

**Data-based Residence Time Estimation for Continuous Process
Data Series Based on the Example of a Sinter Plant for the
Prediction of Return Fines**

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–Empirie–

„Empirie w [von griech. empeiria = Erfahrung; Adj. empirisch], Erfahrung, Beobachtung, der Bereich wissenschaftlicher Forschung, der im Gegensatz zur Theorie mit Beobachtung, Messung oder Experiment, d.h. mit der Gewinnung von Daten, befasst ist. [...]“ [2]

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List of Symbols

Abbreviations

AI	Abrasion Index
BF	Blast Furnace
BF-BOF	Blast Furnace-Basic Oxygen Furnace
BF-RF	Blast Furnace Return Fines or Finished Sinter
BFI	VDEh Betriebsforschungsinstitut GmbH
BTP	Burn Through Point
CB	Coke Breeze
CFD	Computational Fluid Dynamics
CMOS	Complementary Metal Oxide Semiconductor
CRF	Cold Return Fines
CSV	Comma-separated Values
DB	Database
DCS	Distributed Control System
DEM	Discrete Element Modelling
DK	DK Recycling und Roheisen GmbH
DM	Drum Mixer
DRI	Direct Reduced Iron
DWMTM	Double-Window-Modified Trimmed Mean Filter
ELM	Extreme Learning Machine
EU	European Union
FS	Finished Sinter or BF-Sinter
HBI	Hot Briquetted Iron
HC	Hot Crusher
HL	Hearth Layer
HRF	Hot Return Fines
IG	Ignition Hood
IRF	Internal Return Fines
ISO	International Organisation for Standardisation
IT	Information Technology
KI	Künstliche Intelligenz
KPI	Key Performance Indicator
LSTM	Long Short-Term Memory
MAD	Median Absolute Deviation
MinSiDeg	Minimise Sinter Degradation between sinter plant and blast furnace exploiting embedded real-time analytics
ML	Machine Learning
MLR	Multi Linear Regression

MPS	Mean Particle Size
MQTT	Message Queuing Telemetry Transport
MSE	Mean Squared Error
NN	Neural Network
PLC	Programmable Logic Controllers
PM	Post Meridiem
PSD	Particle Size Distribution
RDI	Reduction Degradation Index
RFCS	Research Fund for Coal and Steel
RFID	Radio-Frequency Identification
RM1	Raw Mix, including iron ore
RM2	RM1 + CB + IRF + BF-RF
RMH	Raw Mix Bunker
RNN	Recursive Neural Network
RSE	Residual Standard Error
RSS	Residual Sum of Squares
RSS	Residual Sum of Squares
RT	Residence Time
RTD	Residence Time Distribution
RTE	Residence Time Estimation
SC	Sinter Cooler
SF	Sinter Fines
SM	Sinter Machine
SQL	Structured Query Language
SVR	Support Vector Regression
TDE	Time Delay Estimation
TI	Tumbler Index
TKSE	Thyssenkrupp Steel Europe
TSS	Total Sum of Squares
UTC	Coordinated Universal Time
VASD	voestalpine Stahl Donawitz GmbH
VIF	Variance Inflation Factor
VM	Virtual Machine
VPN	Virtual Private Network
WB	Wind Box

Latin Symbols

a	Variable to vary time lag τ
b	Factor to modify the width of the confidence interval
c_n	Correction factor, $c_n = 1.483$
$\mathbf{d}$	Specific sinter plant distance scalar vector
$D(x)$	Passing through Fraction
$\mathbf{ds}$	Strand length vector, Δ distance in m
$\mathbf{dt}$	Residence time vector, Δ time in mm:ss
E	Expected value
h	Tolerance variable

H_a	Alternate Hypothesis
H_0	Null Hypothesis
I_t	Values in moving window inside confidence interval
k	Window width
$\mathbf{M}$	Matrix
$m, \tilde{m}$	Window parameter, to adjust window width, $\tilde{m} = m$ in symmetric retrospective and $\tilde{m} = 0$ in online case
$max.$	Maximum
min	Minute
$min.$	Minimum
off	Offset
Pos	Position
$Q(x)$	Cumulative distribution
$q(x)$	Density distribution
q_t	Confidence interval
R	Rotation
$\hat{R}$	Rotation estimate
R^2	R-squared, Coefficient of determination
$Ref.$	Reference
$\rho_{(X,Y)}$	Pearson Correlation Coefficient
$\rho_x(\tau)$	Auto Correlation
$\rho_{x,y}(\tau)$	Cross-Correlation
$r_{SC,i}$	Sinter cooler rotation at time i
$R_{SC,i}$	Cumulative sum of sinter cooler rotations at time i
$\hat{RT}$	Residence time estimate
s	Distance
SE	Standard Error
S_i	Cumulative sum of distance (strand length) at time i
sig	Signal
$SR(x)$	Screen retention
t	Time
$\mathbf{t}$	Time vector
t'	Reference time, $t_i + off$
t''	Corresponding time to sinter strand length ($\mathbf{ds}$)
t_s	Sample period s
v	Velocity
v_i	Strand speed at time i in m/min
$w_t^{m,\tilde{m}}$	time window, from m to $\tilde{m}$
w	Window
X	Predictor variable, Attributes, Independent variable
$\mathbf{X}$	Matrix
x	x value, real
$\bar{x}$	Mean of x values
Y	Response variable, Target variable, Dependent variable
y	y value, real
$\bar{y}$	Mean y values

$\hat{y}$	y value, predicted
z	z-score

Greek Symbols

β_0	Intercept, Regression coefficient
β_j	Slope, Regression coefficient
ϵ	Error term
η_{CO}	eta-CO, BF efficiency, utilisation of CO in %
μ	Mean, cf. $\bar{x}$ or $\bar{y}$
$\tilde{\mu}_t$	Moving median
ν	Measuring noise
ρ	rho, Pearson Correlation Coefficient or Linear Correlation Coefficient
σ	Standard Deviation
$\tilde{\sigma}$	Estimated Standard Deviation
σ_t^M	Moving confidence interval
σ^2	Variance
τ	Lag
$\hat{\tau}$	Lag estimate

Index

Corr	Correlation function
downstream SC	downstream SC positions
Feed	Feed position SM
i	Index
in	Input
j	Dimension, Attribute, Predictor
max.	Maximum
min.	Minimum
mov	Moving, running
out	Output
p	Predictor
Pos	Position
r	Index of distribution, $r = 3$ for volume or mass distribution
Ref.	Reference
RT	Residence Time
s	Seconds
Set	Data Set
t	Time
total	total Residence Time
upstream SC	upstream SC positions
x	x values
y	y values

Abstract

The dominant crude steel production method is still the integrated Blast Furnace-Basic Oxygen Furnace (BF-BOF) route which accounts for 71% of worldwide crude steel production. Iron ore sinter is one of the most important iron sources within this process. Iron ore fines have to be agglomerated from dust to $\varnothing$ 5–50 mm particles. Inside the BF-BOF route, sinter plants offer, besides pelletising, the unique capability to recycle residues and agglomerate fines from iron ores for the hot metal production to ensure the required gas permeability in the BF. The production of high-quality, cost-effective, and environmentally friendly sinter is of great economic and environmental significance in the context of hot metal production. Transport and storage degrade sinter quality, generating fines and segregation effects. The raw material must pass through various process steps during the sinter production and is therefore subject to diverse influences such as mixing, agglomeration, feeding, ignition, sintering, crushing, cooling, and screening, before it is provided as finished product to the BF, thereby making material (sinter) tracking impossible. The physical sinter quality values cannot be calculated or tested online; they are obtained through manual testing. The results of these tests take hours to reach the operator, which means that the operation relies on the operator's experience. As a result, the sinter process can be in a disadvantageous state over long time periods associated with high emissions, low efficiency, and large fluctuations in product quality. Consequently, it is necessary to investigate methods for predicting sinter quality online. Fortunately, due to the large-scale application of Programmable Logic Controllers (PLC) and Distributed Control Systems (DCS), it is easy to obtain parameters such as temperature, pressure, and mass flow of the sinter process. Unfortunately, the data collected by PLC and DCS are stored synchronously and chronologically and, hence, do not correspond to the same product unit of sinter material. Various model approaches were developed to describe key values of the sinter process. A key challenge in the prediction of sinter quality originates from the differences in Residence Time (RT) of the various grain fractions of the produced sinter as it passes the sinter plant. Furthermore, these Residence Time Distributions (RTD) vary in time due to disturbances and the dynamical operation of the production process. The current state of the art for determining RTD, e.g. in flow cells, is based on mathematical models that are validated by tracer tests. In sinter plants, the application of RFID tracers is constrained by process temperatures reaching up to 1450 °C. Alternative tracer techniques, such as particle colouring, are applicable only to coarse fractions to ensure reliable recovery of the coloured particles. However, numerous studies show that temporal alignment of time series data is a challenge for obtaining reliable model results. Some of these studies try to overcome the RT problem with Neural Network (NN) models, so-called "black box" models, which optimise the time allocation in the neurons in the hidden layers of the model, but are difficult to interpret. Other studies use manually labelled data at low sampling rates over extended periods, resulting in poor short-term response or restriction to a single process location.

A new method to overcome the missing temporal alignment of time series is presented in

this thesis. The major focus is the development of a Residence Time Estimation (RTE) procedure to align the measuring values to the sinter mass, enabling Machine Learning (ML) methods and tracking of the sinter material. The estimation method is developed on sinter plant data series, examined during the EU RFCS MinSiDeg research project. The RT of the sinter material is determined from a combination of static, dynamic, and estimated RT, depending on the process section of the sinter plant. During the passage of the Sinter Cooler (SC), the sinter material is subjected to a variety of influences, including e.g., mixing and segregation. These influences significantly impact the particle flow and, consequently, the RT, which is therefore challenging to determine. During the conveying process and at transfer points, as well as within the sinter shaft cooler, the RTs are distributed among the particle sizes as a result of segregation effects.

The data-based RTE approach, which was developed in this work, uses the input variables consisting of measured values (predictors) and the target variable representing a sinter quality index (response) in order to find an optimum of prediction accuracy depending on the RT. The predictors with a known time label are used to predict the target variable with an unknown time label. Therefore, an analogous approach to the cross-correlation is applied to iteratively calculate the accuracy of the predicted target value in dependence on the predictors over a range of RT estimates. The optimum (best match) in prediction accuracy development indicates the unknown RT. The correlation function within the developed method is an Artificial Intelligence (AI¹) model, in contrast to the ordinary cross-correlation function. The introduced method is applied to sinter plant data series with the objective of estimating the RTD of fines fractions over the SC with an unknown RT. In a use case, the temporally aligned dataset is used to predict the Cold Return Fines (CRF) amount (response variable). This opens up new possibilities for optimising the efficiency of sinter production and Blast Furnace (BF) operation, as material tracking allows more accurate identification of sources of error along the production chain and provides quality indicators with a shorter time delay compared to conventional quality monitoring. The estimation of RTD is obtained from two datasets (median RT of 52 and 73 minutes) utilising the novel approach. The application of a Multiple Linear Regression (MLR) model to the temporally aligned sets resulted in a prediction accuracy of up to $R^2 = 0.60$ on unseen data (test set). As a result, the CRF can be predicted at the hot crusher with a time advantage of 52 and 73 minutes respectively, before the finished sinter leaves the sinter plant. This can optimise the efficiency of sinter production and BF operation by increasing the amount of optimal particle size distribution (5–50 mm). The amount of sinter fines is reduced, which could cause local clogging and thereby reduce permeability in the BF, which can lead to problems in blast furnace operation. Besides massive savings in energy and CO₂ emissions, a reduction of return fines of only 1% would result in annual savings of 18.6 million € in the EU. The new data-driven approach is using existing and new measurement techniques, leveraging big data technologies and ML approaches. The research was structured around implementing new sinter quality measuring methods, data pre-processing, and the formulation of the RTE method. It also included ML model creation, training, development, and the validation of a new method for predicting sinter quality. Since there does not exist a systematic and well-parametrisable approach in data science for the estimation of distributed RTs, this is a significant improvement in analysing this kind of process.

¹In the remainder of this thesis, the abbreviation 'AI' will be referred to as the Abrasion Index.

Kurzfassung

Die dominierende Prozessroute der Rohstahlerzeugung ist nach wie vor die integrierte Hochofen-Konverter-Route mit einem Anteil von 71 % an der weltweiten Rohstahlerzeugung. Eisenerzfeinanteile müssen vor dem Hochofeneinsatz zu Partikeln mit $\varnothing$ 5–50 mm agglomeriert werden. Eisenerzsinter ist neben Eisenerzpellets eine der wichtigsten Eisenquellen in diesem Verfahren, um die notwendige Permeabilität im Hochofen zu gewährleisten. Innerhalb der Hochofen-Konverter-Route (kurz Hochofenroute) bieten Sinteranlagen die einzigartige Möglichkeit, eisenhaltige Reststoffe und Feinanteile aus Eisenerzen für die Stahlerzeugung zu recyceln und zu agglomerieren. Die Herstellung von qualitativ hochwertigem, kostengünstigem und umweltfreundlichem Sinter ist für die Eisenerzeugung von großer wirtschaftlicher und ökologischer Bedeutung. Transport und Lagerung verschlechtern die Sinterqualität und führen durch Kornzerfall zu Feinanteilen und Entmischungseffekten. Das Rohmaterial durchläuft bei der Sinterherstellung verschiedene Prozessschritte und ist dabei unterschiedlichen Einflüssen wie Mischen, Agglomerieren, Zuführen, Zünden, Sintern, Brechen, Kühlen und Sieben ausgesetzt, bevor es als Fertigprodukt zum Hochofen transportiert wird. Die physikalischen Sinterqualitätskennzahlen können nicht online berechnet oder überprüft werden, sondern sie werden durch manuelle Prüfungen ermittelt. Es dauert Stunden, bis der Bediener die Ergebnisse dieser Tests erhält, und währenddessen hängt die Prozesssteuerung von der Erfahrung des Bedieners ab. Dies hat zur Folge, dass sich der Sinterprozess über lange Zeiträume hinweg in einem ungünstigen Zustand befinden kann, der mit hohen Emissionen, geringer Effizienz und großen Qualitätsschwankungen verbunden ist. Daher ist es notwendig, Methoden zur Vorhersage der Sinterqualität zu entwickeln. Glücklicherweise ist es durch den weit verbreiteten Einsatz von Steuerungssystemen wie DSC (Distributed Control System) und PLC (Programmable Logic Controller) einfach, Parameter wie Temperatur, Druck und Massenstrom des Sinterprozesses zu erfassen. Leider werden die von DCS und PLC erfassten Daten synchron und chronologisch gespeichert und beziehen sich daher nicht auf dieselbe Sinterprodukteinheit. Zur Bestimmung der Kennzahlen des Sinterprozesses wurden verschiedene Modellansätze entwickelt. Eine wesentliche Herausforderung bei der Bestimmung der Sinterqualität ergibt sich aus den unterschiedlichen Verweilzeiten der verschiedenen Kornfraktionen des produzierten Sinters, während er die Sinteranlage passiert. Darüber hinaus variieren diese Verweilzeitverteilungen im Laufe der Zeit aufgrund von Störungen und dynamischen Vorgängen im Produktionsprozess. Untersuchungen haben jedoch gezeigt, dass die zeitliche Ausrichtung von Zeitreihendaten (Material und Messwerte) eine Herausforderung darstellt, um zuverlässige Modellergebnisse zu erhalten. Einige Studien versuchen, das Problem der unbekannten Verweildauer mit Neuronalen Netzwerkmodellen, sogenannten „Black-Box-Modellen“, zu lösen, die die Zeitzuweisung in den Neuronen der verborgenen Schicht der Modelle optimieren, allerdings sind diese schwer zu interpretieren. Andere Studien verwenden manuell zugewiesene Daten (mit niedrigen Abtastraten) über lange Zeiträume mit geringer Aussagekraft für fluktuierende Effekte oder sind auf einen bestimmten Ort (Prozessschritt) beschränkt.

In dieser Arbeit wird eine neue Methode zur Überwindung der fehlenden zeitlichen Zuordnung von Zeitreihen vorgestellt. Der Schwerpunkt liegt dabei auf der Entwicklung eines Verfahrens zur Verweilzeitschätzung (Residence Time Estimation, RTE), um datenbasierte Methoden, maschinelle Lernverfahren (ML) und die Materialverfolgung zu ermöglichen. Das Schätzverfahren wird anhand von Datenreihen einer Sinteranlage entwickelt, die im Rahmen des EU RFCS Forschungsprojekts MinSiDeg untersucht wurde. Die Verweilzeit des Sintermaterials wird dabei aus einer Kombination von statischer, dynamischer und geschätzter Verweilzeit in Abhängigkeit von den Prozessabschnitten der Sinteranlage bestimmt. Während des Durchlaufs durch den Sinterkühler (Sinterschaftkühler) ist das Sintergut einer Vielzahl von Einflüssen ausgesetzt, z. B. Vermischung und Entmischung. Diese Einflüsse haben einen erheblichen Einfluss auf den Partikelstrom und damit auf die Verweilzeit, die daher schwer zu bestimmen ist. Während des Transportprozesses, an den Übergabestellen sowie innerhalb des Sinterschaftkühlers, verteilt sich die Verweilzeit aufgrund von Entmischungseffekten auf die Partikelgrößen.

Der in dieser Arbeit entwickelte datenbasierte RTE-Ansatz verwendet die Prozessmesswerte als Eingangsgrößen (unabhängige Variablen) und einen Sinterqualitätskennwert als Zielgröße (abhängige Variable), um ein Optimum der Vorhersagegenauigkeit in Abhängigkeit von der Verweilzeit zu finden. Die unabhängigen Variablen mit bekannter Verweilzeit werden zur Vorhersage der abhängigen Variablen mit unbekannter Verweilzeit verwendet.

Dazu wird ein analoger Ansatz zur Kreuzkorrelation verwendet, um die Zielgröße iterativ über einen Bereich von Verweilzeitschätzungen zu berechnen und das Optimum (beste Übereinstimmung) in dem Verlauf der Vorhersagegenauigkeit zu finden, das auf die unbekannte Verweilzeit hinweist. Im Gegensatz zur gewöhnlichen Kreuzkorrelation nutzt die entwickelte Methode ein Modell der Künstlichen Intelligenz (KI) als Korrelationsfunktion. Die vorgestellte Methode wird zur Abschätzung der Verweilzeitverteilung des Sinterrückguts (Feinanteils) im Sinterkühler bei unbekannter Verweilzeit angewendet. Im Anschluss werden die zeitlich zugeordneten Daten in einem Anwendungsfall zur Vorhersage der Kaltrückgutmenge (Qualitätskennwert und Zielgröße) verwendet. Die Schätzung der Verweilzeitverteilungen wurde anhand zweier Datensätze (Medianverweilzeit von 52 und 73 Minuten) unter Verwendung des neuen Ansatzes ermittelt. Die Anwendung eines Multiplen Linearen Regressionsmodells (MLR) auf die zeitlich ausgerichteten Datensätze führte zu einer Vorhersagegenauigkeit von bis zu $R^2 = 0,60$ an unbekannten Daten (Testdaten). Dadurch kann die Kaltrückgutmenge mit einem Zeitvorteil von 52 bzw. 73 Minuten bereits am Stachelbrecher vorhergesagt werden, bevor der fertige Sinter die Sinteranlage verlässt. Dadurch ergeben sich neue Möglichkeiten zur Optimierung der Effizienz der Sinterproduktion und des Hochofenbetriebs, da einerseits Fehlerquellen durch die Materialverfolgung entlang der Prozesskette besser lokalisiert werden können und andererseits die Qualitätskennzahl mit geringerer zeitlicher Verzögerung als bei der konventionellen Probenahme zur Verfügung steht. Dies kann dazu beitragen, die für den Hochofenbetrieb optimale Korngrößenverteilung (5–50 mm) zu erhöhen, indem die Menge an Sinterfeinanteil, die zu einer lokalen Permeabilitätsminderung im Hochofen führen kann, reduziert wird. Neben massiven Einsparungen an Energie und CO₂ Emissionen würde eine Reduzierung des Sinterrückguts (Feinanteil) um nur 1 % zu jährlichen Einsparungen von 18,6 Mio. € in der EU führen. Der neue datengestützte Ansatz nutzt dazu bestehende und neu entwickelte Messtechniken unter Verwendung von Big-Data-Technologien und ML-Ansätzen.

