	$W_{VA1,3}$	$W_{VA2,3}$	$W_{VA3,3}$	$W_{VA4,3}$	$W_{VA5,3}$	$W_{VA6,3}$	$W_{VA7,3}$	$W_{VA8,3}$
VA4	0	0	w_{U21}	0	$W_{VA1,4}$	$W_{VA2,4}$	$W_{VA3,4}$	$W_{VA4,4}$	$W_{VA5,4}$	$W_{VA6,4}$	$W_{VA7,4}$	$W_{VA8,4}$
VA5	0	0	w_{U22}	0	$W_{VA1,5}$	$W_{VA2,5}$	$W_{VA3,5}$	$W_{VA4,5}$	$W_{VA5,5}$	$W_{VA6,5}$	$W_{VA7,5}$	$W_{VA8,5}$
VA6	0	0	0	w_{U31}	$W_{VA1,6}$	$W_{VA2,6}$	$W_{VA3,6}$	$W_{VA4,6}$	$W_{VA5,6}$	$W_{VA6,6}$	$W_{VA7,6}$	$W_{VA8,6}$
VA7	0	0	0	w_{U32}	$W_{VA1,7}$	$W_{VA2,7}$	$W_{VA3,7}$	$W_{VA4,7}$	$W_{VA5,7}$	$W_{VA6,7}$	$W_{VA7,7}$	$W_{VA8,7}$
VA8	0	0	0	w_{U33}	$W_{VA1,8}$	$W_{VA2,8}$	$W_{VA3,8}$	$W_{VA4,8}$	$W_{VA5,8}$	$W_{VA6,8}$	$W_{VA7,8}$	$W_{VA8,8}$

In the next step, the matrix is multiplied by itself repeatedly until the row entries converge to a single value. The convergence value represents the value U_{VAi} upon fulfilment of the corresponding value aspect. The value of an application is the sum of all quantified values U_{VAi} for the value aspects that the application fulfils.

4.2 Identification and assessment of effort for data-driven applications

When implementing data-driven applications, the described value must be weighed against the multidimensional implementation effort. The effort involved in data collection, particularly due to the underlying sensors, and the technological requirements are two key dimensions [39]. The effort associated with data-driven applications is subjective for each dimension, as it depends on the company's individual experience, competence, and sensor equipment. The subsequent evaluation results from the individual assessment steps are summed at the end to reflect the overall effort.

4.2.1 Effort for data collection of data-driven applications

From a financial perspective, it is not reasonable to collect all potentially available parameters unless they are actively used to improve processes or products. The identification of the required sensors for each application and the comparison with the company's current state can serve as a metric for assessing the so-called *sensory effort*. In this theoretical part of the methodology, the application-specific sensor identification is carried out at the sensor class level, based on generalisation, and is grounded in a literature review of databases such as Web of Science, Springer Link, and Google Scholar. Users implementing the methodology should conduct a systematic allocation of specific sensors for each application case through comprehensive literature review in scientific databases. The general overview with the sensor classes provides support for assigning the specific sensors to the applications in the use case. The literature review was subject to the requirement that only publications related to (metalworking) manufacturing processes should be considered. The

Table 7 Required sensor classes for the identified applications

		Data-driven applications of a digital twin in the product service phase				
		Service of product quality monitoring and prediction (Service 1)	Service of process monitoring and improvement (Service 2)	Service of energy consumption analysis and forecast (Service 3)	Service of measuring ecological footprint (Service 4)	Service of condition-based and predictive maintenance strategy (Service 5)
Sensor classes	Geometrical	[41]	[42]			
	Time-based	[41]	[42]	[43]	[44]	[45]
	Mechanical	[41]	[42]	[43]	[46]	[45]
	Optical	[47]	[48]			[49]
	Electrical	[41]		[43]	[44]	
	Acoustical	[47]	[50]			[51]

search for suitable publications was based on keywords, which were a combination of the different sensor classes according to Hering and Schönfelder [40] and the identified applications (e.g., Optical Sensors for Quality Monitoring). The results are shown in Table 7.

The listed sources are representative of which sensor classes can be used for which applications. It is to mention that there is no weighting of the importance of the individual sensors for a selected service, nor any indication of whether certain sensor would be sufficient for an application to, for example, predict product quality.