Da es in der Datenwissenschaft keinen systematischen und gut parametrisierbaren Ansatz zur Schätzung verteilter Verweilzeiten gibt, stellt dies eine wesentliche Verbesserung der

Analyse dieser Prozessarten dar. Der derzeitige Stand der Technik beruht auf der Schätzung der Verweilzeitverteilung (RTD) auf der Grundlage mathematischer Modelle, die durch Tracerverfahren in Durchflusszellen validiert werden.

1 Introduction

Steel making using the integrated Blast Furnace-Basic Oxygen Furnace (BF-BOF) process route is still the dominant crude steel production method (71% of worldwide crude steel production in 2022 [3]), and iron ore sinter is one of the most important iron sources besides iron ore pellets, and lump ore [4] within this process. Iron ore pellets are also used in the production of Direct Reduced Iron (DRI) and Hot Briquetted Iron (HBI) [5]. The iron and steel industry is one of the energy-intensive industries. Energy consumption and emissions from the steel industry account for a substantial proportion of the emissions emitted by the industry worldwide [6], responsible for over a quarter of the industry's carbon dioxide (CO₂) emissions [7]. Iron ore fines have to be agglomerated from dust to Ø 5–50 mm particles to ensure the required gas permeability in the BF. Inside the BF-BOF route, sinter plants offer unique capability to recycle residues and agglomerate fines from iron ores for the hot metal production by agglomerating the fines to the desired particle size. The production of high-quality, cost-effective, and environmentally friendly sinter is of great economic and environmental significance in the context of iron production [8].

Along the iron and steel industry, iron ore deposits are becoming increasingly scarce and are therefore exposed to fluctuations in quality and chemical composition due to the varying raw material structure of the different mining areas, as well as other raw materials used. Due to the intensive material supply for sinter plants, this has a strong impact on product quality and energy consumption [1].

The current iron and steel industry is still at a low level of automation and digitalisation, which causes many problems. For example, during the production process, it is difficult to obtain key information and develop process control models. Process control is still, in most cases, based on the empirical experience of plant operators. Thus, the product quality and processing conditions are unstable [6]. Maintenance and sinter quality management have also not evolved to an Industry 4.0 standard and are still under manual control. The current industrial practice to monitor the physical sinter quality is still primarily based on sampling. The sampling method is slow and costly due to its manual laboratory analysis, particularly in view of the Tumbler Index (TI) and screening analysis for determining the Particle Size Distribution (PSD) of the processed material and is unable to reflect fluctuations in the reaction of the raw material or process changes [9].

The sinter process provides raw materials for subsequent Blast Furnace (BF) ironmaking and determines the quality basis of subsequent processes. If the quality of iron ore sinter is poor and fluctuates strongly, the smelting process of BF will be strongly affected, such as unstable working conditions and poor hot metal quality [6].

Due to rising prices and limited availability of high-quality ores, the European steel industry is under increasing pressure to use ores of lower quality (e.g. Fe content, gangue, PSD). At the same time, the political and economic pressure to decrease energy consumption and emissions is gaining momentum [8]. Hence, the steel process technology research must be intensified and propose innovations which improve high-quality sinter production of sinter plants. Despite intensive activities in the areas of the steel research in the past, there has

been a lack of research dealing with the sinter process [1].

In conclusion, the highly intransparent situation prevents both the optimisation of the sinter quality and the improvement of the BF operation. Moreover, the sinter process is one of the most energy-intensive stages in the iron-making process with process temperatures about 1400–1500 °C. The whole sinter process mainly depends on coal and coke as fossil fuel, which produce a large amount of carbon emissions [6]. The substitution of coal and coke with carbon-neutral biochar and biomass [10, 11, 12] is one potential solution to reduce global CO₂ emissions. However, further investigation is required to analyse the impact of biochar and biomass on the ignition behaviour of the sinter. To achieve the goals of improving quality, improving production efficiency, saving energy, protecting the environment, and sustainable development, the sinter process will need extended research in the future.

1.1 Motivation and Objective of this Work

The conventional quality monitoring of the physical sinter properties to describe the shape, porosity, strength and Particle Size Distribution (PSD) of sinter is unable to provide information on short-term fluctuations in quality during the sinter process due to the low sampling intervals of once a day from the bulk sample (collected over the day). As a consequence, the control and adjustment of the sinter parameters are dependent on the operator's experience and expertise. This can result in an unfavourable situation in the sinter process, characterised by high emissions, low efficiency and fluctuations in product quality over extended periods, with the consequence that the quantity of the fractions in a PSD of produced sinter is unknown but has a reasonable influence on the permeability in the BF in the further course of the process.

The optimum PSD for the BF lies between a size of approximately 5–50 mm [13]. In general, a uniform particle size distribution is desired in the BF. In this regard, the focus lies on the uniform distribution of fines in the layers of the burden material, as a concentrated deposit of fines can result in local clogging in the BF [14], leading to disruptions in BF operation due to a local decrease in the permeability of the burden material.

Depending on the BF's operating status and gangue, the BF operator has to adjust the burden material, e.g. the proportion of ore mixture to be charged into the BF. These adjustments are usually made after a manual analysis of the input materials. In the case of incoming sinter, it can take more than 5 hours for analysis results to be available, as reported in [15]. As the raw materials must pass through various process steps during the sinter production, they are therefore subject to different influences like mixing, agglomeration, feeding, ignition, sintering, crushing, cooling, screening, and up to the finished product and manual sampling. Such a long-time lag often makes it difficult to make precise operational recommendations. To handle this long delay, the plant operator uses empirical estimation methods to predict these indicators; however, the effectiveness of these methods is clearly dependent on the operator's experience, and the results obtained by using these methods are inconsistent and make it difficult to accurately control the properties of the sinter and BF operation as reported from [6].

To improve the lag of information during iron ore sintering, it is necessary to study the quality prediction of the sinter process. In general, industrial process models are divided into mechanism and data models [6, 16]. The mechanism of some industrial processes

is based on relatively simple physical phenomena. In these cases, the mechanism model is relatively easy to establish, e.g. for calculating the temperature distributions within the sinter bed for a specific sinter composition during a sinter pot test [17]. However, when complex physical and chemical reactions are involved and the material composition changes, the reaction mechanism is complex and the reaction conditions fluctuate, making it difficult to develop an accurate mechanism model, as stated in [16]. The use of physical models is limited by the inability to adapt to changing boundary conditions, such as varying raw material grades and production parameters, which are sometimes unknown. This inflexibility results in models that are unable to provide accurate results. The quality of downstream products of many industrial processes depends on the changes in load and raw materials; thus, the processes operate under fluctuating conditions. However, in the iron ore sintering process, due to the complex composition of the sinter reaction of the raw materials, and difficulty in monitoring the material composition in real time, and few controllable combustion conditions, there is no accurate mechanism model yet [6].

In addition, as stated in [18], the sinter quality values cannot be calculated or tested online; they are obtained through manual tests. The results of these tests take hours to reach the operator, which means that the operation relies on manual experience, as already mentioned. As a result, the sinter process is in a disadvantageous state, characterised by high emissions, low efficiency, and long-term fluctuations in product quality. Consequently, it is necessary to investigate methods for predicting sinter quality.

The development of a capable sinter quality prediction model can provide timely and important machine-supported information for improving and stabilising sinter quality and improving iron quality. Expert systems are often based on historical experience and knowledge and need to be constantly updated and revised. In modern industry, it is often difficult to adapt the accuracy of expert systems to the requirements of the plant [19]. Some mathematical models are based on physical principles, due to the complexity of the actual industry they rely often on simplified models, such as 1-D or 2-D simulation, and because some parameters need destructive testing, it is difficult to meet the actual prediction conditions [20].

Fortunately, with the widespread use of Programmable Logic Controllers (PLCs) and Distributed Control Systems (DCSs), it is easy to obtain the process parameters of the sinter process. Unfortunately, all the data along the spatially distributed process are recorded synchronously and chronologically, so the data are available at a point in time and not in relation to the particle fractions of the sinter output material belonging to a particular sinter segment. Therefore, in the complete process, the measurement of each process variable has different time delays [18], resulting in multiple and distributed time delays.

Through numerous sensors, process parameters such as temperature, pressure and flow can be collected. Therefore, data soft sensor models can be established with numerous data to calculate key parameters online that are difficult to measure directly in real time, such as the PSD or TI of the sinter [6]. This is an untapped opportunity which can enhance the frequency of quality controls and, in the long term, also reduce costs. In practice, the temporal relationship between the measuring points and the sinter material is usually difficult to identify. Due to the long conveying distances and the mixing and segregation effects of the sinter particles, the Residence Time (RT) of the sinter is almost unknown as it passes the sinter plant.

The current state of the art for estimating the Residence Time Distribution (RTD) of particles in liquid flows is based on mathematical flow cell models, which are validated

by tracer tests [21, 22, 23, 24, 25, 26, 27, 28]. Due to the complex characteristics of the industrial process, it is difficult to accurately establish the boundary conditions for the mechanism model. Therefore, data-based models are popular [16]. In the context of time series analysis, there are various methods based on mathematical statistics, such as autoregressive moving-average models [29]. Numerous research studies are available on models that use the least-squares method [30]. However, the mentioned models generally require strict assumptions which limit the predictive accuracy under industrial conditions due to the large fluctuations, transient and strong non-linearity of the industrial process. Various model approaches were developed, as shown below, to describe key values of the sinter process. However, it is obvious from the research works that the temporal alignment of the obtained time series data is a challenge to obtain reliable model predictions. Some works try to overcome the RT problem with Neural Network (NN) models, known as "black box" models [15, 31], which optimise the time alignment in the neurons in the hidden layers of the model. Other research uses manually labelled (low sampling rates) data over large periods of time [6, 18, 32] or are locally restricted to process sections [9].

For example, in the work of [33], Extreme Learning Machine (ELM) and Support Vector Regression (SVR) machine models were used to predict the energy consumption (from solid and gas fuels) of a sinter plant. The RT over the short physical distance between the raw material input to the feed position on the sinter strand is comparatively short and easy to determine. In [33] it is also reported that the amount of return fines is difficult to predict as it is influenced by many parameters, such as ignition temperature and strand speed. The authors are unaware of any study that predicts the amount of return fines based on the mechanisms involved. Another work used a NN method to predict the moisture content, fuel ratio, sinter speed, and cold strength of the sinter [9]. In the work of [28] a NN was applied to predict the Mean Particle Size (MPS), TI, and Reduction Degradation Index (RDI). The authors reported that their model is flexible in numerically describing the relationship between the input and output values of the complex process, which other tools cannot fully capture, even with a large dataset. It was observed that the error of the predictions was higher for RDI than for the other two parameters (MPS & TI) studied in the work of [34]. The deviation was explained due to the small number of available data from the plant. The studies demonstrated the potential for reliable prediction of major sinter properties. Such modelling enables the determination of key parameters affecting various sinter properties and a better understanding of the effects of different parameters, such as machine parameters. However, the traceability of the sinter material remains unclear in the work of [34] as the NN does not allow interpretable RT statements.

Nevertheless, as outlined in [18], the temporal alignment of the input values to the target variable is a mandatory criterion for generating accurate predictions with Machine Learning (ML) methods when time series are examined. In order to generalise the data and decouple it from temporal lag influences, it is necessary to establish a connection between the observed changes in the signals and the specific product, e.g. bulk material segment. This is precisely the basic requirement of any data-based approach: being able to link the data to a discrete product unit at any point in the process.

This thesis presents a new method to overcome the lack of temporal alignment in time series. Tracking bulk materials, such as iron ore sinter, is challenging as segregation occurs along the conveying route, making it difficult to label and track the loose particles. The RT of sinter material remains, at least in part, unknown. The costs associated with tracer studies are considerable or not feasible due to the high temperatures up to 1450 °C at the

Sinter Machine (SM), and the labelling of sinter is subject to local limitations. But the implementation of a data-driven method to predict the sinter quality requires the temporal alignment of time series measurements of process variables and sinter material in sinter production.

The major focus of this thesis is the development of a Residence Time Estimation (RTE) method to estimate the RT that enables ML techniques and to track bulk material flow. The estimation procedure will be developed on sinter plant data series, including datasets from two sinter plants which were examined during the EU RFCS MinSiDeg [1] research project. To overcome the lack of temporal alignment of the sinter mass, three different RT approaches are used in this thesis, static, dynamic, and estimated RTs. The RT can be used to align measurement values to a specific reference time and location. The developed RTE method is based on determining the maximum of the quality function, which indicates the optimal pairing of input (predictor) and output (response) variables depending on the RT estimates. The quality function is an ML model that is trained using multiple datasets, each containing a distinct set of RT estimates. The ML model is utilised to identify the optimal alignment (best match) between the patterns introduced by the incoming variables and the corresponding output value.

The new data-driven approach will be using existing and new measurement techniques, leveraging big data technologies and ML approaches to estimate the RT and enable continuous monitoring and prediction of sinter quality. Two datasets from one sinter plant containing 77 attributes of measuring values along the sinter manufacturing process are available. These datasets include data from several new online measurement techniques to enhance the existing data with additional data points that are collected in a frequency of seconds to precise the analysis results. These new techniques include consideration of the power consumption of the hot crusher and a device for continuous PSD measurement along the transfer route to the BF.

The first step is data pre-processing to enable the use of ML models. The incoming data with different sampling times from the sinter plant must first be aggregated and adapted to the data structure of the ML models, reprocessed, filtered, compressed, or restructured, which requires a considerable amount of system knowledge. The next major step is the application of the three RT methods for temporal alignment of the measurement data with the sinter mass. The dynamic RT approach calculates the actual RT at the SM, while the static RT information is used where the sinter mass is conveyed on transport belts where no belt speeds are available. The RTE approach is utilised to estimate the RT at the Sinter Cooler (SC), where the sinter particles are subjected to mixing and segregation. The RTE method is applied to the two voestalpine Stahl Donawitz GmbH (VASD) datasets. To validate the newly proposed RTE method, the approach is applied to various sub-datasets with different parameters, such as the amounts of Cold Return Fines (CRF) and SC rotation speeds, to examine RTE sensitivity. The development of the RTE method, the custom dynamic RT calculation, and the development of online measurement techniques (except online PSD measurement) were all developed by the author of this thesis and documented in [1, 35, 36].

The application of the novel RTE approach to the dataset and the resulting time alignment of the measured values of the sinter plant should enable the use of ML methods that can be applied to predict sinter quality indices with increasing sample rates to quantify sinter quality fluctuations in daily practice.

This breakthrough in continuous sinter quality monitoring along the sinter production

process should enable combined optimisation of the sinter plant and BF operations. It will provide continuous sinter quality data in terms of CRF predictions for the produced sinter in order to optimise the sinter plant and give important quality information to the BF before the sinter reaches the BF, and enable material tracking.

The RTE approach enables the sinter to trace back the source of disturbances, thereby simplifying the optimisation of the sinter production process at specific problem locations. The proportion of sinter fines could be reduced and the proportion of the preferred uniform 5–50 mm fraction size for the BF [13] could be increased.

Predicted CRF values result in a considerable time advantage (Figure 1.1, right), which benefits the sinter process and the subsequent BF process. As previously mentioned, the quality information obtained from conventional quality determination is usually not available to the sinter plant until several hours after the sample has been taken (Figure 1.1, left). The PSD and sinter strength information is usually not even available to the sinter plant until the following day. Model-based predicted quality information on time scales from minutes to hours for CRF can help to adjust the sinter plant process promptly in case of insufficient sinter quality. The sinter plant can thus react to unfavourable operating conditions on time before the results of the conventional quality assessment are available. The predicted sinter quality data provided by the ML approaches can also be used for the quantification of the sinter quality fluctuations in daily practice. The BF process also receives important information about the incoming sinter in a timely manner and can decide before charging whether to charge unfavourable sinter qualities, depending on the actual BF operating condition. The temporal advantage of model-based quality prediction is depicted in Figure 1.1. A reduction of unfavourable operating conditions at the sinter

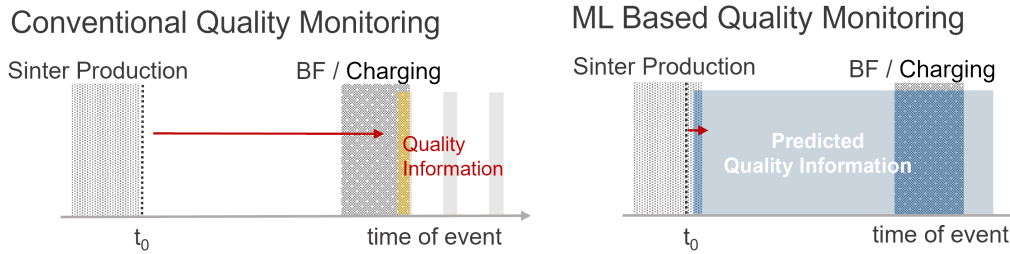


Figure 1.1: Availability of sinter quality, t_0 : Time of measurement. Left: Conventional quality monitoring. Right: ML-based quality monitoring.

plant (decrease in return fines) and the BF leads to lower operating costs and to a more ecological mode of operation. This results in lower consumption of raw materials and energy, as well as lower emissions of greenhouse gases and other pollutants. In addition to the benefits of energy savings and reductions in CO_2 emissions with 200 kg CO_2/t sinter [37] in 2009, a mere 1% decrease in return fines would result in annual savings of 18.6 million € in the European Union [38, 39] alone within the context of sinter production. The new method developed in this thesis to estimate the RT can therefore support the EU targets to reduce CO_2 emissions from hot metal production.

1.2 Structure of the Dissertation

The thesis is structured as follows:

- In Chapter 2 the state of the art is introduced. It addresses the state of the art of sinter plants, the sinter process and sinter quality indices. Chapter 2 also provides information on bulk material characteristics, as flow and effects regarding mixing and segregation. The chapter concludes with a brief overview of the Residence Time (RT) and how it is estimated.
- Chapter 3 covers the methods used in this thesis. From big data and data mining, to the data pre-processing methods, including filter approaches based on moving median techniques for outlier detection. Chapter 3 also provides insights into basic supervised ML methods such as Multiple Linear Regression (MLR), which will be applied as quality function in Chapter 5 and for estimating RT. Basic model accuracy measures are also presented in Chapter 3 as well as an introduction to RT calculation methods.
- The experimental Setup and operational measurements are described in Chapter 4. It contains new online sinter quality measuring methods, data aggregation, and data pre-processing of the operational raw data from one sinter plant. Two datasets represent the basis of data collection on which the new RTE model from Chapter 5 was designed. Dynamic and static RT are calculated up to the section with unknown RT, which will be dealt with in Chapter 5.
- Chapter 5 covers the results and discussion part. The development of the RTE method to estimate the RT and RTD at the sinter cooler (unknown RT), as well as the general formulation of the RTE method, is included in Chapter 5. The steps of initial ML model creation and training are also contained in this chapter. Application of the new RTE method on different plant scenarios to analyse and validate the RT distributions with regard to different fines amounts is examined. Finally, a demonstration will be conducted to illustrate the application of a basic ML model to predict the quantity of Cold Return Fines (CRF) generated during sinter production, based on the previous estimated RT.
- Chapter 6 shows the potential application of the presented new RTE method and first attempts to use it as an online application for quality prediction on a sinter plant.
- Finally, the results and open questions are summarised in the conclusion in Chapter 7.

1.3 Publications

During the research for this thesis, a number of results have already been published. Some of the sections from these publications are reused directly in this thesis, while others form the basis for certain sections. The following section will present a brief overview of these publications:

New Measurement Techniques Describing the Sinter Process

The conference contribution [35] from the "World Conference on Information Systems and Technologies 2023 (WorldCist'23)" in Pisa, Italy, presents new online measuring techniques for determining sinter quality. The measurement techniques include optical and acoustical methods, as well as the examination of the hot crusher's power consumption. All three applications were developed at the sinter plant of DK Recycling und Roheisen GmbH in Duisburg, Germany. First, the raw data pre-processing is described, followed by the filter development up to the finished soft sensor. Due to the installation position at the sinter discharge position at the end of the sinter strand and the associated increased dust load, it has been shown that the acoustic and hot crusher performance, as measured values, have an advantage over the optical measurement method, as they are not affected by the high dust contamination. Furthermore, it was demonstrated that there is a correlation between the acoustic measurement values, the hot-crusher performance, and the amount of return fines.

Application of Big Data approaches for model-based prediction of sinter quality indices

In the conference paper for the "European Steel Technology and Application Days 2023 (ESTAD 2023)" [36] in Düsseldorf, Germany, the application of ML methods, including operational data and new measurement data from [35], was presented. It was demonstrated that after successful temporal alignment of the measurement values of the sinter bulk material, quality indices such as the quantity of CRF can be predicted.

Minimise sinter degradation between sinter plant and blast furnace exploiting embedded real-time analytics (MinSiDeg)

The publication presents the Periodic Report of the RFCS "MinSiDeg" project (RFCS Grant No. 847285, Periodic Report 1&2, 2019–2023)[1]. One of the objectives was to study and optimise the degradation of the sinter material as it passes through the sinter plant and is conveyed to the BF. The work regarding the prediction of sinter quality in the sinter plant forms the basis of this thesis. The essential requirement is the temporal alignment of the measured values with the sinter bulk material, which is the main topic of this thesis. The author of this thesis is mentioned in this publication as co-author.

2 State of the Art

The following chapter provides an overview of the current state of the art in the production of iron ore sinter, which will be referred to simply as “sinter” throughout this thesis. It also provides an overview of the sinter plant, the plant units in which the sinter process is carried out in iron and steel works, and a selection of sinter quality indices relevant to this work. Furthermore, an overview of the bulk material properties is provided, and finally, a summary of the research field of the various methods for determining the Residence Time (RT) is presented.

2.1 Sinter Plant & Sinter

The sintering process plays an essential role in the integrated steel plant, providing raw materials for the BF. The sinter process also enables the reuse of the internal iron bearing fine dust generated throughout the steelmaking facilities. Sinter plants agglomerate, at high temperature, fine ferrous compounds, mainly iron ore fines (dust), but also internal iron bearing waste such as flue dust, mill scale or dusts from electrostatic precipitators, in order to form a product that can be (re-)used in a BF. The product obtained, called “sinter”, consists of small, porous, and irregularly shaped lumps of iron ore mixed with small amounts of other minerals, see Figure 2.1. Sintering is generally defined as: “[...]”



Figure 2.1: Iron ore sinter, just before being charged into a blast furnace [40]

a heat treatment that converts highly porous bodies pressed from powdery or granular material into solids and compact bodies. Baking [...] of the grains results in a ceramic structure with lower porosity” [41]. In this work, “sinter” is referred to as iron ore sinter as it is common in the primary industrial ironmaking process route. This chapter gives an overview of sinter. Particular attention is paid to the quality characteristics of the sinter, which will be a key parameter for the target variable. In the ironmaking process route, sintering is defined as: “[...] the agglomeration of fine mineral particles into a

porous mass by incipient fusion caused by heat produced by combustion within the mass itself” [42]. The process of sintering to improve the physical and chemical properties of iron ore for use in BF is well documented in the literature and is outside the scope of this work. But to understand the process, a short overview will be given. Figure 2.2 gives a

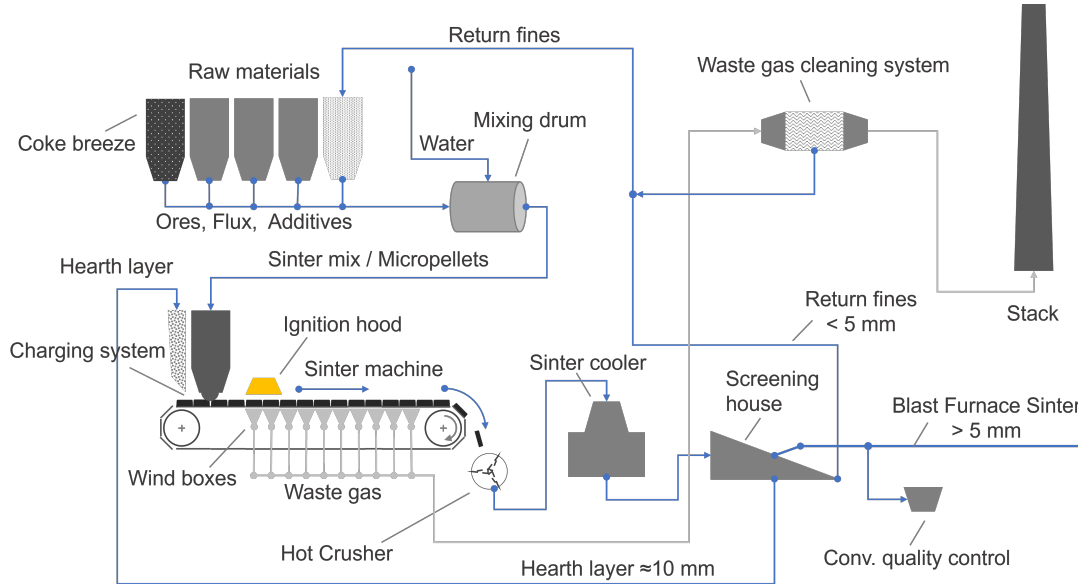


Figure 2.2: Schematic view, sinter plant process flow chart [42, 43, 44]

schematic overview of a common sinter plant and the sinter process flow. Iron ore fines are premixed together with fluxes (limestone, lime, dolomite, serpentine) and reverts (mill scale, flue dust, BOF and off-gas sludge, and other iron-bearing wastes) in the blending yard and conveyed to the sinter plant. In the sinter plant, the raw materials are stored in bunkers, such as raw mix, return fines, fluxes and coke breeze (fuel) [42, 45]. First, the raw materials are homogenised in a drum mixer. Water is added to the sinter mix to achieve the desired moisture content, allowing the materials to form a cohesive mass with enhanced micropellet formation to improve bed permeability [42, 46]. The machine used for sintering nowadays is a Dwight-Lloyd sinter strand, which is a moving conveyor of perforated pallets made of heat-resistant steel [47]. The moist sinter mix, along with bed layer material, is continuously charged onto the moving sinter grates via a metering device to form the sinter bed. The coke breeze in the sinter mixture is ignited at the surface of the bed by passing the ignition hood. Air is sucked continuously through the sinter cake by wind boxes, and a burning zone is formed, which is quasi-linearly distributed across the height and along the sinter strand in the sinter cake. The sintering process is initiated by the heat generated in the burning zone. The vertical sintering speed is controlled by strand speed and gas flow rate to ensure that the Burn-Through Point (BTP) occurs just before the end of the strand where sinter cake is being discharged [46]. The location of the BTP is identified by the number of the wind box ($\approx$ length of sinter strand) that has reached the highest temperature [46]. During the sinter process, the raw materials fuse into a single porous mass, with minor changes in the chemical properties of the various components. Due to the short heating of the mass to melting temperatures, complete melting is not taking place, but partial liquefaction occurs on the particle surface. Partial melting of the particle surface causes the liquid phase to agglomerate during cooling, and,

simultaneously, unwanted accompanying elements and compounds are expelled. After discharge from the sinter strand, the hot sinter cake is crushed by the hot crusher and subsequently cooled in the Sinter Cooler (SC) system. The cold sinter is sieved, and the undersized fraction $x < 5\text{ mm}$ called “return fines” is delivered back to the raw material feed system. The oversized fraction is transported to the BF. The screen fraction of approximately $10\text{ mm} < x < 20\text{ mm}$ is used as the mentioned “bed layer” or “hearth layer” material, which is deposited prior to the raw sinter mixture to prevent the sinter particles from falling through the grates. Different feedstocks have distinct functions to ensure the productivity of the process and the quality of the finished sinter. A brief description will be given in the following sections. The main quality requirements for sinter are high resistance to mechanical stress under BF conditions, good reducibility and uniformity of PSD, and high iron content. The final sinter has a desired grain size of approximately $5\text{ mm} < x < 50\text{ mm}$ suitable for charging into the blast furnaces [42, 48].

2.1.1 Raw Materials

This section describes the raw materials that are usually sintered in the sinter plant. The composition of the raw mix is summarised in Table 2.1 and for the sinter mix in Table 2.2. The iron-bearing material consists of iron ore concentrate, iron ore fines $x < 10\text{ mm}$, flue

Table 2.1: General raw mix composition [42, 49]

Component	Raw mix amount <i>in wt.% (approx.)</i>	Grain size <i>in mm</i>	Ingredients
Iron-bearing fines	50–60	0–10, incl. 70% > 0.2	–
Additives, mostly flux	10–15	< 3	limestone, lime, dolomite, olivine
Circulating materials	4.5–5.0	–	mill scale, blast furnace and converter dusts
Return fines	25–30	usually < 6.3–10	–

Table 2.2: General sinter mix composition [42, 49]

Component	Raw mix amount <i>in wt.% (approx.)</i>	Grain size <i>in mm</i>	Ingredients
Raw mix	86–93	–	Raw mix, cf. Table 2.1
Solid fuel	2–4	0–3	coke breeze, anthracite
Moisture	5–10	–	Water

dust, recycled sinter fines and sometimes other recycled materials (mill scale, precipitator dust, pyrites, etc.). Coke breeze is the major reductant and the most common solid fuel

(fraction less than $x < 3\text{ mm}$), but coal and other carbonaceous materials, such as biomass and biochar, are also used. Limestone, burnt lime, dolomite and dunite are composed almost entirely of olivine (fraction less than $x < 3\text{ mm}$) and are used as flux. Water (5–10% of the sinter mixture) is needed as a liquid binder to agglomerate the loose mixture. Hydrated lime can be used as a solid binder to improve the granulation efficiency [50]. The agglomeration process gives rise to various physical and chemical phenomena. Sintering, as explained above, is a process that requires hot temperatures close to the melting point of the raw material. Many different parameters affect the transformation of the mixture, such as the degree of humidity, the intake air flow, the fuel addition of coke and anthracite [42, 45].

Many theories try to explain what really happens to the individual grains under these working conditions. Although it is the subject of many scientific publications and numerous discussions at conferences, this process is still not fully known in many details [6, 18, 45]. This thesis will also not examine this phenomenon further, as it would go beyond its scope.

2.1.2 Sintering

The charging system consists of a hopper, a charging drum, and facilities to ensure porous charging of the sinter mix onto the sinter grate. The sinter strand itself, or travelling grate, is an endless chain of stringed pallets made from heat-resistant cast iron, with a driving wheel and a turning-back wheel. Before the sinter mix is charged onto the grate, a grid layer of coarse sinter, the "hearth layer", is applied after screening on the pallets to protect them from overheating and prevent the sinter mix from slipping through the pallet grates. Typically, a screened fraction of sinter is used for the grid layer.

After the charging area, fuel (typically coke breeze) in the sinter mix is ignited by an ignition hood on the surface of the bed to initiate the sintering process. Gas burners, fuelled by coke oven gas, blast furnace gas or natural gas, are used. From this point onwards, air is sucked down through the bed to sustain combustion of coke breeze to supply heat energy for the sinter process. The combustion zone moves down through the entire layer of the bed as sintering proceeds, and at the end of the process, all the fuel has been consumed and the whole sinter mix (typically 400–600 mm height of the bed) has been sintered. In Figure 2.3, the sinter strand is depicted coming from the ignition hood. The sintering process is finished when the flame front reaches the bottom of the sinter bed, which describes the BTP. A typical development of waste gas temperature vs. time is shown in Figure 2.4. During the first 2–3 minutes after starting the process, waste gas temperature does not exceed room temperature. Then the temperature increases to the dew point (60–70 °C) due to condensation of the water steam from the upper layers of the sinter mix. After this, the temperature remains constant until the combustion zone approaches the grate. From this time on, waste gas temperature rises sharply, reaches a maximum, and then starts to decrease. The peak of waste-gas temperature corresponds, as mentioned above, to the completion of sintering process (BTP). The typical horizontal strand speed ranges from 1.5–3 m/min [51, 52] and the vertical speed of the flame front from 12–30 mm/min [53, 54, 47] resulting in 20–50 minutes sintering time to reach the BTP (at a sinter bed height of 600 mm). The discharging of the sinter is followed by the hot crusher, where the falling sinter cake is broken into smaller pieces. Optionally, a hot screening station is following. Afterwards, the hot sinter is cooled down and screened into different fractions. The undersized fraction (typically $x < 5\text{ mm}$) is fed back to the sinter plant



Figure 2.3: Sinter strand [1]

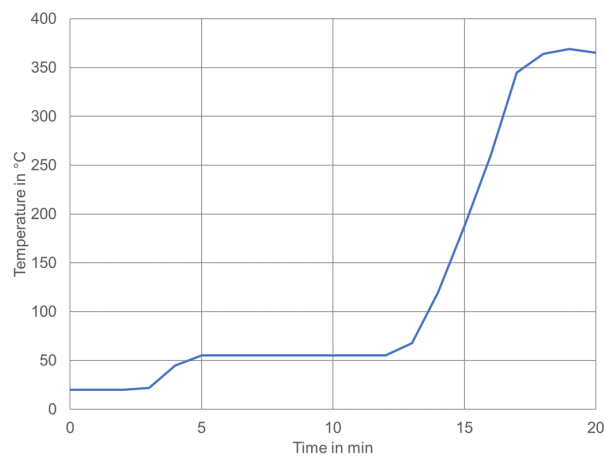


Figure 2.4: Waste gas temperature development during sintering [42]

as recycling material (return fines), the oversize fraction is supplied to the blast furnace ($5\text{ mm} < x < 50\text{ mm}$) and parts of the middle-size fraction (about $10\text{ mm} < x < 20\text{ mm}$) might be used as hearth layer on the grate.

2.1.3 Thermal and Chemical Processes

During the sintering process, the surfaces of individual particles are activated by the heat generated from coke breeze combustion. As the temperature reaches the melting temperature, the particle surfaces begin to melt along with the fluxes, forming a slag bonding matrix. This molten phase promotes wetting, dissolves fine particles, and glues larger ore particles together. As the flame front continues to descend, the temperature decreases, leading to re-crystallisation, diffusion, and slag formation from the melt. The iron ore and contents of magnetite components are partially re-oxidised to hematite in the air. These processes result in the formation of lumpy agglomerates of ore bonded in a slag matrix [17, 45, 47, 55]. Due to the phase changes and associated volume change, cracks are formed. Consequently, the fusion process reduces the quantity of small pores while forming larger voids between the agglomerated particles, thereby improving the permeability of the iron

ore sinter. Figure 2.5 shows the temperature distribution and different zones along the sinter bed height reflecting the main thermal and chemical processes in the sinter bed a few minutes after ignition. The individual zones are described from the bottom of the

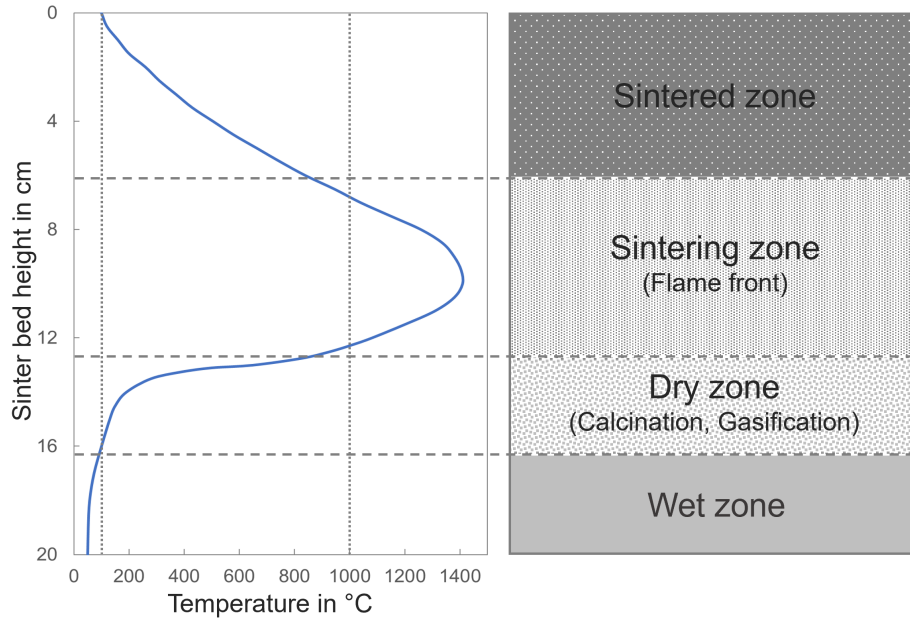


Figure 2.5: Schematic arrangement of zones along the sinter bed a few minutes after ignition on the sinter surface (0 cm) [56, 44]

sinter bed (20 cm) to the top (0 cm). The lower layers (wet and dry layers) of the sinter bed are heated by the hot process gas emitted from the upper layers. The temperature in the lowest layer of the sinter bed is below the dew point, so a wet zone forms where the water accumulates. The drying zone is located above the wet zone, and its temperature range typically ranges from approximately 100–600 °C. In that zone, the sinter mixture is dried by the heat of the outflowing gases from the combustion layer directly above. At temperatures between 600 °C and 800 °C, the first agglomeration of the fine particles into a porous material takes place, the swelling grains adhere weakly to each other, and calcination of limestone or dolomite, respectively, occurs. At the next temperature level of 800–900 °C the combustion zone is formed. The carbon dioxide reacts with coke breeze, and the resulting carbon monoxide reduces hematite to magnetite and later to wustite as described in Equation (2.1-2.2). By reaching more than 1000 °C, the grains soften, resulting in homogenised physical and chemical conditions to complete the agglomeration process. The maximum temperature can reach 1300–1450 °C. It depends on the composition of the sinter mix, the reaction rate, the location and combustibility of the coke breeze and other fuels, as well as the depth of the bed and the air flow rate. Fusion occurs at high temperatures by interfacial formation, diffusion, slag formation and recrystallisation. Partial reoxidation of magnetite to (secondary) hematite can occur when the magnetite reacts with the oxygen from the incoming air at the top surface, confirming Equation (2.3). Above the sintering zone follows the cooling zone, where crystallisation (solidification) of the sinter takes place. The sinter is cooled by the cold gas flow coming from the upper section (air inlet). The temperature in the cooling zone lies between the ignition temperature and the maximum temperature. In sum, there are basically three layers in the sinter bed:

the raw material (wet and cold), the burning front, and the cooling zone, consisting of the sintered material (Figure 2.5). In the cooling zone, the sinter cake becomes brittle due to volume shrinkage, which leads to the formation of cracks due to the introduced stress. The temperature profile in the sinter bed is characterised by a sharp and fast increase to the maximum temperature during the heating cycle and by a relatively slow cooling of the finished sinter. The heating of the raw sinter mixture to the maximum temperature typically takes about two minutes. The cooling time depends on the maximum temperature. The complete sinter process typically takes about 20–50 minutes depending on the suction rate and sinter bed height, cf. Section 2.1.2. In Figure 2.5, the thermal and chemical processes are summarised over the sinter bed height and in Figure 2.6 along the sinter strand length. During sintering generally 5 chemical reactions take place. The first reaction is