There are scenarios like manufacturing process sequences that rely on complete sensor coverage across multiple manufacturing stages. The produced outcome is influenced by all manufacturing processes involved in a sequence, particularly in terms of quality and sustainability. For instance, the wear of a tool of a fine blanking machine can impact the input geometry of a component to be milled, leading to quality degradation [32]. Therefore, complete process coverage is necessary for *"Service 1"*, *"Service 2"* and *"Service 4"*. In contrast, *"Service 3"* and *"Service 5"* do not necessarily require complete sensor coverage of the process. Maintenance actions directly affect a machine (e.g., by reducing downtime) and indirectly impact the entire production process. The same applies to energy consumption. Even though the entire manufacturing sequence benefits from an increase in energy efficiency, measures to reduce energy consumption focus on individual value-adding stages. The *effort for sensory process coverage* of a manufacturing process sequence is more demanding compared to a partial process, as integrating additional sensors into existing machines is both time- and cost-intensive. Therefore, the *effort for sensory process coverage* across manufacturing sequences must be determined for each value-adding stage involved. The results for each stage are summed across the entire manufacturing process sequence and normalised by the number of process steps involved. It is important to note that for applications requiring sensory process coverage, the *sensory effort* is not considered separately, as it is already included in the *effort for sensory process coverage*.

In addition to the *sensory effort* or *effort for sensory process coverage*, the collection of process performance indicators to assess the process outcome also influences the effort involved in data collection. Without the collection of process performance indicators, applications cannot be implemented or their effectiveness evaluated. Like the *sensory effort*, the *effort of process performance indicators* is determined by comparing the required process performance indicators with the company's current state.

4.2.2 Technological effort of data-driven applications

In addition to the effort involved in data collection, the selection of the most suitable data-driven application is also subject to *technological effort*. In this work, this effort is represented by a company's methodological competence in implementing an application, as well as its experience and willingness to share data beyond its organisational boundaries, since data sharing is necessary for selected applications to realise their value. When considering methodological competence, particular emphasis is placed on data analysis methods from the field of Machine Learning (ML). The company's experience in ML-based data analysis is evaluated using the Technology Readiness Level (TRL) scale. The organisation must assess its ML proficiency across ten evaluation levels. A value of"0"indicates no experience, while a value of"1"signifies that a proven system is already operational in practice. This assessment framework allows for a systematic evaluation of the organisation's ML maturity and practical implementation capabilities. [52]

In addition to data analysis methods, *"Service 4"* requires competence in conducting a LCA according to ISO 14040. This assessment is carried out in four stages:"Defining the scope of the study"(Stage 1),"Compiling an inventory"(Stage 2),"Performing impact assessment"(Stage 3), and"Reducing environmental impacts"(Stage 4) [53]. To evaluate the *effort of an LCA*, the company's experience with the four stages of an LCA according to ISO 14040 is relevant. The stage-specific evaluation scale ranges from 0, indicating a lack of experience, to 1, representing experience in all four phases of a complete LCA as per ISO 14040.

Implementing data-driven applications requires not only methodological competence but also experience and a willingness to share data beyond the company's boundaries. Cross-company data sharing can enable continuous improvement and transparency in products, processes, and their sustainability [54]. The effort related to data sharing stems from the challenges of identifying a suitable cooperation partner and ensuring legal security and data sovereignty [55]. For *"Service 4"*, data sharing is essential [56]. Therefore, evaluating the *data sharing effort* is only relevant for this application.

Data sharing can take different forms. There are manual, paper-based approaches, semi-automated methods with manual steps (e.g., a file attachment in an email), as well as fully automated real-time transmissions [57]. The evaluation of *data sharing effort* is based on these forms, ranging from a score of 0 for the unwillingness to share data, to a score of 1 for automated data sharing. A manual data sharing is rated with a value of 1/3, while semi-automated data sharing is rated with a value of 2/3.