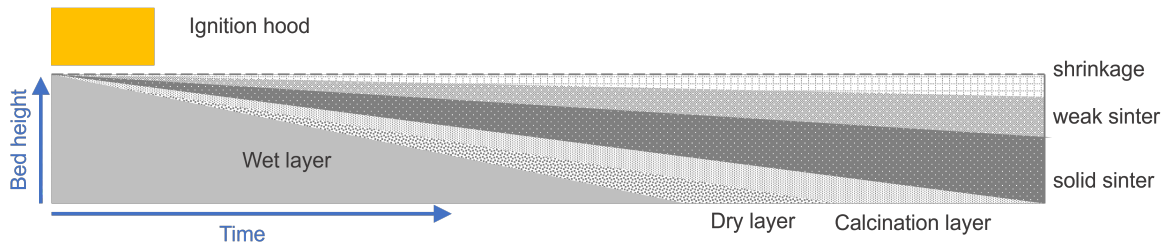
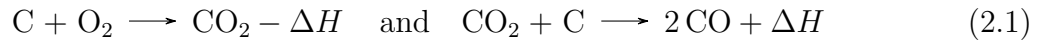
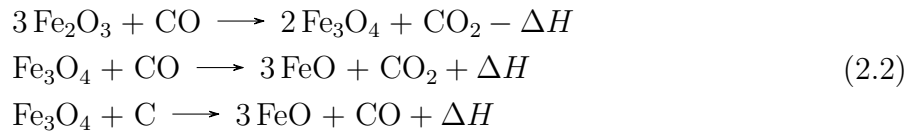


Figure 2.6: Longitudinal and vertical sections of sinter layers on a sinter belt

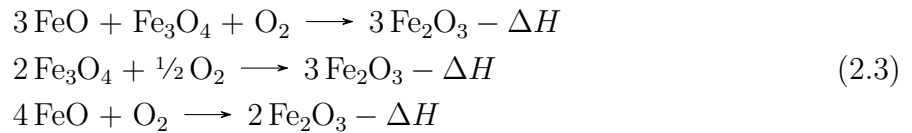
the generation of heat by burning the fuel to carbon monoxide (CO):



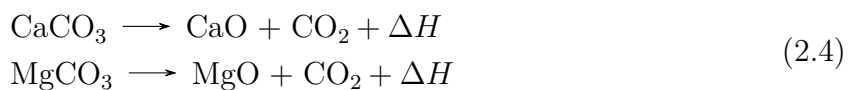
Then different reactions can occur, like the reduction of iron ore (hematite or magnetite) to wustite by CO, and magnetite can be reduced by carbon at higher temperatures (last reaction). The reactions from Equation (2.2) represent the main sinter reactions:



FeO (wustite) can form solid compounds with Fe₃O₄ (magnetite). With oxygen (air) which is sucked through the burning sinter, secondary Fe₂O₃ (hematite) can also be formed out of the following compounds:

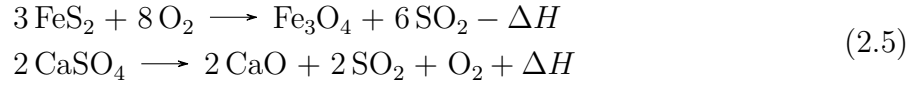


Calcination is taking place by decomposing limestone or dolomite:



CaO can react with FeO, SiO₂ and Fe₂O₃ and form compounds with a low melting point like fayalite (FeO · SiO₂ (1180 °C), 2 FeO · SiO₂ (1205 °C) and FeO · SiO₂ · CaO (1223 °C))

and calcium ferrites ($\text{FeO} \cdot \text{CaO}$ (1120°C) and $\text{Fe}_2\text{O}_3 \cdot \text{CaO}$ (1205°C)) [42, 45, 57]. Above 1000°C , sulphur (if present) is removed:



2.1.4 Sinter Cooler

After leaving the Sinter Machine (SM), the sinter is crushed in the Hot Crusher (HC). The hot crushed sinter is sometimes screened to remove Hot Return Fines (HRF), which are sent back to the raw material bunker. The remaining sinter particles with temperatures up to $600\text{--}700^\circ\text{C}$ are cooled down to approximately 100°C in the Sinter Cooler (SC) [47, 58, 59, 60], so that the sinter can be handled on conveyor belts. Depending on the sinter plant, different types of SCs are operated, including annular, straight or shaft coolers. In this thesis, the focus is limited to the shaft cooler, as it is part of the VASD sinter plant. Shaft coolers are constructed with a reduced number of moving parts and fewer components that are in contact with abrasive sinter than annular coolers. This design feature enhances the lifetime of the cooler and reduces maintenance requirements. A common type of sinter shaft cooler has a circular shaft into which the sinter is fed and subsequently cooled. A charging device, such as a chute, is placed above the shaft, whereas the shaft itself is rotatably mounted. During operation, the shaft is rotated so that different sections of the shaft are sequentially charged with sinter by the charging device. Air inlet vanes are tangentially arranged in the inner and outer walls of the shaft. The top of the inner shaft is covered by an airtight hood, which is connected to an air fan at the bottom, cf. Figure 2.7. The rotation of the cooler is driven by electric motors, which are connected to lantern gears

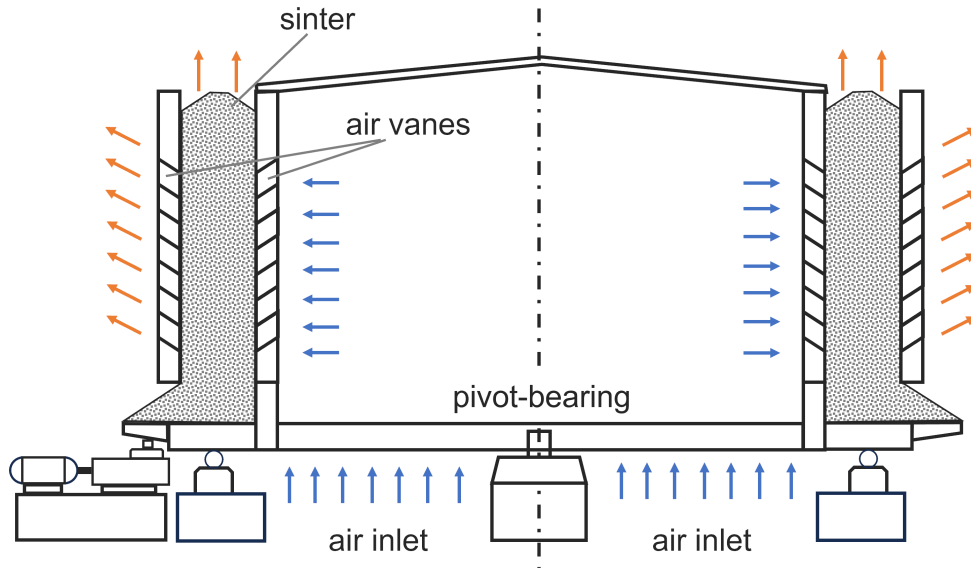


Figure 2.7: Schematic view of sinter shaft cooler [58]

located underneath the rotating table. The sinter will make various complete rotations with the cooler, thereby performing a pseudo-helical movement. The cooling air stream is pushed from below into the inner diameter of the shaft through the radial inner inlet vanes

and moves upwards and sideways through the sinter bed in counter-current operation and leaves the SC through the outer vanes and through the top surface. The general motion of the cooling gas is vertically upwards through the sinter, while the sinter moves in the opposite direction, downwards. However, this includes smaller regions where the airflow is oblique or perpendicular to the movement of the sinter. The sinter is charged at the top of the shaft and is continuously discharged from the bottom by means of a scraper. A wrong filling with a segregated bulk can lead to an uneven cooling air distribution, which in turn leads to inefficient cooling and increased dust emissions. The cold sinter is discharged by a tilting discharge beam (scraper). It is supported in a heavy steel structure, and its movement is powered by means of a hydraulically actuated lever system. The discharge of the cold sinter is performed by driving the beam into the lower opening of the cooler shaft. From there, the cold sinter falls into the discharge chute [58, 59, 60].

During the cooling process, euhedral and skeletal crystals of magnetite and hematite continue to exsolve from the slag, with hematite predominating [47]. After cooling, coarse sinter particles larger than 50–75 mm [58, 59] are usually crushed in a secondary crusher and conveyed to a screening station where the finished BF sinter, hearth material, and (cold) return fines are separated. SC can be equipped with a heat recovery system that uses the thermal energy of the hot sinter, e.g., by recirculating heated cooling air for heat recovery, to produce steam, which may drive a power generator to convert the heat energy into electrical energy.

2.2 Sinter Quality Indices

In addition to the chemical properties (FeO content, gangue composition, basicity [61]) which are not discussed in this thesis, the physical and metallurgical characteristics of the sinter are of significant importance for the BF process. Given the large number of quality indices currently available, only the quality characteristics relevant to this work are presented here. These are in detail:

- Particle Size Distribution (PSD) [42, 61]
- Cold strength [42, 61, 62]
- Return fines [62]

2.2.1 Cold Strength

To get information on the tendency to generate fines during the handling and transport of the sinter from the sinter plant to the BF, the tumbler test is conducted to determine the cold strength of the sinter. The Tumbler Index (TI) and Abrasion Index (AI), both denoted as percentage by mass (*wt.%*), inform about the size reduction due to impact and abrasion of the sinter during handling, transportation, and in the BF process [61, 57].

The TI depends on the strength of each single component, the strength of the bonding matrix components and the ore compositions [57, 61, 62]. The test indicates the particle size reduction due to impact and abrasion of the sinter in the subsequent process steps. The cold strength is directly related to the tendency to form fines during the transportation and handling between the Sinter Machine (SM) and the BF throat [57]. The TI of sinter

is dependent on critical flaws in the sinter and their propagation through sinter particles. Flaws (e.g., cracks) are unavoidable because different minerals and phases precipitate from the melt at various times during the cooling cycle. The phase transition from liquid to solid is associated with volume changes, which in turn result in the generation of stresses and, consequently, the formation of cracks [45, 57] (Section 2.1.3). The test bench for the tumbler test consists of a drum fitted with two lifters. By rotating the drum, the sinter is subjected to several rotations. At the end of the test, the material is screened with 6.3 mm and 0.5 mm size screens and $x > 6.3 \text{ mm}$ and $x < 0.5 \text{ mm}$ material is weighed. The indices are represented as follows:

Tumbler Index:

$$TI = \frac{mass_1}{mass_0} \cdot 100 \quad \text{in wt.}\% \quad (2.6)$$

Abrasion Index:

$$AI = \frac{mass_0 - (mass_1 + mass_2)}{mass_0} \cdot 100 \quad \text{in wt.}\% \quad (2.7)$$

where:

- $mass_0$: is the mass of the test portion in kg before tumbling
- $mass_1$: is the mass in kg, of fraction $> 6.3 \text{ mm}$ of tumbled test portion
- $mass_2$: is the mass in kg, of fraction $< 6.3 \text{ mm}$ and $> 500 \mu\text{m}$ of tumbled test portion
- TI : is the Tumbler Index in $\text{wt.}\%$
- AI : is the Abrasion Index in $\text{wt.}\%$

A high value of the TI (70–80%) and a low value for the AI ($< 5\%$) indicate preferred values for sinter to withstand BF conditions [42].

2.2.2 Particle Size Distribution (PSD)

Sinter consist of particles of different sizes. To characterise the Particle Size Distribution (PSD), screen analyses are performed on bulk samples of the daily sinter production. As described in [42] the sinter should ensure a sufficient gas flow in the BF. A minimum grain size is required to reach the desired permeability. For this reason, disadvantageous fine fractions are separated by continuous screening from the sinter production already in the sinter plant and later before BF loading. The PSD can be represented by two distribution curves: the cumulative distribution $Q(x)$ and the differential distribution $q(x)$. The cumulative distribution $Q(x)$ describes the proportion of particles that are smaller than the particle size x in relation to the total quantity. For sinter, the quantification of the PSD is typically specified as cumulative mass distribution $Q_r(x)$ (index $r = 3$; for volume or mass distribution), as is common for screen analysis [63]. In this thesis, only the mass distribution ($r = 3$) will be considered. The mass distribution is formulated as follows:

$$Q_r(x) = \frac{\text{mass proportion}(x_{min.} \dots x_i)}{\text{total mass}(x_{min.} \dots x_{max.})} \quad (2.8)$$

Figure 2.8(a) shows a general distribution curve. The vertical axis shows the cumulative distribution $Q(x)$, which ranges from zero to one due to the reference to the total quantity. The particle size is plotted on horizontal axis. The particle size range between two particle

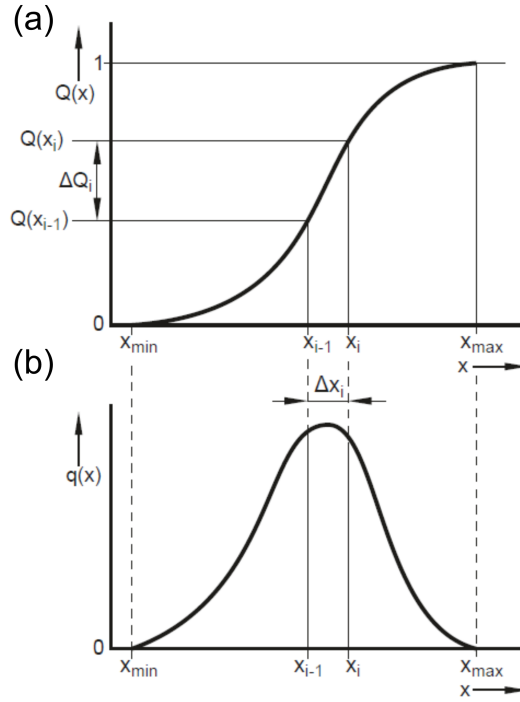


Figure 2.8: (a) Cumulative distribution $Q(x)$, (b) differential distribution $q(x)$ [63]

sizes x_{i-1} , and x_i is called particle class i or fraction Δx_i , cf. Equation (2.9).

$$\Delta x_i = x_i - x_{i-1} \quad (2.9)$$

The width of fraction i with respect to the cumulative density is the quantity ΔQ_i , cf. Figure 2.8(a). The differential distribution $q(x)$ as shown in Figure 2.8(b) is the derivative of the cumulative distribution $Q(x)$ with respect to the particle size x :

$$q(x) = \frac{dQ(x)}{dx} \quad (2.10)$$

$q(x)$ is the quantity in the interval $[x \dots x + dx]$ in relation to the interval width dx . The dimension of $q(x)$ is length^{-1} [63]. Within the mass fractions produced by the screening process, the mass of the passing-through fraction $D(x)$ corresponds to the cumulative distribution $Q_3(x)$, and the screen retention $SR(x)$ is determined by $SR(x) = 1 - Q_3(x)$. The mass of the passing-through fraction $D(x)$ thus describes the mass proportion that does fall through a screen of mesh size x , i.e. the proportion of particles that are smaller than x . The screen retention $SR(x)$ describes the mass proportion that would not fall through the screen, i.e. the proportion of particles that are larger than x . To calculate the particle size distribution from individual values, the particle mass quantity from the individual fractions i is converted into the quantity ΔQ_i . The mass distribution is gained from the masses of the particles in the individual fractions. For the mass of the fraction i ($\Delta mass_i$) and the mass of all fractions ($mass_{total}$), the mass proportion of fraction i is obtained following Equation (2.11):

$$\Delta Q_{3,i} = \frac{\Delta mass_i}{mass_{total}} \quad (2.11)$$

2.2.3 Return Fines

During passing the sinter plant and between the sinter plant and the Blast Furnace (BF), the sinter passes through various conveying systems, coolers, sieves, and bunkers, where it partly degrades due to mechanical stress (Section 2.3). Particle breakage is particularly critical during the transport and storage of sinter. Before leaving the sinter plant and before being fed to the BF, the generated undersized grain sizes (return fines) are screened out and returned to the feeding of the sinter plant, where they are re-sintered. In general, the undersized grain size is $x < 5 \text{ mm}$ [31, 34, 39]. The productivity of the sinter process is related to the amount of return fines, because a high proportion of fines indicates a low proportion of raw materials agglomerated. A reduction of the return fines percentage means an increase in the strength of the sinter product as a result of low sinter strand speed and high coke content in the mix. Vice versa, an increase in return fines percentage indicates a lack of coke in the sinter mix, irregular combustion and moisture changes in the sinter mix that implies a decrease in productivity [61]. Table 2.3 presents a list of requirements on the sinter properties in German sinter plants [42]. The return fines due to

Table 2.3: Requirements on the physical and metallurgical properties of sinter [42]

Property	Grain size	Amount
Strength (TI)	$> 6.3 \text{ mm}$	70–80%
Grain size	$< 5 \text{ mm}$ or $< 6 \text{ mm}$	max. 5%
	$< 10 \text{ mm}$	max. 30%
	$> 50 \text{ mm}$	max. 10%

transport and storage are 6.3% of the total mass flow on average in the EU [64]. Sintering is a highly energy-intensive process, leading to excessive costs and emissions. In 2009, direct CO_2 emissions in Europe from sinter plants accounted for $0.200 \text{ t CO}_2/\text{t}$ produced sinter [37]. The energy consumption (fuel and electricity) for sinter production reached up to 2.265 GJ/t of sinter in 2004 [64]. This results in a savings potential of 143 MJ/t sinter regarding conveying technology and sinter plant optimisation. According to [64], the average process costs are 20 €/t return fines. Besides massive savings in energy and CO_2 emissions, a reduction of return fines of only 1% would result in annual savings of 18.6 million € in the EU [38, 39].

2.3 Bulk Material

The transport route of the sinter runs several hundred metres through the sinter plant, starting at the raw material bunker until it leaves the sinter plant as finished sinter after passing through various process steps. After leaving the sinter plant, the sinter must be conveyed again over long distances to the blast furnace. This thesis focuses on material tracking within the sinter plant. There, the sinter is transported over distances of hundreds of metres in a time span of approximately 60–120 minutes [6, 18], depending on the considered sinter plant setup. This is commonly accomplished by belt conveying systems. The

resulting plant is a complex system where the sinter passes through various processes or stations, is buffered in bunkers, transported via conveyor belts, transfer points, switches, and screens until it reaches the plant outlet. In most of these steps, the sinter lumps are exposed to various mechanisms that influence the movement of the sinter particles (bulk material) and the flow properties.

The sinter particle movement and flow properties are influenced by:

- Particle Size Distribution (Section 2.2)
- Particle shape
- Agglomeration, material accumulation
- Segregation
- Wall friction
- Abrasion and degradation (MinSiDeg [1])
- Irregularities due to local cross-section changes

Each of these mechanisms affects the bulk flow and makes it difficult to track or label the mixture at the distinct measurement positions because the individual particles change their position at different speeds. The result is that produced sinter at time t_1 is partly mixed with particles produced at earlier times t_0 or later times t_2 . The detailed examinations of these mechanisms are well documented in the literature and not within the scope of this thesis. But to give a fundamental understanding of those mechanisms, a concise explanation of the most important mechanisms is provided in this section.

2.3.1 Degradation

Due to mechanical stress during conveying and storage, the sinter partly degrades. As a result, the PSD changes constantly as the transport route increases and the enumerated mechanisms of particle movement are continuously influenced. As already mentioned, before leaving the sinter plant and before feeding into the BF, resulting fines are screened out and returned as "return fines" to the sinter plant (Section 2.2). According to [64], 60 kg fines per ton of sinter on the EU average are screened out before being charged into the blast furnace. Thus, 6% of the mass flow is conveyed in a circuit. The journey of the sinter is illustrated in Figure 2.2 [42, 43, 44, 65]. In most sintering plants, production capacity has been increased by raising mass flows over the years by simply increasing belt conveyor speeds. Furthermore, installations for reducing equipment wear, measuring, and sampling have been added to conveying systems. All this, however, leads to undesired material flow, material accumulation, and, in some cases, additional impacts on equipment, which further increases material degradation [1, 66] and makes it less accurate to track the sintered material. Detailed work on the degradation of sinter was conducted during MinSiDeg [1] and in [39]. As sinter is a product of the sinter process (see Section 2.2), sinter degradation characteristics are also dependent on process parameters, composition and phase chemistry as evaluated in [67].