4.3 Comparison of value and effort for selecting the most suitable application

The selection of the most suitable application requires a balance between value and effort. Since value and effort are measured on different scales, a direct comparison is not possible without prior normalisation. Therefore, before the TOPSIS method can be applied, the calculated value and effort scores for each application must be normalised. This is achieved by dividing the calculated value or effort score of an application by the sum of all value or effort scores across all applications.

The purpose of normalisation is twofold. Firstly, it ensures that the results for value and effort are comparable, regardless of their original measurement units. It can be interpreted within a standardised range. Secondly, it prevents disproportionate influence of any single application on the final ranking by scaling all values to a standardised range between 0 and 1. The values "0" and "1" serve as extreme reference points for value and effort. The maximum value or minimum effort is represented by "1", indicating the ideal application. The minimum value or maximum effort is represented by "0", marking the least favourable application.

After normalisation, the TOPSIS method is used to determine a ranking of the most suitable applications for a company by calculating the distance measure C_i^*. The required Euclidean distances D_i^+ and D_i^- represent the previously determined normalised value U_i and normalised effort A_i of the i-th application.

$$D_i^+ = \sqrt{\left(1 - \mathrm{U_i}\right)^2 + \left(1 - \mathrm{A_i}\right)^2} \tag{4.6}$$

$$D_i^- = \sqrt{\left(0 - \mathrm{U_i}\right)^2 + \left(0 - \mathrm{A_i}\right)^2} \tag{4.7}$$

The distances are calculated in a two-dimensional space, where the x-axis represents effort and the y-axis represents value. The ideal application (highest value, lowest effort) is located at (1,1), while the least favourable application (lowest value, highest effort) is located at (0,0). These reference points ensure a structured ranking, allowing decision-makers to prioritise applications that provide the highest value with the least effort.

5 Application of the methodology

The following section applies the developed methodology to a fictional example of a manufacturing process sequence for producing gears. This sequence consists of the value-adding stages of fine blanking, grinding, and milling [32]. For the determination of the value, the company's preferences regarding the value categories are first recorded. In this example, the fulfilment of regulatory requirements is more important to the company than process quality. Product quality and regulatory requirements are prioritised equally (Table 8). Additionally, the VA within each category are compared in terms of the company's preferences (Table 9 illustrates this for the VA of the value category product quality). The same approach applies to the VA of the other categories but is not explicitly shown.

Table 8 Pairwise comparison of the value categories (C)

	Product quality	Process quality	Fulfilment regulatory requirements
Product quality	(1,1,1)	(3,4,5)	(1,1,1)
Process quality	(1/5,1/4,1/3)	(1,1,1)	(1/6,1/5,1/4)
Fulfilment regulatory requirements	(1,1,1)	(4,5,6)	(1,1,1)

The creation of priority vectors is based on calculating the geometric mean of each pairwise comparison of the VA categories and the VA. The geometric mean $\mathrm{r_{U1,1}}$ for the first row of the results of Table 9 is calculated as follows:

$$\mathrm{r_{U1,1}} = \left(\prod_{n=1}^{s} \mathrm{a_{ij}}\right)^{\frac{1}{s}} = \left(1 \bullet \frac{1}{5} \bullet \frac{1}{4}\right)^{\frac{1}{3}}, \left(1 \bullet \frac{1}{4} \bullet \frac{1}{3}\right)^{\frac{1}{3}}, \left(1 \bullet \frac{1}{3} \bullet \frac{1}{2}\right)^{\frac{1}{3}} = (0.37, 0.44, 0.55) \tag{5.1}$$

The whole evaluation matrix U1 $\mathrm{r_{U1}}$ is as follows:

$$\mathrm{r_{U1}} = \begin{pmatrix} 0.37 & 0.44 & 0.55 \\ 1.44 & 1.59 & 1.71 \\ 1.26 & 1.44 & 1.59 \end{pmatrix} \tag{5.2}$$

After column-wise normalisation of $\mathrm{r_{U1}}$, the following applies:

$$\mathrm{r_{U1,normalized}} = \begin{pmatrix} 0.12 & 0.13 & 0.14 \\ 0.47 & 0.46 & 0.44 \\ 0.41 & 0.42 & 0.41 \end{pmatrix} \tag{5.3}$$

The priority vector $\mathrm{w_{U1}}$ is obtained after defuzzification:

$$\mathrm{w_{U1}} = \begin{pmatrix} 0.13 \\ 0.457 \\ 0.413 \end{pmatrix} \tag{5.4}$$

After calculating these vectors, the supermatrix is constructed (Table 10). The priority vector of the evaluation matrix of the VA categories is marked in red, the priority vector of the VA of the category product quality in blue, the priority vector of the VA of the category process quality in green, and the priority vector of the VA of the category fulfilment of requirements in yellow. The quantified interdependencies of the VA, which are outlined in black, are displayed.

The created supermatrix is raised to a power to solve the ANP, until the row entries of the value aspects converge. A matrix power is the result of repeated matrix multiplication.

Thus, the matrix is multiplied by itself until convergence of the entries in rows VA1 to VA8 is achieved. In this example, ten iterations were required to calculate the value of the individual value aspects. The converged supermatrix (limitmatrix) is shown below (Table 11).

The evaluated value of the individual VA is normalised and can be derived. To determine the value for each use case, the quantified value of the relevant VA influenced by the applications is added. For the quantification of the effort, it is assumed that only time series data from the grinding process is available.

In Table 12, the comparison of the actual data basis with the required target state for each application is shown (*sensory effort*).

To represent the *effort for sensory process coverage*, for all applications requiring data collection from the entire manufacturing process chain, the ratio of collected to required data from the *sensory effort* study is considered. Since no data is recorded for the fine blanking and milling process steps, the *sensory effort* for these applications is multiplied by "1/3" to represent the *effort for sensory process coverage* (Table 13).

Table 9 Pairwise comparison of the value aspects of the category product quality (U1)

	Improvement product quality	Minimisation quality fluctuations	Improved quality control
Improvement product quality	(1,1,1)	(1/5, 1/4, 1/3)	(1/4,1/3,1/2)
Minimisation quality fluctuations	(3,4,5)	(1,1,1)	(1,1,1)
Improved quality control	(2,3,4)	(1,1,1)	(1,1,1)

Table 10 Supermatrix in this example

	Goal	K1	K2	K3	VA1	VA2	VA3	VA4	VA5	VA6	VA7	VA8
Goal	0	0	0	0	0	0	0	0	0	0	0	0
K1	0.432	0	0	0	0	0	0	0	0	0	0	0
K2	0.102	0	0	0	0	0	0	0	0	0	0	0
K3	0.466	0	0	0	0	0	0	0	0	0	0	0
VA1	0	0.13	0	0	0	0.171	0.199	0.060	0.060	0.060	0.060	0.349
VA2	0	0.457	0	0	0.249	0	0.199	0.349	0.349	0.349	0.060	0.060
VA3	0	0.413	0	0	0.249	0.171	0	0.060	0.060	0.060	0.349	0.349
VA4	0	0	0.743	0	0.063	0.171	0.068	0	0.349	0.060	0.060	0.060
VA5	0	0	0.257	0	0.063	0.171	0.068	0.349	0	0.060	0.060	0.060
VA6	0	0	0	0.271	0.063	0.171	0.068	0.060	0.060	0	0.349	0.060
VA7	0	0	0	0.608	0.063	0.072	0.199	0.060	0.060	0.349	0	0.060
VA8	0	0	0	0.121	0.249	0.072	0.199	0.060	0.060	0.060	0.060	0

Table 11 Limitmatrix in this example

	Goal	K1	K2	K3	VA1	VA2	VA3	VA4	VA5	VA6	VA7	VA8
Goal	0	0	0	0	0	0	0	0	0	0	0	0
K1	0	0	0	0	0	0	0	0	0	0	0	0
K2	0	0	0	0	0	0	0	0	0	0	0	0
K3	0	0	0	0	0	0	0	0	0	0	0	0
VA1	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123
VA2	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185
VA3	0.154	0.154	0.154	0.154	0.154	0.154	0.154	0.154	0.154	0.154	0.154	0.154
VA4	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106
VA5	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106
VA6	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106
VA7	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108
VA8	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100