In [39] it was concluded that the rate of degradation is directly proportional to the number of impacts encountered by the particles. An influence of lump size on degradation was also

observed in [68]. A study in [69] revealed that large lump sizes of iron-making materials were more likely to break. This is in accordance with Griffith's theory of fracture [70, 71], which implies that larger particles are more likely to contain larger cracks and thus are more susceptible to breakage. Physical stress on bulk material has a two-sided effect: on the one hand, stress may lead to degradation and fines generation, but on the other hand, this stabilises the strength of the remaining material [1].

2.3.2 Segregation

Segregation or separation of one fraction of a material from others in the bulk is due to some difference in particle properties and a force to 'drive' the fractions apart. Segregation means that the components or fractions, respectively, of a bulk material are less homogeneously distributed than expected. This makes it difficult to track the original mixture as it passes through the several measurement positions and process steps. The sinter mass is separated due to the segregation and mixed with other material from other production times. Segregation occurs during the handling of bulk material and has a major impact on the ability to obtain a representative sample from bulk with respect to given sections of measurement time series and, therefore, can result in inaccurate results from characterisation tests. Every time the bulk material is in motion, it is typically exposed to segregation. The impact of segregation can lead to changes in, e.g., the appearance, texture, and flow behaviour of the material and may result in production difficulties, safety hazards, and plant shutdowns [63, 72]. The processes involved in segregation are complex and cannot be quantitatively predicted. Bulk materials segregate primarily according to particle size, particle density, shape, and surface roughness. The main segregation mechanisms, sifting or percolating, occur when smaller particles in the bulk material are able to move through a lattice of larger particles. Even if the particle bed is static, large differences in particle size (around 10 times) can result in a purely gravity-induced sifting [72]. When the whole bulk is in motion, e.g., slides down a heap, the opportunity for smaller particles to move into the voids between their larger neighbour particles is significantly increased, and even a small size difference can result in significant segregation (see Figure 2.9(a)). The fine particles then remain in the voids, while the larger particles prefer to slide or roll to the bottom of the slope. This effect is more noticeable the more the particles differ in size. If coarse and fine components with different angles of repose are present in the bulk material, other segregation effects also occur in the bulk material during stacking on stockpiles. The particles with the steep angle of repose are preferably located in the upper, steeper part of the pile, while the particles with the flat angle of repose are located further down (Figure 2.9(b)) [72, 63].

Segregation by percolation can occur when bulk material is deformed, which occurs when particles move against each other. This creates small spaces between individual particles, into which preferably fine particles can enter, as shown in Figure 2.10. Since gravity is the dominant external force in most bulk material applications, the fine particles will migrate downwards within a moving bed. The sifting effect described above can also be attributed to percolation. The deformation of the bulk material required for percolation occurs in different situations, e.g., when a bed of material is shaken or vibrated vertically, particles move up (up-thrusting) and down. The voids that form at this moment are preferentially filled with fine particles, so that smaller particles move beneath larger particles. Therefore, the large particles cannot move back down to their original position. Over time, larger par-

tics therefore move further and further upwards, while the smaller particles accumulate at the bottom [72, 63].

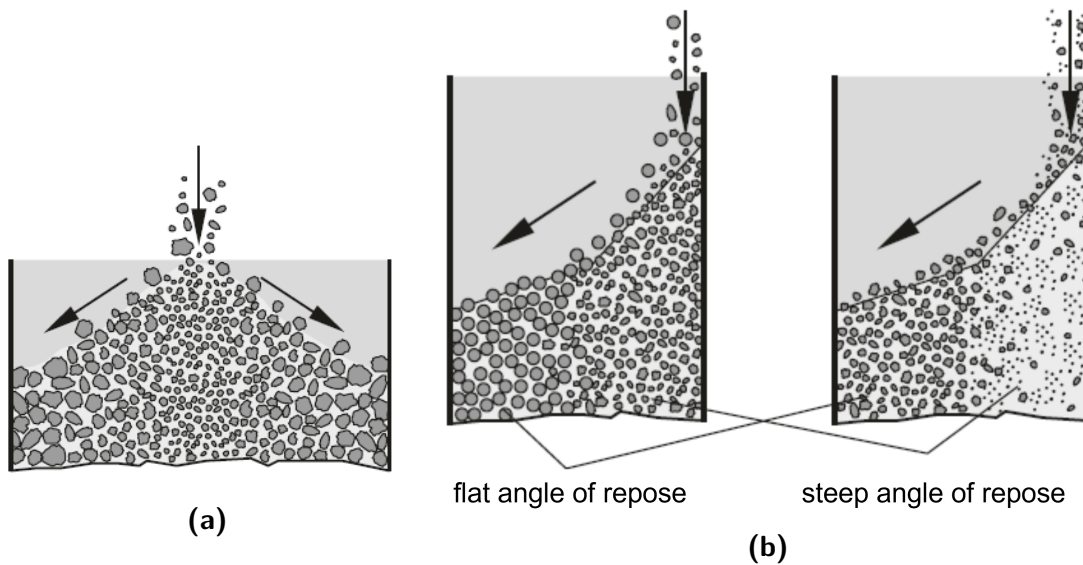


Figure 2.9: Segregation by sifting (a) and due to different angles of repose (b) [63]

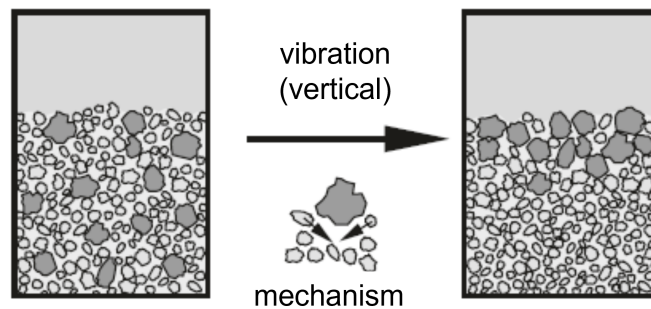


Figure 2.10: Segregation due to percolation in vertically shaken container [63]

Also, in transition areas between dead zones and flow zones in a core flow silo, fines can penetrate dead zones (or slower-flowing areas) through percolation and accumulate there. The effects of sifting and percolation are primarily affected by the differences in particle size. The particle shape is important for segregation on slopes, e.g., due to rolling particles. Segregation effects are already noticeable with particle size ratios of 1:1.3. Furthermore, the segregation effect becomes stronger with increasing width of the particle size distribution [63]. If a particle flow is discharged from a conveying belt, e.g., during bunker filling, at transfer points or when feeding the screens, different trajectories will occur depending on the particle size. Large and heavy particles are slowed down less by the air than smaller and lighter particles and, therefore, fly longer distances, due to their different velocities. Thus, whenever a bulk material moves with a horizontal velocity component through air (gas), segregation due to different trajectories is to be expected, as visible in Figure 2.11. Figure 2.11(a) shows a cone of debris generated by a laterally arranged chute. The coarse particles accumulate in the conveying direction away from the chute, and small particles accumulate against the conveying direction in the bunker, whereby the segregation due to

the sifting effect described above also plays a role here. If a bunker is filled from the side (see Figure 2.11(b)), the effect described above can result in a one-sided distribution of the coarse material throughout the bunker. If this flows significantly better than the fine material, a one-sided bulk material flow can occur during discharge in such a way that the coarse material flows out preferentially. This can lead to fluctuations in blast furnace operation [1, 38]. Also, on conveying belts during the transport of the bulk, large particles

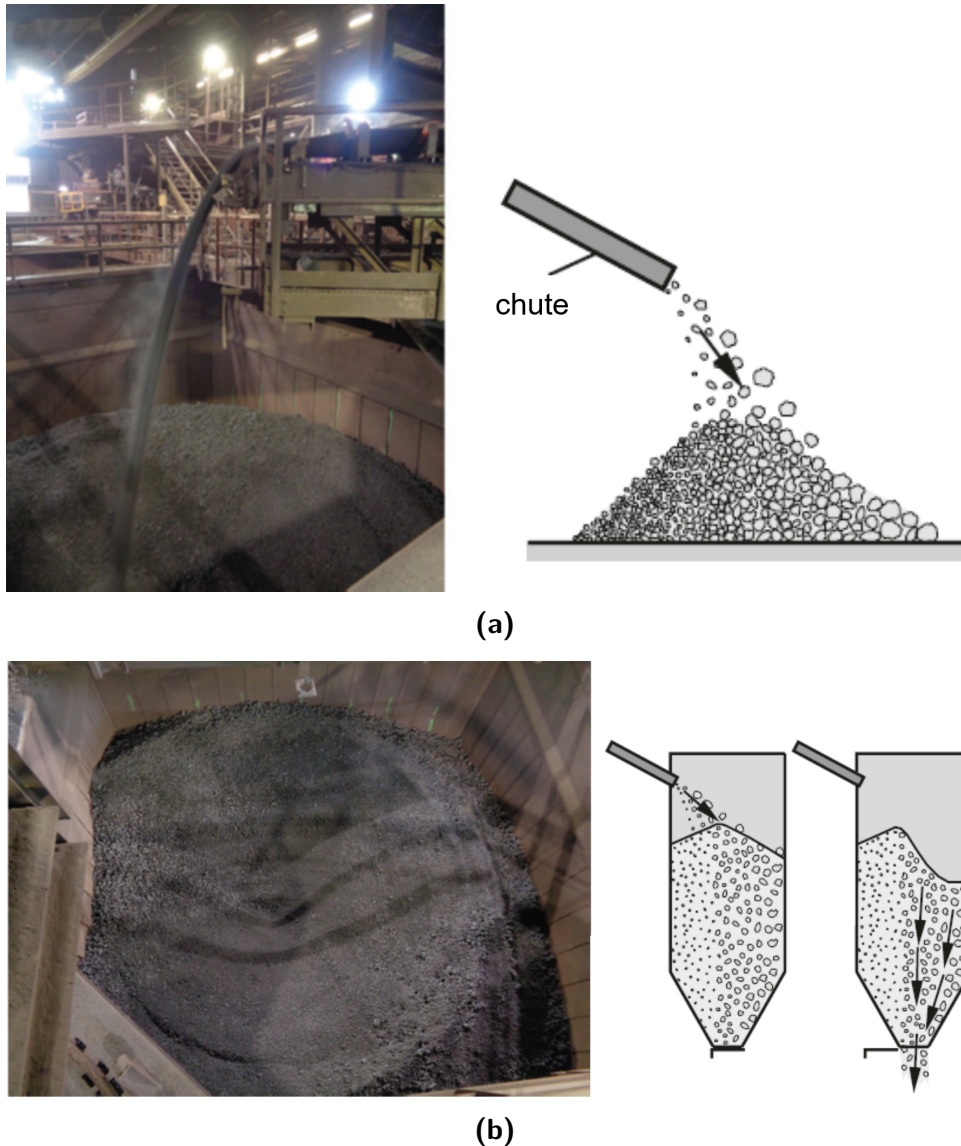


Figure 2.11: Segregation effects during bunker filling: (a) side view, (b) top view [38, 63]

accumulate at the top of the belt conveyor and small particles accumulate at the bottom as described in [63], resulting in an inhomogeneous PSD on the conveyor belt as illustrated in Figure 2.12.

Other Segregation Causes

Other reasons for disturbance of the material flow are imperfections, due to irregularities in the bulk mass or bunker walls, e.g., when the material is horizontally compressed. The

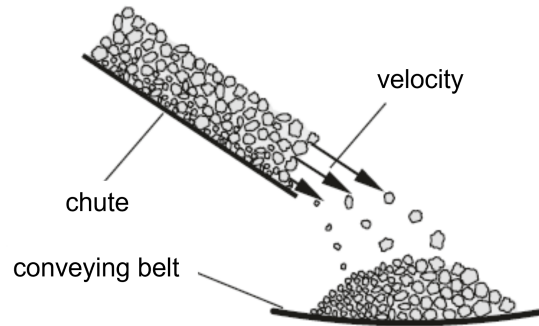


Figure 2.12: Transfer from a chute to a conveyor belt [63]

imperfections mainly affect the bulk material when it flows, e.g., when a container is emptied. This is due to the fact that a layer of bulk material, which has a certain width immediately after filling, is deformed as it flows past imperfections. The bulk material is compressed horizontally when it reaches a local cross-sectional constriction, but it can also expand horizontally when the cross-section expands.

Flow Profiles of Bulk Material

When bulk material is discharged from a bunker, two flow profiles are common: mass flow and core flow. Regarding the mass flow, the entire bunker contents are in motion when bulk material is discharged. Mass flow is only possible if the bunker walls are sufficiently steep and/or smooth. If the walls are too flat or too rough, core flow occurs. The different flow profiles are depicted in Figure 2.13. During core flow (Figure 2.13(b)–(d)), initially

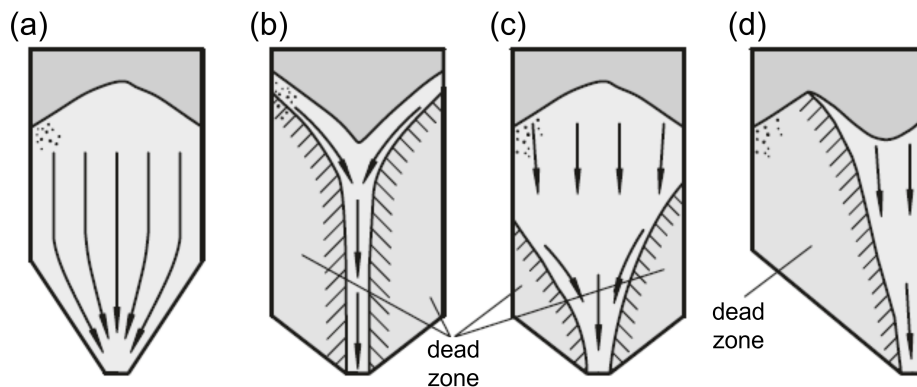


Figure 2.13: Flow profiles: (a) mass flow, (b) core flow with dead zones that reach far upwards, (c) core flow with dead zones in the lower part of the bunker (mixed flow) with asymmetrical dead zones, (d) core flow with eccentric flow zone [63]

only the bulk material in the area above the outlet is in motion. The particles in the "dead zones" that grow on the bunker walls at the edges of the bunker are only discharged when the bunker has been completely emptied. The dead zones can extend up to the surface of the bulk material so that a flow funnel develops at that position, which is recognisable from above. It is also possible that the dead zones only form in the lower area of the bunker, so that the flow profile cannot be detected at the material surface. (Figure 2.13(c)).

Dead zones in the bunker can also form asymmetrically, e.g., due to an eccentric outlet opening in combination with a bunker wall that is too flat, Figure 2.13(d). In case of mass flow, all bulk material in the bunker is in motion when the bulk material is discharged (Figure 2.13(a)); different velocities can occur across the silo cross-section. The rougher or flatter the wall, the lower the velocity at the wall. If the bunker wall is too rough or too flat, the bulk solids do not move along the wall and form dead zones [72, 63].

Discharge Devices

Discharge devices like scrapers are used in sinter shaft coolers. In Figure 2.14(a), a typical arrangement of the scraper is shown, in this case the scraper does not reach the wall of the bunker. As a result, a dead zone and thus a core flow can form on the bunker wall, which can lead to flow problems.

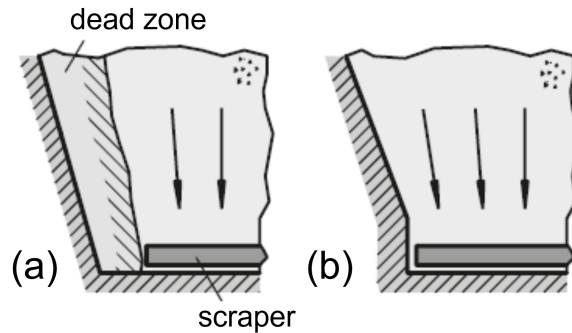


Figure 2.14: Bunker discharge with scraper [63]

2.4 Residence Time and Estimation Methods

As discussed in the previous sections, the sinter process is a complex industrial process. According to [6] and [18], it is difficult to obtain the key quality variables in real time during the sinter process, so there is a lack of real-time information to guide the production process. The labelled laboratory data, e.g., chemical composition, Tumbler Index (TI) and screen analysis (for PSD), often take several hours [1] to obtain results, which leads to a low resolution of the labelled data.

As reported in [1, 18, 35, 36], online sensors can achieve a ten-second sampling interval up to 1 Hz sampling rate, which can enhance the data basis for sinter quality evaluation. Even when a large data basis is available for sinter quality examination, the sinter process data are recorded synchronously and chronologically at all measurement positions in the sinter plant and, therefore, do not match without pre-processing or time shift adjustments to a specific segment (product unit) of sinter material [1]. Therefore, the prediction error in ML models is inevitably influenced (accuracy loss) by using different characteristics and time series data without time and material alignment (misaligned data) for sinter quality prediction models [18].

In this thesis, the term "sinter segment" [73] refers to a specific, discrete "product unit" (ISO 3443-7:1988(en) [74]) of sinter material. In the context of daily operations at sinter plants, the term "sinter pallets" is commonly utilised to denote the volume of sinter material

from a specific sinter pallet at the SM. The term "sinter segment" is not restricted to the location and volume of the sintered material that belongs to one sinter pallet; it emphasises a variable segment of the sintered material.

As observed at the sinter plants investigated in [1] and described in [6], the labelled data are obtained by manual testing in daily sampling, which is expensive and leads to a lack of labelled data as mentioned before. At the end, most of the measured process data at sinter plants are unmarked data samples. Therefore, the data-based soft sensing and quality prediction performance is impaired by the lack of labelled data samples, and the attention to the unlabelled data is insufficient, as mentioned in [6]. In regard to the problems described above, the question of how to use fewer labelled and more unlabelled samples at the same time has become a critical issue in recent years [75]. To improve the suitability and usability of the measured unlabelled process data available for soft sensing and ML approaches, they must be aligned to the sinter mass flow. This can be achieved by aligning the unlabelled data to the product section to transform them into labelled data, which is a large and important area of research, as time alignment is a fundamental requirement for many applications [76]. In the case of the same signal $sig(t)$ measured at two different locations from the sensors $x_1(t)$ and $x_2(t)$, the Residence Time (RT) of material passing between the two sensing positions can be formulated by the time delay τ between both measuring points with uncorrelated measuring noise $\nu_1(t)$ and $\nu_2(t)$ [77, 78, 79, 80]:

$$\begin{aligned} x_1(t) &= sig(t) + \nu_1(t) \\ x_2(t) &= sig(t - \tau) + \nu_2(t) \end{aligned} \tag{2.12}$$

In [81], it is stated that accurate time alignment of independent variables is crucial to obtain regression models with acceptable validation that are influenced by temporal phenomena like those occurring in industrial processes. In the present work, the time alignment constitutes the central objective of the thesis and will be achieved by estimating the RT of the sinter as it passes through the sinter plant—from the raw material bunker (following the blending yards) to its exit from the plant as finished BF sinter.

Various studies have already addressed the estimation of the RT (or time lag) across different applications. A part of these studies is presented in this section. Section 4.3 and Chapter 5 present a new method developed in this work for estimating the RT of the sinter material as it passes through the sinter plant.

According to [82], the RT can be divided into two parts: the static RT with constant time lags, and parts due to the dynamics of the system with varying time delays.