Table 12 Sensory effort in this example

	Service of product quality monitoring and prediction (Service 1)	Service of process monitoring and improvement (Service 2)	Service of energy consumption analysis and forecast (Service 3)	Service of measuring ecological footprint (Service 4)	Service of condition-based and predictive maintenance strategy (Service 5)
Share captured data	3/5	4/5	1	1	2/4

Table 14 Effort of process performance indicators in this example

	Service of product quality monitoring and prediction (Service 1)	Service of process monitoring and improvement (Service 2)	Service of energy consumption analysis and forecast (Service 3)	Service of measuring ecological footprint (Service 4)	Service of condition-based and predictive maintenance strategy (Service 5)
Share captured indicators	1/3	2/4	1	1	2/3

In the final part of the effort for data collection, the *effort of process performance indicators* is represented by comparing the collected indicators with the required ones for each application (Table 14).

The technological effort requires querying the capabilities and experience related to ML methods. The organisation reports a Technology Readiness Level (TRL) of 3, indicating they possess theoretical knowledge and experimental experience in data analysis through proof-of-concept implementations. Regarding the life cycle assessment, the company indicates that in past projects, it has only defined the study framework (Stage 1 of ISO 14040). All results of the method-based effort are shown in Table 15. Finally, the willingness and competence in data sharing are examined. The grinding company practises a manual data sharing with other participants in the value chain. This effort is quantified with a value of 1/3.

To identify the best application of the digital twin in the product service phase for the grinding company, the results of the value and effort quantification are combined after a normalisation. Normalisation represents the total value or effort of an application in relation to the sum of the total value or effort across all applications. As defined in Chapter 4, the highest value or lowest effort is represented by “1”. This facilitates the graphical representation of the TOPSIS analysis results. The ideal application would be positioned at the top right corner, while the least favourable application would be represented by the tuple (0,0).

The calculation of the Euclidean distance of the considered value and effort of an application from the theoretically best and worst value and effort using TOPSIS is required to calculate the distance measure C_i^*. This distance measure helps rank the data-driven applications. The value-effort pairs for each application (blue points) and the distances to the positive ideal solution and the negative ideal solution (light blue lines) can be graphically represented. In Fig. 2, the individual applications are shown as blue points, while the positive ideal solution is marked in green and the negative ideal solution in red.

The final ranking of the applications for the given context of the fictional example is shown in Table 16. The *"Service of product quality monitoring and prediction (Service 1)"* appears to be the most suitable application in terms of the value-effort ratio.

6 Conclusion and discussion of the results

This work presented a value-effort-oriented decision model designed to enable companies to select the most suitable digital twin application in the product service phase for their specific needs, based on the underlying time series data. The approach addresses the challenge that companies often cannot quantify economic value or costs in advance, making it difficult to decide on the most appropriate application purely based on monetary metrics. By applying a data-to-value

Table 13 Effort for sensory process coverage in this example

	Fineblanking	Grinding	Milling	Sum	Effort for sensory process coverage
Service of product quality monitoring and prediction (Service 1)	0	3/5	0	3/5	$\frac{1}{3} \bullet \frac{3}{5} = \frac{3}{15}$
Service of process monitoring and improvement (Service 2)	0	4/5	0	4/5	$\frac{1}{3} \bullet \frac{4}{5} = \frac{4}{15}$
Service of measuring ecological footprint (Service 4)	0	1	0	1	$\frac{1}{3} \bullet 1 = \frac{1}{3}$

Table 15 Overview of the efforts in this example

	Sensory effort	Effort sensory process coverage	Effort process performance indicators	Effort ML method	Effort LCA	Effort data sharing	Sum
Service of product quality monitoring and prediction (Service 1)	-	3/15	1/3	4/10	-	-	0.933
Service of process monitoring and improvement (Service 2)	-	4/15	2/4	4/10	-	-	1.166
Service of energy consumption analysis and forecast (Service 3)	1	-	1	4/10	-	-	2.400
Service of measuring ecological footprint (Service 4)	-	1/3	1	-	1/4	1/3	1.916
Service of condition-based and predictive maintenance strategy (Service 5)	2/4	-	2/3	4/10	-	-	1.566