A differentiation must be made if a constant RT is assumed for reasons of simplification or if a "true" constant RT is applicable. For bulk material, this is the case when the material flow is not disturbed by internal or external influences. In the case of simplification, it must be considered whether external or internal effects, such as segregation effects, are present or not, in order to take them into account in the error analysis (detailed explanation is given in Section 5.1). Dynamic RT can be classified into two categories: those resulting from sources such as segregation or mixing (challenging to quantify), and those arising from factors such as varying transportation speeds or changing material flows with a constant composition (easier to measure). In industrial applications, all these sources can coexist, making it difficult to determine the RT, as shown in the following examples. Thus, for various reasons, only constant RT may be known or available, even though mixing effects

are present. However, these effects cannot be adequately measured, as they occur in bulk solids or liquids. From [63], it is known that the variety of influencing variables makes it impossible to accurately determine the discharge mass flow rates of bulk material from bunkers. There are numerous equations in the literature, some obtained empirically and others by dimensional analysis. Many relationships are based on analogy to the outflow of liquids from an open-top container under gravity. The mass flow is further influenced by the transient pressure gradient at the outlet, which is almost impossible to predict. Also, porosity and flow resistance are required, but this is difficult to determine due to the inhomogeneity of the bulk material.

In the case of bulk material transport, the material is constantly more or less mixed (Section 2.3). The quantity that influences the dynamics of mixing is time-dependent, and this fact causes an additional difficulty in the determination of the RT [82]. The material flow in industrial processes is subject to constant changes, both for random reasons, such as malfunctions of various kinds, and deliberately, for example, if the production quantity is increased or decreased by varying the conveyor speed, which leads to dynamic time delays, even if the internal material composition remains unchanged. The volume flow can also change in plant sections such as bunkers and because of flow variation control [38, 82] or change of composition during transportation as described in Section 2.3. However, the actual processing times in industrial factories are almost always unknown and likely follow a complex distribution [83].

In the work of [81], the material flow of wood particles in the industrial manufacturing process of particleboards was investigated. The commonly used static form of time alignment, where only the distances between consecutive process parameters and the average production speed are considered, is compared to the dynamic calculation of RTs. The dynamic calculation of RTs was achieved by modelling the continuous bulk material flow, thereby enhancing traceability and quality prediction. As stated in [84], one key challenge is the coherent mapping of dynamic and event-based sensor data for real-time tracking purposes with static data, which are mostly needed for retrospective tracing purposes. Therefore, a graph-based traceability model was developed, which integrates static and dynamic sub-models in one connected traceability graph for an automotive application.

A parametric method is presented in [82] for estimation of RT in continuous flow systems with varying dynamics. A resampled dataset is used for the identification of parameters in a recursive least-squares algorithm to calculate the RT. Time-delay estimation also plays a vital role for soft sensor modelling in wastewater treatment plants [85]. In that work a weighted relevance vector machine model based on dynamic time-delay estimation is proposed to predict quality variables.

Experimentally, a tracer can determine the RT. For example, in [86], a developed RFID tracer was used to track the RT of grain. Another example is given in [21] where the RT distribution was evaluated to measure the deviation from ideal flow of liquids in vessels by introducing an inert tracer and monitoring its concentration with time at the outlet or anywhere along the system. In [87], the RT of a bubble stream in a two-phase air-water flow between two points was measured using a noise analysis technique. The RT was determined by the maximum of the cross-correlation function. Other examples are presented in [27] where the RT distribution (RTD) was measured with a tracer response experiment and used to validate different empirically based mixing models ("stirred tanks in series") in Siemens flotations cells, and in [88] and [89] for continuous lines in Pharmaceutical Manufacturing in order to address the traceability of raw materials. Tracers were also used in [90] to

study the RTD of low-density particles, holdup, and bed depth profile in a rotary kiln containing ilmenite particles, and in [91] to investigate the RT of sinter raw material in the axial direction in a continuous drum mixer. A similar approach is used in [92] to measure the RTD in a rotary calciner. The RT also plays an important role in acoustics, speech and signal processing, like in [93]. In that work, an adaptive technique is developed that iteratively determines the time delay between two sampled signals that are highly correlated. The adaptive delay algorithm uses a gradient technique to find the value of the adaptive delay that minimises the mean-squared error (MSE) function. The work of [84] presents a method to identify the time delays of a linear system with time delays by the usage of frequency responses and negative gradient search.

In [77], the Time Delay Estimation (TDE) is based upon generalised cross-correlation for speech signal time delay estimation by minimising a robust statistical error measure. In [78, 79, 80, 94] and [95], techniques for TDE are presented to estimate the time delay between two differently delayed versions of the same signal. Another approach was investigated in [96] to estimate the time lag of X-ray time lag spectra in active galactic nuclei using Fourier-based methods. The work in [97] investigates the integration of laser and ink marking (labelling) technologies to measure the RT during lithium-ion battery cells manufacturing. The authors of [95] present the methodology for the design of a tracking and tracing system based on a morphological analysis where the authors refer to the standard "ISO 9000 2015 Quality management systems - Fundamentals and vocabulary", which defines the term as "(...) the ability to trace the history, application or location of an object (...)" [98]. As already demonstrated in the previous work of [85], ML methods are used after estimating the RT in order to enhance the accuracy of the model. Other examples are given in [83] where the authors consider estimating the unknown processing time using ML models. In [6], an unsupervised learning strategy for industrial processes is introduced to label unlabelled samples. In [6], the calculated dynamic time lags of the process were used to label the unlabelled process data as input features for different ML models (Gradient Boosting, Decision Tree, Recurrent Neural Networks) in order to predict the sinter process quality index (FeO content).

An alternative methodology for determining the RT is the numerical simulation of particle flow using the Discrete Element Method (DEM). The results depend on multiple boundary conditions, which are sometimes unknown or based on assumptions. Consequently, the results represent an approximation of the real particle movement. Typically, the results must be validated through empirical experimentation, which can be conducted using either Radio-Frequency Identification (RFID) or tracer techniques.

For example, in [99] the RT was obtained by tracking the particle of a moving fuel bed on a forward-acting grate. The RT of the fuel particles on a grate was calculated to favour a more reliable design of grate furnaces. The method yielded satisfactory agreement with measurements. In another study from [100], the DEM was utilised to analyse the behaviour of iron ore granules in a continuous drum mixer. The effects of the gradient angle of the drum mixer on the behaviour of granules were investigated using a numerical simulation. To validate the granulation, occupancy and RT, the numerical simulation was again supported by experiments. In [101], DEM was used to study the RT distributions, local different drying conditions, and inhomogeneous drying behaviour of a mixed-flow grain dryer. The results were used to optimise the design elements and different air duct arrangements. The validation was performed by RT experiments, grain drying experiments and discrete element simulations at pilot and industrial scales. In the research of [102], the

RT distributions of particles in flat-bottom and wedge-shaped silos were obtained using the DEM. It was observed that the DEM using the multi-sphere method could successfully simulate the granular flow of elliptical barley grains in flat-bottom and wedge-shaped silos, compared to results from experimental models. The Residence Time Distribution (RTD) of the silos were obtained using the DEM results, which can be used for different purposes, including filling, maintenance, and geometric design of the silo. From the studies [99, 100, 101, 102], it is obvious that the numerical simulation can approximate the real conditions to determine the RT, but the parameters of the models must be calibrated and validated by experiments during model development. In [103], a 3D DEM model of the Sinter Cooler (SC) charging chute system was developed to simulate the segregation pattern in the trolleys. The numerical models yield a qualitative agreement with the measurement of particle size segregation inside the trolleys. The boundary conditions of the sinter material were modelled as dry particles, and the size distribution of the simulated particles was larger than in reality in order to keep the simulation in a reasonable run time. During model development, it is also usual to simplify the geometry, like in [104], to develop a coupled DEM-Computational Fluid Dynamics (CFD) 2D simulation of a sinter shaft cooler. In this case, the SC geometry was axisymmetric with central inlets and outlets, which allowed such simplifications from 3D to 2D simulation. The model was used to calculate the momentum exchange and convective heat transfer between the solid and fluid phase to enable the reproduction of the granular flow phenomena, such as segregation and to predict the pressure drop across the packed bed and to determine the heat exchange between particles and fluid.

In [103] and [104], the effects of sinter segregation were simulated by DEM on simplified models. In [103], the particle size was limited to 25, 50 and 100 mm to reduce the computational effort. The particle size of interest in this study is below 5 mm, which could present a challenge in establishing reliable results within a reasonable time limit. In the work of [105], the flow characteristics of sinter in bunker and SC were examined using DEM and were validated by tracer studies with RFID and colour tracer in the operating facilities of the VASD sinter plant. A transitional function for the material flow was identified for the SC. The results of the SC were validated by colour tracer, due to the high temperatures that make the use of RFID tracers difficult. The application of RFID technology was examined in the storage bunker area, where product temperatures are moderately high, in contrast to the temperatures in the SC. The outcomes of [105] concerning the SC are partly used in this work (Section 5.1) for comparison of the results of the introduced RTE method. The complete results are not available for publication due to confidentiality considerations.

The static and dynamic RT determination approach presented in this thesis will be considered at the sinter machine (SM) and conveying route, where the sinter material moves almost with the same speed as that of the sinter strand or conveyor belt. For reasons of simplification, local particle movements on the conveyor belt are not considered, and therefore the determined static and dynamic RT is valid for all particle sizes. In the SC, these approaches would result in uncertain RTs because the material flow is subject to segregation and other transient effects that affect the particle movement and RT. In this case, the RT is distributed across the Particle Size Distribution (PSD). The application of parametric methods would suffer from unknown parameters, which are challenging to estimate, resulting in poor model accuracy. Multiple process parameters are changed or fluctuate during the sinter process, and some are not documented or are only available

offline.

Experimental determination of RT with tracer is only applicable for large sinter particles that can be detected in the moving sinter mass, and the RFID tracer has to withstand the high abrasive behaviour of the sintered particles, high temperatures up to 1450 °C in the SM and up to 800 °C in the SC. The raw material movement before the SM and downstream in the SC can be tracked by RFID approaches, like in the work of [105], but is not available in the hot segments of sinter production. The tracer experiments are used for validation in this thesis, but only for large $x > 100\text{ mm}$ particles. Sinter bulk material cannot be labelled like in the work of [97] with ink marking technologies or barcodes.

Numerical DEM methods need experimental validation of the boundary conditions as described above, and small particles need enormous computational effort, as described in [103]. Therefore, if DEM were applied for the system considered in this thesis, the interesting small fraction size $x < 5\text{ mm}$ must be simplified in the DEM simulation, which would affect the significance of the results.

In this thesis, a different new approach is developed using the existing plant data and operational values without knowing the parameters of the individual conditions of the material movement caused by segregation. The RTD depends on the fluctuating particle size and is, therefore, also distributed across it. The developed method should be able to estimate the RT for a specific particle size. Depending on the data situation and information density, this method can also be applied to other particle size fractions. In the first step, this approach is limited to the $x < 5\text{ mm}$ fraction as there is a continuous signal (Cold Return Fines) at the sinter plant of VASD. If continuous side measurements of the remaining particle bands are available, the method newly developed in this thesis can be applied and verified on the remaining particle bands.

3 Methods

In the following sections, the methods used will be described in detail. First, a brief overview of big data will be given with a focus on data pre-processing techniques and Machine Learning (ML) methods used in this work. The major focus is on supervised ML methods. Pre-processing techniques are necessary to prepare the collected raw data for later processing and to enable ML applications. Accuracy measures will also be presented to quantify the outcome of the used models and to compare the results. The applied methods to determine the static and dynamic RT are presented as well as the terminology used to describe the different types of "time lags". After this chapter, the experimental setup will be presented.

3.1 Big Data and Data Mining Methods

In Industry 4.0 applications, huge amounts of data are generated and stored every day, resulting in a humongous amount of data. The authors of [106] define big data in five aspects:

- Data is received at a high frequency, requiring real-time processing
- Information can be found in many formats:
 - structured
 - semi-structured
 - unstructured
- Implying variety
- Data also needs to be cleaned to maintain veracity
- Information must provide value to the organisation

The five characteristics mentioned in that work are summarised in Figure 3.1. The volume, frequency, and variety aspects refer to the data generation process and how to capture and store the data, while the veracity and value aspects deal with the quality and usefulness of the data, as stated in [106]. The aspects of veracity and value are essential to any big data process, as the extraction of valuable knowledge is highly dependent on the quality of the data used.

The amount of data is constantly increasing these days, which [107] attributes to three main reasons: On one hand, thousands of applications, such as sensors, social media services and other devices, collect information continuously. On the other hand, the improvement of storage capacity, technology, and low prices makes it preferable to increase the storage capacity instead of deleting the information. Finally, the improvement of ML approaches

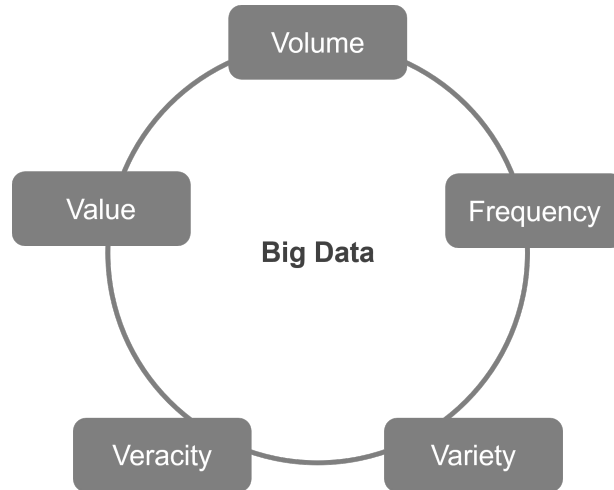


Figure 3.1: Definition of big data from [106]

in recent years make it possible to extract a higher level of knowledge from data. In daily practice, over 77 different process attributes (cf. Chapter 4) are stored 24/7 in sinter plants at sampling rates of 0.1 Hz.

According to [108], analysing huge amounts of data offers the opportunity to enable decision support systems that combine data collection, data storage, and knowledge management with analytics to provide input to the decision process. But from [109, 110] it is known that enormous effort must be invested to pre-process the data. As a result, problems in the data will affect the extracted models in case of insufficient data preparation. The developed models must adapt to dynamic data trends and be fault-tolerant to ensure reliability in long-term applications. Specifically, they should preserve signal characteristics such as linear, monotonic, or abrupt trends, as well as long-term level shifts. Additionally, they must be capable of generalising to new data [111]. In [112], it is indicated that the actual benefit of big data does not lie in the data itself, but in the ability to uncover (unexpected) patterns and extract knowledge from it by applying suitable data science techniques (data mining). Industries that can extract valuable knowledge from big data in a reasonable time can gain significant advantages over their competitors [113, 114]. Much research work focuses on developing robust and accurate ML models for big data applications [115]. The number of research studies is increasing significantly [116], and this trend is not expected to change in the future.

The accuracy of knowledge extracted by ML methods depends not only on the design and performance of the method, but also on the quality and suitability of the data itself, as mentioned before. Unfortunately, negative factors such as noise, missing values, inconsistent and superfluous data, and large amounts of features strongly influence the input data used for ML model training and knowledge extraction. Furthermore, [117] concludes that low-quality data leads to low-quality knowledge. Therefore, data pre-processing is an essential step aimed at obtaining final datasets that are correct and useful for ML algorithms [109]. The goal of data pre-processing [118] is to clean and correct input data, so that an ML process may be applied later faster and with greater accuracy. Nevertheless, these methods are also heavily affected by the increasing size and complexity of datasets and may not be able to provide a pre-processed dataset promptly, thus they need to be redesigned using big data technologies. The recipe for application of big data methods can

be divided into the following sub-steps [106]:

- Data acquisition
- Aggregation
- Pre-processing
- Data- and dimension reduction
- Discretisation

In this study, data acquisition and aggregation will be treated in Section 4.2 for real sinter plant data used in this thesis. The major pre-processing techniques used which deal with imperfect data, missing values and noise data will be presented in the next Section 3.2. Data and dimension reduction will be applied in Chapter 5 as well as the aspect of discretisation. To enable discretisation and conditional independence of datasets, Sections 2.4, 4.3 and Chapter 5 deal with the time alignment which is also covered in the work describing the "new measurement techniques for sinter quality determination" in [1, 35, 36].

3.2 Data Pre-Processing

Industrial process data can be incomplete, incorrect, noisy, and inconsistent, subjected to various kinds of fluctuation which can disguise useful patterns [119, 120]. The causes can be of various kinds. They can be caused by control interventions but can also originate in the measurement method itself, which leads to noisy data, containing errors or outliers. In addition, the individual process steps can lead to further fluctuations as well as unforeseen process irregularities, stoppages, and malfunctions, such as lacking attribute values. In addition, malfunctions due to wear or failure of individual control measurements and system components can also lead to fluctuations and noisy or missing values. Thus, the raw datasets may contain missing features of interest, contain only aggregated data, or even incomplete or inconsistent values and discrepancies in the variable names [119]. Also, these fluctuations and disturbing aspects in the raw values would lead to accuracy loss in applied models. Thus, the irregularities in the process data time series must be removed or replaced as well as possible in order to get clean values which reflect the process situation of the actual processed product. This section describes the task of data preparation. Data pre-processing generates a dataset smaller than the original raw dataset, which can significantly improve the efficiency of ML models. Pre-processing includes filtering, removing anomalies, or eliminating duplicate records, recovering incomplete data (filling in missing values), correcting errors, or removing outliers [119]. As the sinter process is a continuous process, the continuous process data series must be pre-processed. From Sections 2.1 and 2.3, it becomes evident that the continuous sintering process is subjected to various process and condition changes caused, e.g., by the fluctuating raw material quality; therefore, the data pre-processing should be able to deal with temporary shifts, while removing short sequences of irrelevant outliers in the measured values. Thus, the primary filters used in this thesis are moving window techniques which allow to preserve relevant signal details like level shifts and provide considerable robustness against deviations from outliers [111].

As outlined in [111], a time window slides through the time series observations to locally approximate the signal using the data within the window. In the cited work, it is stated that moving averages and linear filters are generally not suitable for removing outliers and tend to blur level shifts. The filter techniques most frequently used in this work are, therefore, running median filters for data smoothing, presented in the next section. Moving median filters with Median Absolute Deviation (*MAD*) confidence intervals for outlier detection (DWM-TM-filters) are also presented. The raw data handling and development of selected new measurements for soft sensing and enhanced sample rate are described in detail in the studies of [1, 35, 36].

The data series in this thesis are mainly time series. Thus, the common index $i = 1, 2, \dots, n$ of the variables x_n and y_n is referred to as $t = 1, 2, \dots, n$ from "time".

3.2.1 Moving Median

The moving median is a more robust alternative to the moving average when it comes to estimating the underlying trend in a time series [121, 122]. While the moving average is optimal for recovering the trend, when the fluctuations around the trend are normally distributed, it is susceptible to the impact of rare events such as rapid shocks or anomalies. In contrast, the moving median, which is determined by sorting the values within the time window and finding the value in the middle, is more resistant to the impact of such rare events [121]. The usual median or central value is given by the middle value of the ordered sample of x_n containing x_t discrete observations with $t = 1, 2, \dots, n$ [123]:

$$median = \begin{cases} x_{[(n+1)/2]} & \text{if } n \text{ is odd} \\ \frac{1}{2}(x_{[n/2]} + x_{[n/2+1]}) & \text{if } n \text{ is even} \end{cases} \quad (3.1)$$

where:

$median$: is the median or central value
 x_n : are the x values with n observations

The moving window filter can be set up for retrospective (fixed sample, historical data) or online (sequential) application. In this thesis, the retrospective case is applied for the development of the RTE, while the online case is selected for the online measurements mentioned in [1, 35, 36] and in Section 6. In retrospect, the signal value in the centre of the window, including both past and future observations in the calculations, can be considered, as time delays cause no problem. In the online analysis, the most recent time is selected for filtering the signal, i.e. the end of the window with values from the past [111]. The window $w_t^{m,\tilde{m}}$ of a data series x_n with discrete points $t \in \mathbb{Z}$ consisting of the measurements $x_1, \dots, x_n$ can be denoted as [111]:

$$w_t^{m,\tilde{m}} = x_{(t-m)}, \dots, x_{(t+\tilde{m})} \quad \text{with } t \in \mathbb{Z} \quad (3.2)$$

where:

$w_t^{m,\tilde{m}}$: are the values in the window
 $x_{(t-m)}, \dots, x_{(t+\tilde{m})}$: is the time window
 $m, \tilde{m}$: is the window parameter, to adjust the width of the window

and where $\tilde{m} = m$ in the case of a symmetric retrospective and $\tilde{m} = 0$ in the online case. The resulting window width is obtained as follows [111]:

$$k = m + \tilde{m} + 1 \quad (3.3)$$

where:

k : is the window width

$m, \tilde{m}$: is the window parameter, to adjust the width of the window.