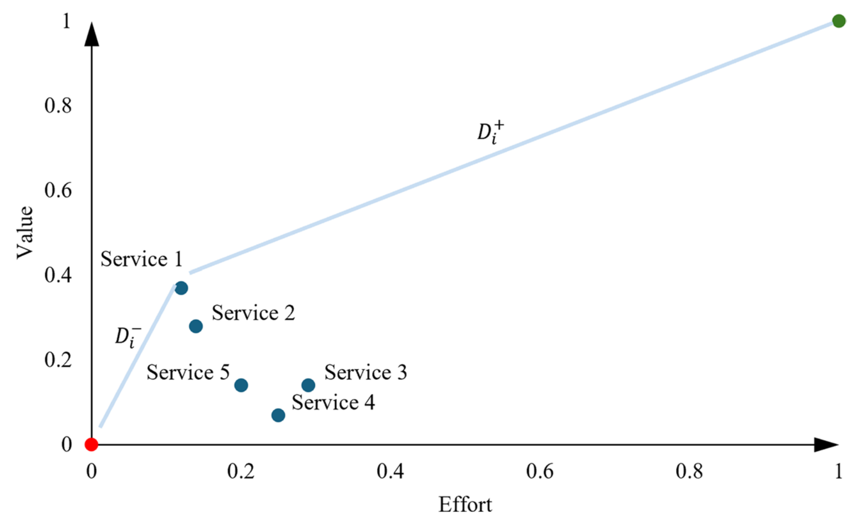

Fig. 2 Results of TOPSIS in this example

Table 16 Ranking of the applications in this example

	Service of product quality monitoring and prediction (Service 1)	Service of process monitoring and improvement (Service 2)	Service of energy consumption analysis and forecast (Service 3)	Service of measuring ecological footprint (Service 4)	Service of condition-based and predictive maintenance strategy (Service 5)
C^*	0.25	0.22	0.22	0.18	0.21
Ranking	1	3	2	4	5

strategy, the proposed model aims to bridge the gap between data collection and utilisation, unlocking the full potential of digital twins. Additionally, the model enables scenario simulation to explore how different data availability, methodological knowledge, or expanded application areas affect value and effort assessments.

While the proposed decision model offers a structured approach to application selection, several limitations need to be considered. The method and evaluation results rely on expert-based weightings, which can introduce bias and variability. Incorporating quantitative KPI, such as production efficiency gains or energy savings, could provide a more objective assessment. However, deriving such benchmarks requires broader adoption of digital twin applications beyond the pilot stage. Another limitation is that the model currently does not incorporate implementation costs, which could play a crucial role in decision-making. Integrating rough monetary value and cost estimations could enhance its practical applicability by allowing companies to make more informed investment decisions. Additionally, the decision model assumes sufficient and high-quality time series data, which may not always be available in practice. Data incompleteness or inaccuracy could significantly affect the reliability of the model's recommendations. To address this, future research should explore integrating a data quality assessment into the decision model to ensure that selected applications are supported by reliable input data.

The proposed approach can be expanded both in terms of the data considered and the application cases. Following the approach of Kreutzer [6], the scope could be extended to include field data. Accordingly, the number of value aspects and the interactions to be considered would need to be adjusted. If new application cases are added, it is necessary to evaluate whether additional data collection or technological efforts should be included and whether new value aspects need to be defined. It may also be worth considering adjusting the value and effort scales based on the economic impact of the monetary benefits and costs, to provide a more realistic recommendation for an application. However, this would require knowledge or at least a rough estimation of the monetary consequences of each application.

Building on the results of this paper, further steps can be taken towards data assessment. With an understanding of the most suitable application in terms of the value-effort ratio, reviewing the quality of the underlying data set and evaluating which manufacturing technology target features should be prioritised would be the next steps to further enhance the value of the company's data.

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Declarations We, the authors, confirm that this submission adheres to the ethical standards of the Journal of Production Engineering. This work is original and has not been published or submitted elsewhere. All sources are properly cited. All listed authors have made significant contributions to the research and take responsibility for its content. No inappropriate authorship has been included. The data presented is accurate, transparent, and free from manipulation. No conflicts of interest exist that could influence the objectivity of this work. The research involving humans has received necessary ethical approval. By submitting this manuscript, we affirm that all ethical guidelines have been followed.

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