The selection of a suitable value for m depends on the characteristics of the individual signal in order to preserve relevant signal details such as level shifts and to increase robustness against deviations from outlier and other short anomalies. To distinguish between relevant temporary level shifts and irrelevant spike sequences, [111] assume that the latter have a shorter duration.

In the case of low fluctuating signals, m can be selected small, as the values within each time window are almost constant. This results in less smoothing. Higher values of m generate less variability, produce smoother estimates, and increase robustness, but generate a constant level within each window even when the signal is varying. This assumption can lead to information loss. In general, the window width must be chosen, making a compromise between the degree of smoothing and the depth of detail. Moving median filters, also called running medians, have been introduced by [124] and are perhaps the most prominent robust location-based filters, calculating the median over each window of Equation (3.2), as suggested in [111]:

$$median_{t,mov} = \tilde{\mu}_t = median(x_{(t-m)}, \dots, x_{(t+\tilde{m})}) \quad (3.4)$$

where:

$\tilde{\mu}_t$: is the moving median

$x_{(t-m)}, \dots, x_{(t+\tilde{m})}$: is the time window

The moving median is obtained by calculating the median of the subset in the window $x_{(t-m)}, \dots, x_{(t+\tilde{m})}$ and each modified subset by "shifting forward" the window.

3.2.2 Outlier Detection

Real-world data are far from being clean or complete, as described earlier. In data pre-processing, it is common to employ techniques to either remove the noisy data (see moving median, Section 3.2.1) or to impute (fill in) the missing data as mentioned in [120]. Another technique to detect anomalies or outliers in the dataset is based on the Median Absolute Deviation (*MAD*) as proposed in [125] and modified versions in [111] and [126].

The *MAD* is defined by:

$$MAD = median(|x_t - median(x)|) \quad (3.5)$$

where:

MAD : is the Median Absolute Deviation

x_t : is the actual x value at time t

$median(x)$: is the median of all x values

To achieve unbiasedness in the case of Gaussian noise, a correction factor is usually chosen $c_n = 1.483$ according to [111] and [126]. Multiplying the MAD with the factor c_n results in estimation of the standard deviation $\tilde{\sigma}$:

$$\tilde{\sigma} = c_n \cdot MAD \quad (3.6)$$

where:

$\tilde{\sigma}$: is the estimated standard deviation

c_n : is the scale factor to transform the Median Absolute Deviation (MAD) into standard deviation estimate

MAD : is the Median Absolute Deviation, cf. Equation 3.5

The standard deviation is estimated from the MAD according to Equation (3.6) because the direct calculation of the standard deviation would be affected by the outlier contained in the moving window. The standard deviation (cf. Equation (3.27)) is calculated from the sample mean (cf. Equation (3.19)), which is sensitive to outliers [127]. By applying Equation (3.6) to the window from Equations (3.2) and (3.4), a moving confidence interval for the series x can be evaluated:

$$\tilde{\sigma}_t^M = c_n \cdot \text{median}(|x_{(t-m)} - \tilde{\mu}_t|, \dots, |x_{(t+\tilde{m})} - \tilde{\mu}_t|) \quad (3.7)$$

where:

$\tilde{\sigma}_t^M$: is the moving confidence interval

c_n : is the scale factor, $c_n = 1.483$, cf. Equation (3.6)

$x_{(t-m)}, x_{(t+\tilde{m})}$: is the time window

$\tilde{\mu}_t$: is the moving median, cf. Equation (3.4)

Equation (3.7) wraps a confidence interval around the values from x_t . By default, an outlier can be determined for values of x_t greater than two or three scaled $\tilde{\sigma}_t^M$ thresholds according to [111, 128]:

$$q_t = b \cdot \tilde{\sigma}_t^M \text{ with } b = 2, \dots, 3 \text{ (default values, [111, 128])} \quad (3.8)$$

where:

q_t : is the limit value, or confidence interval

b : is the factor to modify the width of the confidence interval

$\tilde{\sigma}_t^M$: is the confidence interval, running threshold, cf. Equation (3.7)

The range of the limit q_t can be adapted to the characteristics of the signal. All values greater than q_t are omitted; the remaining values can be averaged for better reduction of observation noise. The values greater than q_t exceed the confidence interval and are identified as outliers in accordance with the specified procedure. The so-called Double Window Modified Trimmed Mean (DWMTM)-filters are constructed in this way, with [111]:

$$DWMTM(x_t) = \frac{1}{|I_t|} \sum_{w \in I_t} x_{t+w} \quad (3.9)$$

$$I_t = \{w = -m, \dots, \tilde{m} : |x_{t+w} - \tilde{\mu}_t| \leq q_t\}$$

where:

- I_t : are the values in the moving window smaller q_t , cf. Equation (3.8)
- w : is the window
- x_{t+w} : is the moving window
- $\tilde{\mu}_t$: is the moving median cf. Equation (3.4)
- $DWMTM(x_t)$: is the Double Window Modified Trimmed Mean

In MATLAB (Version: R2024a, 1994–2025 The MathWorks, Inc.), which was used in this thesis, this filter is included in the "filloutliers" function, where the median or mean value can also be selected from the remaining values as in Equation (3.9) to decrease the noise of the signal. Truncated values (greater than q_t) can be filled in with values obtained from the moving median in the range of the window width k from Equation (3.3) [129].

3.3 Supervised Methods

In this section the ML methods are introduced which will be applied to the data collected from the sinter plants after pre-processing. The goal of ML methods is to develop the most accurate possible model for predicting a value of interest from a set of independent input variables. The value of interest, which is the output variable of the model, is also referred to as the dependent variable or response and typically denoted by the symbol Y ; the mentioned independent variables, which represent the input variables, are also referred to as predictors [130] and are denoted by X . As X is usually specified as a matrix, the individual input variables are separated from each other by an index $X_1, X_2, \dots, X_p$. The model is developed on the assumption that there is a relationship between the response Y and the predictor X :

$$Y = f(X) + \epsilon \quad (3.10)$$

where:

- Y : are the response variables
- $f(X)$: is an unknown function
- ϵ : is an error term

In this setting f is an unknown function of $X_1, X_2, \dots, X_p$ and ϵ is a random error term, which is independent of X . The function f connects the predictor variables to the response variables and must be estimated on known observed points. The goal of the ML model development is to estimate the best approximation of f . In general, the ML approaches can be separated into two categories: supervised and unsupervised [131]. In the domain of supervised models for each observation of the predictor x_t , $t = 1, 2, \dots, n$ an associated response measurement y_t exists. The aim is to find a model that relates the response to the predictors and predicts the response for future observations as accurately as possible. The ML method used in this work will be a Multiple Linear Regression (MLR) model from the supervised domain. In contrast, unsupervised approaches describe a situation in which, for each observation $t = 1, 2, \dots, n$, a vector of values x_t is provided, but no associated response y_t is given. This setting is referred to as unsupervised because there is no response variable that can supervise the analysis [130, 132]. The subject of unsupervised models is extensively documented in the literature and is therefore not addressed in this thesis.

In this work, an extension of simple linear regression is used, which is referred to as Multiple Linear Regression (MLR) and will be briefly described in the next section. The MLR model will be used to predict the return fines in Section 5.3 and used as a correlation function (kernel function) in Section 5.1 and 5.2.

3.3.1 Multiple Linear Regression

The MLR model can accommodate multiple predictors $j = 1, 2, \dots, p$ and each observation $t = 1, 2, \dots, n$ from training data in $n \times p$ matrix $\mathbf{X}$ whose (t, j) . element is x_{tj} :

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix} \quad (3.11)$$

The response variable $\mathbf{y}$ can be written as a column vector ($n \times 1$ matrix) in the case of a single response variable or as a matrix $\mathbf{Y}$ in the case of multiple response variables:

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \quad (3.12)$$

By giving each predictor X_j a separate regression coefficient β_j in a single model, [130] this requires:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon = \beta_0 + \sum_{j=1}^p X_j \beta_j \quad (3.13)$$

The regression coefficients $\beta = (\beta_0, \beta_1, \dots, \beta_p)$ (or regression weights w) can be estimated by using the least squares algorithm to minimize the sum of squared residuals (RSS) [132, 131]:

$$\begin{aligned} RSS &= \sum_{t=1}^n (y_t - \hat{y}_t)^2 \\ &= \sum_{t=1}^n (y_t - \beta_0 - \sum_{j=1}^p X_{tj} \beta_j)^2 \end{aligned} \quad (3.14)$$

where:

- RSS : is the sum of squared residuals
- y_t : are the real response variable values
- $\hat{y}$: are the predicted response variable values

This approach is suitable if the training observations (x_t, y_t) represent independent random draws from their population. Even if the x_t 's are not drawn randomly, the criterion is still valid if the y_t 's are conditionally independent given the inputs x_t [132]. In other words, the model should be capable of generalising with respect to new data [111].

The model from Equation (3.13) assumes a linear behaviour of the regression function $E(Y|X)$, which represents the average or expected value "E" of the predicted values Y as a function of the predictors X . As described by [132], the variables X_j can be extended by polynomial representations such as $X_2 = X_1^2$ or $X_3 = X_1^3$ etc., and also interaction between two variables is possible, such as $X_3 = X_1 \cdot X_2$ to increase the performance of the model in non-linear cases [130].

Before the MLR model is trained on data, the dataset should be pre-processed as mentioned in Section 3.2 to achieve a better prediction accuracy, but also dimension reduction [106] (not applicated in this thesis) or predictor selection to reduce the irrelevant predictor from the dataset (Section 5.1.2) should be considered. At time series without time alignment all variables should be temporally aligned as mentioned in Section 2.4 to achieve the best possible conditional independent values.

Different scales of the predictor can lead to unbalanced loads of the used data. Small, scaled values will have less effect than large, unscaled variables in the generated model. To overcome this effect, the input data should be standardised as mentioned in [130] and [131]. In this thesis all predictors will be standardised using the z -score standardisation z_{tj} , so that all values have a mean μ of zero and a standard deviation σ of one [130, 133] along their dimension j :

$$z_{tj} = \frac{x_{tj} - \mu_j}{\sigma_j} \quad (3.15)$$

where:

μ_j : is the mean over variables x_j of dimension j

σ_j : is the standard deviation over variables x_j of dimension j

x_{tj} : are the variable values of each observation x_t of each predictor (x_j)

z_{tj} : are the z -score values of the (t, j) . element

Thereafter, all values have a comparable scale. Another issue arises when the dataset has high dimensionality (large p). MLR performs no predictor selection automatically, thus all regression coefficients are nonzero. Various approaches have therefore been proposed [132]. For example, in [33] the predictors were selected using the RReliefF method, which is based on a k -nearest neighbors approach for estimating the ranking of the most important variables. The RReliefF method is well documented in [134, 33] and was applied to the dataset to rank the predictor in Section 5.1.2. If $p < n$, the statistically important predictor can be estimated by determining the F -statistic and p -value of each variable as described in [130, 132]. The F -statistic determines whether there is a relationship between the response and the predictor. In the case of no relationship, the null hypothesis H_0 would be true, which means that the regression coefficients are zero ($H_0 : \beta_1 = \beta_2 = \dots \beta_p = 0$). In reverse, the alternative hypothesis H_a is true when there is a relationship between response and predictor (H_0 : one of $\beta_j \neq 0$). Values of the F -statistic close to one indicate that H_0 is true; in contrast, values larger than one indicate that H_0 can be rejected and that H_a is true [130, 132]. The hypothesis test can be applied by determining the F -statistic:

$$F = \frac{TSS - RSS/p}{RSS/(n - p - 1)} \quad (3.16)$$

where:

F : is the F-Statistic

TSS : is the total sum of squares

RSS : is the sum of squared residuals (Equation (3.14))

n : are the total numbers of observations

p : are the total numbers of predictors

An additional method for examining the relationship between an individual predictor and the response is to calculate the p -value. A p -value that is relatively small indicates that there is an association between the predictor and the response, thereby supporting the alternative hypothesis H_a and rejecting the null hypothesis H_0 . In contrast, a larger p -value suggests that the null hypothesis is correct and that there is no association between the predictor and the response. The p -value is determined by calculation of the t -statistic [130]:

$$t\text{-statistic} = \frac{\beta_j - 0}{SE(\beta_j)} \quad (3.17)$$

where:

β_j : is the regression coefficient j

$SE(\beta_j)$: is the standard error of the regression coefficient j , cf. Equation (3.18)

and determining the probability that $\beta_j = 0$. Typically, the cutoffs for rejecting H_0 are 5 or 1% of the t -statistic [130]. The standard error SE can be calculated as follows:

$$SE(\beta_j) = \frac{\sigma^2}{\sum_{t=1}^n (x_t - \bar{x})^2} \quad (3.18)$$

where:

$SE(\beta_j)$: is the standard error of the regression coefficient j

x_t : is an observation value of predictor variable

σ^2 : is the $var(\varepsilon)$, which can be estimated by the Residual Standard Error:

$$RSE = \sqrt{RSS/(n - 2)}, \text{ } RSS \text{ cf. Equation(32)}$$

The mean $\bar{x}$ of the predictor variable is calculated by:

$$\bar{x} = \frac{1}{n} \sum_{t=1}^n x_t \quad (3.19)$$

where:

$\bar{x}$: is the mean of all observations from the predictor

x_t : is a value of the predictor variable

Also, collinearity can affect the MLR model accuracy when two or more predictors have a close relation to each other (high correlation). The authors in [130] explain that these predictors reduce the accuracy of the estimated regression coefficients, thus making it difficult to determine the association with the response, resulting in uncertainty in the coefficient estimates and increasing the standard error. It becomes difficult for the model to estimate the relationship between each predictor variable and the response independently because

the collinear predictors tend to change in unison [135, 136, 137]. Collinearity can be detected using a correlation matrix or by determining the variance inflation factor (*VIF*). The detected predictor can be removed from the dataset to omit collinearity [130, 137]. Another approach proposed in [138] is the determination of collinearity between the predictor and response variables through the calculation of condition indices and variance decomposition proportions introduced as "Belsley collinearity diagnostics". This methodology is employed in this study, as it is provided by MATLAB.

Unbalanced datasets with $p > t$ can lead to high variability in the least-squares fit, resulting in overfitting and lower accuracy of the MLR model for predictions on unknown data. Thus, datasets should have more observations (t) than predictors (p) as proposed in [130, 132]. In general, for model development, the dataset should be divided into a training set of a size of 75% of all observations in the training and 25% of data in the test set. The training set with (t) observations and (p) predictors can be formulated as in Equation (3.11), and the associated response can be written as a vector according to Equation (3.12). The model will be trained on the training dataset and can then be used to predict the reserved response values from the test dataset without presenting the values to the model. In that way, the accuracy of the created model can be calculated by comparing the original target values of the training and test values (Section 3.4) with the calculated values from the model, which can help to choose the best-matching model.

3.4 Determination of Model Accuracy and Quality

To quantify the accuracy of the predicted and the real data values from machine learning (ML) models, the Mean Squared Error (*MSE*), the R^2 statistic (*R*-squared), and the linear correlation coefficients $\rho(X, Y)$ are utilised in this thesis. Further, to evaluate the (time) lag between two signals, the cross-correlation will be presented in this section. The *MSE* is determined from real data and prediction $y_t, \hat{y}_t$ to calculate the mean of Residual Sum of Squares (*RSS*) [6, 130] (Equation (3.14)), given by:

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \quad (3.20)$$

where:

MSE : is the Mean Squared Error

y_t : are the real response variable values

$\hat{y}_t$: are the predicted response variable values

The *MSE* is one of the most used measures to describe how close the real response values y_t match the predicted response values $\hat{y}_t$ [6, 18, 130]. A small *MSE* indicates that the predicted response values are close to the real response, while a large *MSE* indicates that the predicted response values differ significantly from the real response. The *MSE* is calculated for both the training dataset (training *MSE*) and the test dataset (test *MSE*) and provides information about the performance of the model on unseen data. To avoid overfitting, the focus should be on the test *MSE* of the model. This is because, as the degree of freedom of the created model increases, the flexibility of the model will increase, too, which, on the one hand, leads to a low training *MSE*, but on the other

hand, the test MSE will increase, as demonstrated in [130]. This is an indication of the low generalisation ability of the model. If the trained model has a low training MSE , but a high test MSE , the model tends to overfit, in which case it can perfectly reflect the training data and some random patterns in the data, but performs poorly on new test data where the (random) patterns from the training data do not exist. During model development, the main objective is to find a compromise between sufficient flexibility of the model and, at the same time, avoiding overfitting.

Another way to measure the quality of the prediction of the response variables is expressed as the proportion of explained variance by the model $R^2(y_t, \hat{y}_t)$, which is also known as coefficient of determination [31, 135, 136, 137]. The R^2 statistic takes on values between 0 and 1, so it is independent of the scale of the prediction Y [130], from Equation (3.14), and (3.22) the R^2 -statistic can be calculated as follows:

$$R^2 = \frac{\sum_{t=1}^n (y_t - \bar{y})^2 - \sum_{t=1}^n (y_t - \hat{y}_t)^2}{\sum_{t=1}^n (y_t - \bar{y})^2} = \frac{TSS - RSS}{TSS} = 1 - \frac{RSS}{TSS} \quad (3.21)$$

where:

- R^2 : is the coefficient of determination
- y_t : are the real response variable values
- $\hat{y}_t$: are the predicted response variable values
- $\bar{y}$: is the mean of the (real) response values

The total sum of squares (TSS) or variance is defined by:

$$TSS = \sum_{t=1}^n (y_t - \bar{y})^2 \quad (3.22)$$

where:

- TSS : is the total sum of squares
- y_t : are the real response variable values
- $\bar{y}$: is the mean of the (real) response values

The TSS measures the total variance of the response, representing the variability included in the response before the regression model is performed. The RSS (Equation (3.14)) measures the amount of variability that is left unexplained after performing the regression. The difference of TSS and RSS measures the amount of variability in the response that is explained by performing the regression model. Values of R^2 close to 1 indicate a sizeable proportion of variability that the model explains, and values near 0 indicate a poor explanation of the variability covered by the model [130]. To measure the linear relationship between two variables X and Y , the correlation coefficient or Pearson correlation coefficient can be used, like in [34], which is defined in [130, 131, 139]:

$$rho(X, Y) = \frac{\sum_{t=1}^n (x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=1}^n (x_t - \bar{x})^2 \sum_{t=1}^n (y_t - \bar{y})^2}} = \frac{cov[X, Y]}{\sqrt{var[X]var[Y]}} \quad (3.23)$$

where:

y_t : are the y variable values
 x_t : are the x variable values
 $\bar{x}$: is the mean of x values, cf. Equation (3.19)
 $\bar{y}$: is the mean of y values, cf. Equation (3.19)
 $\rho(X, Y)$: is the linear correlation coefficient (Pearson correlation)

In this thesis, the linear correlation coefficients by Pearson will be referred to as " ρ " from ρ . If the relationship of the response variable is linear, the R^2 statistic from Equation (3.21) yields the same results as the linear correlation coefficient $\rho(X, Y)$ or $\rho(y_t, \hat{y}_t)$ from Equation (3.23). The correlation coefficient ρ can take values from 1 to -1 , indicating the noise and direction of the correlation. Values close to 1 indicate a positive correlation, and values close to -1 indicate a negative correlation. Values close to 0 indicate low or even no correlation, because the variance is zero; in this case, no correlation is defined [131]. As defined in Equation (3.23), the linear correlation ρ can be expressed as the covariance $\text{cov}[X, Y]$ divided by the standard deviation of X and Y (Equation (3.27)). The covariance measures the degree to which X and Y are linearly related. By division with the standard deviation, the result becomes the (linear) proportion analogue to the calculation of R^2 .

A conventional method for describing the correlation between a variable from a time series at two separate times (t and $t \pm \tau$) is to apply the sample autocorrelation function, as described in [123, 131, 140]:

$$\rho_x(\tau) = \frac{\sum_{t=1}^{n-\tau} (x_t - \bar{x})(x_{t+\tau} - \bar{x})}{\sum_{t=1}^n (x_t - \bar{x})^2} = \frac{\text{cov}[X^{(t)}, X^{(t+\tau)}]}{\text{var}[X^{(t)}]}; \quad \tau = 0, \pm 1, \pm 2, \dots \quad (3.24)$$

where:

τ : is the lag
 x_t : are the x variable values
 $x_{t+\tau}$: are the x variable values with lag τ
 $\bar{x}$: is the mean of the x values, cf. Equation (3.19)
 $\rho_x(\tau)$: is the auto-correlation coefficient

This is a conventional statistical technique frequently used to evaluate the correlation between current and past values and can help identify patterns, trends, or periodic data. High autocorrelation at a specific lag indicates that past values strongly influence future values. The delay τ is called lag (Equation (2.12)) and has the unit of the time series time index. The prefix "auto" results from the correlation of the variable with itself and describes the correlation of the variable at two separate times: The current time t and the lagged time $t \pm \tau$ [123, 131]. Autocorrelation can be used to measure the similarity of a signal at two different locations, helping determine the time delay between time series values. The procedure from Equation (3.24) can also be applied on two different variables to determine the lag by observing the correlation development. For time series with different variables, the cross correlation of the two signals X and Y (X and Y are used here for better readability) is given by replacing $X^{(t+\tau)}$ from Equation (3.24) with $Y^{(t+\tau)}$ [141]:

$$c_{x,y}(\tau) = \begin{cases} \frac{1}{n} \sum_{t=1}^{n-\tau} (x_t - \bar{x})(y_{t+\tau} - \bar{y}); & \tau = 0, +1, +2, \dots \\ \frac{1}{n} \sum_{t=1}^{n+\tau} (y_t - \bar{y})(x_{t-\tau} - \bar{x}); & \tau = 0, -1, -2, \dots \end{cases} \quad (3.25)$$

where:

- τ : is the lag between x_t and y_t
- x_t : are the x variable values
- y_t : are the y variable values
- $x_{t-\tau}$: are the x variable values with lag τ
- $y_{t+\tau}$: are the y variable values with lag τ
- $\bar{x}$: is the mean of the x values
- $\bar{y}$: is the mean of the y values

$$rho_{x,y}(\tau) = \frac{c_{x,y}(\tau)}{\sigma_x \sigma_y}; \quad \tau = 0, \pm 1, \pm 2, \dots \quad (3.26)$$

The standard deviation of x and y (square root of the variance), which is also used in the denominator in Equation (3.23), is defined as:

$$\begin{aligned} \sigma_x &= \sqrt{var(X)}, \quad \sigma_y = \sqrt{var(Y)} \\ \text{or general for } x: & \\ \sigma_x &= \sqrt{var(X)} = \sqrt{\frac{\sum (x - \bar{x})^2}{n}} \end{aligned} \quad (3.27)$$

where:

- σ_x : is the standard deviation of the x values
- σ_y : is the standard deviation of the y values
- X : values from X variable
- Y : values from Y variable
- x : are the x values
- $\bar{x}$: is the mean of the x values
- n : total number of x observations

With Equation (3.26), the correlation for two different variables with unknown lag τ can be analysed by searching the highest correlation from Equation (3.26) [79]:

$$rho_{max}(\tau) = \arg \max \frac{c_{x,y}(\tau)}{\sigma_x \sigma_y} \quad (3.28)$$

From Equation (3.28), the lag τ with the highest correlation between the variables X and Y can be determined for the case that the correlation function has one maximum (unimodal). The method is described in the work of [141] and available as a function in MATLAB [142].

3.5 Theory and Methods for Residence Time Estimation

The Residence Time (RT) is described in Section 2.4 and is utilised in a variety of application areas. The RT is defined as the time that a specific product unit, e.g. a particle, spends within a domain from its entry into the system to its exit from that domain [143].

Various approaches were developed to estimate the RT as reported in Section 2.4 for various applications and in [143] for particles in fluids. The term RT is used not only for particles in liquids but also for specific particles in bulk solids, as described in [144].

In this thesis, the RT is estimated for sinter material (bulk material), from the raw material inputs to the finished product leaving the sinter plant as "BF-Sinter" (Blast Furnace-Sinter). The RT is also calculated between all relevant measuring points. After determining the RT, the information can be used to align the measuring values (variables) with the sinter material by shifting forwards or backwards the values in time to correct the temporal misalignment. The temporal alignment prevents misleading conclusions caused by temporally misaligned data. The continuous flow of sinter mass (bulk material) is discretised by the spatio-temporal quantification. One approach to find the best time lag between two measuring positions or variables is the application of the cross-correlation (Section 3.4). This method is preferred for samples with constant RT. In this thesis, the cross-correlation is used to verify the empirically measured static RT (Section 5.1.3) and to determine constant RT values. However, in areas where the conveying speed is not constant, other methods are required.

Therefore, different RT techniques are applied in this thesis to estimate the RT depending on the sinter plant process sections. The determination of the static, dynamic and estimated RT is introduced in the following section. First, the terminology used in this thesis for the time terms is summarised in Section 3.5.1.

3.5.1 Terminology of the Use of Time Terms

This section defines the "time" terms used in this thesis. The terms have their origins in a variety of fields, including, but not limited to, fluid dynamics, chemistry, environmental science, and engineering. In this thesis, applications in the context of bulk material and time series are used and summarised in Table 3.1.

Table 3.1: Time terms used in this thesis

Term	Definition
Dynamic RT	RT calculated from actual strand speed, cf. Section 4.3.1
Estimated RT	RT estimated by the RTE approach, cf. Section 4.3.3
lag (τ)	The number of time periods separating two time series, or, in the case of autocorrelation, a series from itself. The lag (τ) is the temporal displacement or shift between the time series [77, 96, 111]. The unit of τ is the same as the unit of the time axis of the time series. If the time series data period is given in minutes, the lag unit is also expressed in minutes.
Residence Time (RT)	Average time a material spends within a system before exiting [81, 143, 144], e.g. bunker, conveyor, reactor, hopper. Measured in time units.

Continued on the next page

Table 3.1: Time terms used in this thesis (cont.)

Term	Definition
Static RT	Constant RT, empirically determined by sinter plant operator, cf. Section 4.3.2
Time alignment	The process of adjusting two or more time-dependent time series to obtain time lag corrected data [81, 145, 146], so that corresponding events, patterns, signals, material, occur at the same points in time, thus ensuring meaningful comparison in correlation analysis.
Time lag	Lag measured in time unit [6, 18, 81, 111]
Time offset	Measuring the time delay (shift) between two time series. Fixed time difference between two signals or events [147].
Time shift	Manually shifting a series forwards or backwards in time [81].
Transport time	Time required for a material to move from one location to another within a system, with constant velocity and constant distance [81]. $t = \frac{\text{distance}}{\text{velocity}}$

3.5.2 Static RT

The static RT was measured by the VASD plant operator during the MinSiDeg project [1] by recording the time required to pass through specific sections of the plant, e.g., from the feed position to discharge from a conveyor belt. In the case of conveyor belts, this time t corresponds approximately to the time required to travel a certain distance s on a conveyor belt at a constant velocity v ,

$$t = \frac{s}{v} \quad (3.29)$$

where:

- t : is the transport time in s
- s : is the distance (length of the conveyor) in m
- v : is the constant belt velocity in m/s

and is referred to as transport time. However, the static RT also contains information for transfer points (e.g. from belt to belt or belt to screen) and the passage through screens, which cannot be represented in a simplified way using the constant distance/velocity approach from Equation (3.29). The static RT information is thereby determined by the summation of different processing times of various transport and process components, such as conveyors, transfer points, and screens. These include averaged duration values and are therefore referred to as static RT. This is consistent with the definition of RT as the average time required to pass through a given system.

3.5.3 Dynamic RT

In contrast to the static RT (cf. Section 3.5.2), the dynamic RT considers the actual strand speed of the SM. In general, the relationship between distance s , time t and instantaneous velocity v is given by [148]:

$$\lim_{\Delta t \rightarrow 0} \frac{\Delta s}{\Delta t} = \frac{ds}{dt} = \dot{s} = v \quad (3.30)$$

where:

s : is the distance, integral of velocity over time, $s = \int v \, dt$

$\dot{s}$: is the derivate of s

t : is the time

v : is the instantaneous velocity, rate of change of distance with respect to time

The function of v is unknown in the context of this thesis; thus, the change in distance is approximated for each sample time over the sampling period by applying the following relationship:

$$\Delta s_i \approx t_s \cdot v_i \quad (3.31)$$

where:

Δs_i : is the change of distance

t_s : is the sampling period, $t_s = \Delta t = t_{i+1} - t_i$

v_i : is the actual velocity

By calculating the cumulative sum of Equation (3.31) $S_i \approx \sum_i \Delta s_i$, the total change of distance with respect to time is approximated (cf. Equation (3.30)). The distance for the measuring position with respect to the reference position Δs and the reference time are well known at the SM, so that Δt can be determined by:

$$\begin{aligned} S_2 - \Delta s &= S_1 \\ S_1 &\mapsto t_1 \\ t_2 - t_1 &= \Delta t \end{aligned} \quad (3.32)$$

where:

S_2 : is the actual cumulative strand length S_2 at reference time t_2

Δs : is the actual distance to the measuring position with respect to the reference position at the SM

S_1 : is the actual cumulative strand length at the measuring position

t_2 : is the reference time

t_1 : is the time at measuring position

Δt : is the time difference between reference time t_2 and measuring time t_1 at measuring position

The dynamic RT is represented by the time Δt from Equation (3.32), in this case, discretised over the sampling period (time-discrete intervals of 10 s) and one specific measurement position. By repeating the procedure for each reference time t_i and for each measurement position at the SM, the dynamic RT can be calculated. In Section 4.3.1 the procedure from Equation (3.31) and Equation (3.32) is performed for several measuring positions simultaneously (cf. scalar vector $\mathbf{d}$ in Equation (4.3–4.7)) and repeated for each reference time.

3.5.4 Estimated RT

For sinter plant process sections where sinter particles from several sinter pallets are mixed or undergo segregation, e.g. in the bunker, hopper or cylindrical sinter shaft cooler, the RT is estimated. In this thesis, the RTE method is applied to estimate the RT of a specific sinter fraction passing through the Sinter Cooler (SC). The estimation is necessary because the particle movement of the sinter particles can no longer be calculated with adequate accuracy using the regular transport equations as introduced in Sections 3.5.2 and 3.5.3, since the RT is distributed over the particle size. In the case of the static and dynamic RT calculation, the sinter particles are also subject to mixing and segregation, but the proportion is relatively small compared to the influence of the moving conveyor belt or sinter strand.

The newly developed RTE algorithm is introduced in Section 5.2. The development and application of the RTE method on sinter plant data is shown in Section 5.1.

4 Experimental Setup and Operational Measurements

Operational data from sinter plants and additional values from new measurement techniques [1, 35, 36] were considered as the data basis for the data-driven approach to develop an RTE method. Subsequently, an MLR model is trained based on the previously estimated Residence Time (RT) for demonstration purposes as a use case to predict the amount of Cold Return Fines (CRF). Data from two sinter plants acquired during the EU RFCS project MinSiDeg [1] were considered from DK Recycling und Roheisen GmbH (DK) and voestalpine Stahl Donawitz GmbH (VASD). The development of the RT approach was conducted on voestalpine data only. To enhance the data density and resolution of values related to sinter quality, various online measurement methods were investigated at the sinter plants of DK and VASD. Online measuring systems installed at the outlet of the sinter plant to continuously measure the PSD played a key role in the development of MinSiDeg [1]. The online measuring devices were utilised to obtain continuous PSD information, to enhance the sampling rate that would otherwise only be available via the daily bulk samples. Furthermore, the power consumption of the hot crusher at the discharge position of the sinter at the end of the Sinter Machine (SM) was considered and implemented as an online measurement for early assessment of the sinter quality [1, 35, 36]. At the discharge position, the RT (Section 4.3) can be determined more accurately by calculating the dynamic RT as a function of the sinter strand speed, which should improve data quality in terms of temporal alignment. It could be demonstrated that the energy consumption of the hot crusher is influenced by the quality of sinter (particle size) [1, 36]. Hard sinter with high sinter strength showed higher power peaks than loose sinter with low sinter strength. Also, correlations between a newly developed acoustical measurement and the energy consumption (power peaks, kW) of the sinter crusher and the production of return fines could be shown in [1, 36]. To enhance the data density of continuous PSD information of the finished produced sinter, different measurement methods were evaluated during MinSiDeg [1], which were installed at the conveying lines between the sinter plant and the blast furnaces of DK and VASD. As outlined in detail in [1], only an optical measuring device, which was provided by VASD, was able to reflect the changes measured by the conventional quality measurement (manual screen analysis). Tests with this optical online PSD system (VASD in-house development) were quite successful; however, in the long term, the device requires a certain maintenance effort for cleaning the optical parts. Therefore, only one dataset with online PSD data was provided by VASD (Section 4.2). Figure 4.1 shows a schematic view of the sinter process flow chart, including the main measuring positions.

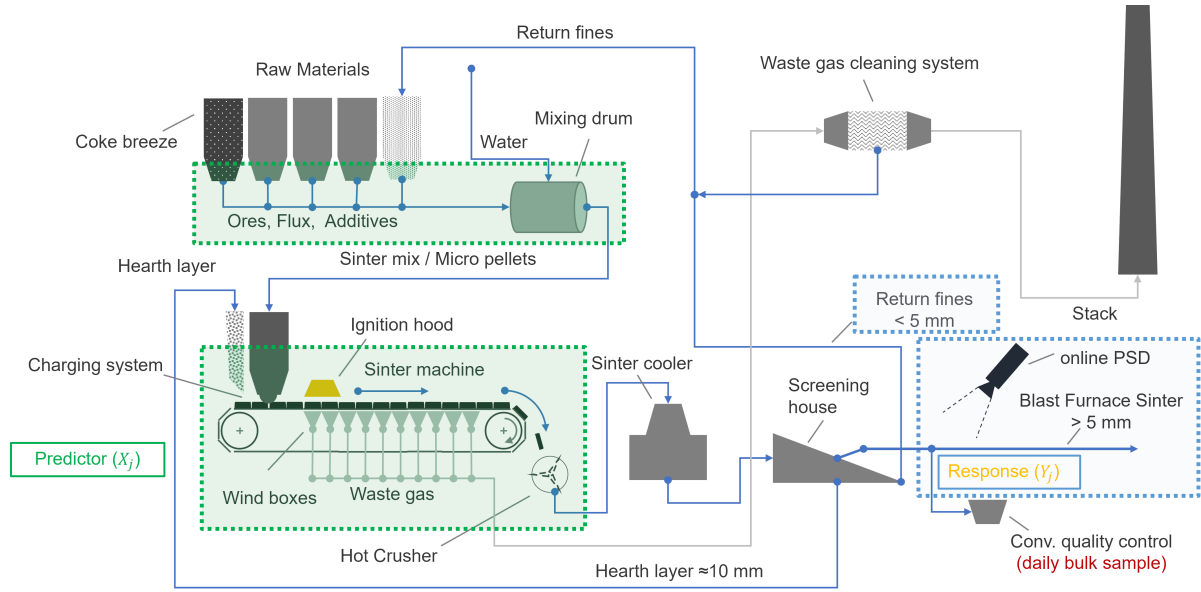


Figure 4.1: Schematic view, sinter plant process flow chart

The operational data from the sinter plant, mainly upstream of the Sinter Cooler (SC) were used as input variables; the predictors are highlighted in green in Figure 4.1 and contain:

- Raw material and sinter mix components (mass flow rates)
- Water flow rate to regulate moisture of sinter mix
- Sinter mix mass flow rate
- Sinter strand speed
- Sinter cake height and width
- Sinter cake mass flow rate
- Ignition hood, values (fuel, combustion air, flue gas rate)
- Windbox temperature and pressure values
- Total wind box suction pressure
- BTP temperature and position
- Hot crusher (HC) power consumption
 - HC power peaks (maximum, 2nd peak)
 - Duration (discharge sequence)
 - Energy of discharge sequence

The output variables (response) are located downstream of the SC and highlighted in blue, Figure 4.1, and contain:

- Cold Return Fines (CRF) mass flow
- BF-Sinter (or Finished Sinter) mass flow
- Online PSD measurement values in % (only for the June 2020 dataset)

In addition, the following measurements and parameters of the sinter plant were acquired:

- Sinter cooler revolution speed in rpm
- Sinter mass flow rate before and after hearth layer screening
- Sinter temperature before hearth layer screening

4.1 New Continuous Measurement Methods

In the context of the EU RFCS MinSiDeg [1] project, new continuous measuring techniques were developed at the sinter plants of DK, TKSE¹ and VASD as described in [35] and [36]. This measurement is intended to increase the sampling rate of information about sinter quality. The relevant measuring techniques for this thesis are summarised in this chapter.

4.1.1 Power Consumption of the Hot Crusher

Based on the assumption that hard material requires more energy to be crushed, as described in [149] for rocks crushed by a jaw crusher, the power consumption of the sinter hot crusher was considered as an indicator of sinter quality. As already mentioned during MinSiDeg [1], it could be demonstrated that a correlation between the power consumption of the hot crusher (HC) and sinter quality is present. Data of the HC power consumption are easily available on every sinter plant without major effort for additional measuring equipment (Figure 4.1). The raw signal with a sample rate of 1 Hz is shown in Figure 4.2 (left side). A short series of three peaks is shown in Figure 4.2 (right side). The blue line represents the raw power values in kW. The peak characteristic is extracted in a similar procedure to the processing of the acoustic signals described in [1, 35], applying a custom filter (designed with MATLAB (Version: R2024a, 1994–2025 The MathWorks, Inc.)) developed as part of MinSiDeg [1]. After determining the local maximum, a cut-off value based on the minimum values is defined. To follow fluctuations over time, a moving minimum value was used. The start and end points of the peak value sequence (sinter discharge) are determined by the intersection points of the cut-off value and the moving maximum of the raw signal, highlighted by the green and black markers in Figure 4.3 (visualised filter values). In the next step, all values between the end and start values were set to zero. With that procedure, the peak duration, time location, and maximum peak height could be identified. The peak energy was determined by integrating the power values between the start and end points of each peak sequence (peak duration). Subsequently, the base load was subtracted from these periods by determining the mean value between the minimum power at the start and end of the peak sequence and multiplying it by the peak duration. By locating the local maxima in a second pass, subpeaks could also be determined by ignoring the previously detected maximum values. Finally, for each

¹thyssenkrupp Steel Europe AG

peak, all mentioned features could be determined and stored in a PostgreSQL database. All steps, including auxiliary values, are summarised in Figure 4.3. The developed online filter was applied to DK and VASD data and implemented into the sinter plant's IT infrastructure for online data pre-processing and to avoid large data traffic. Two of the

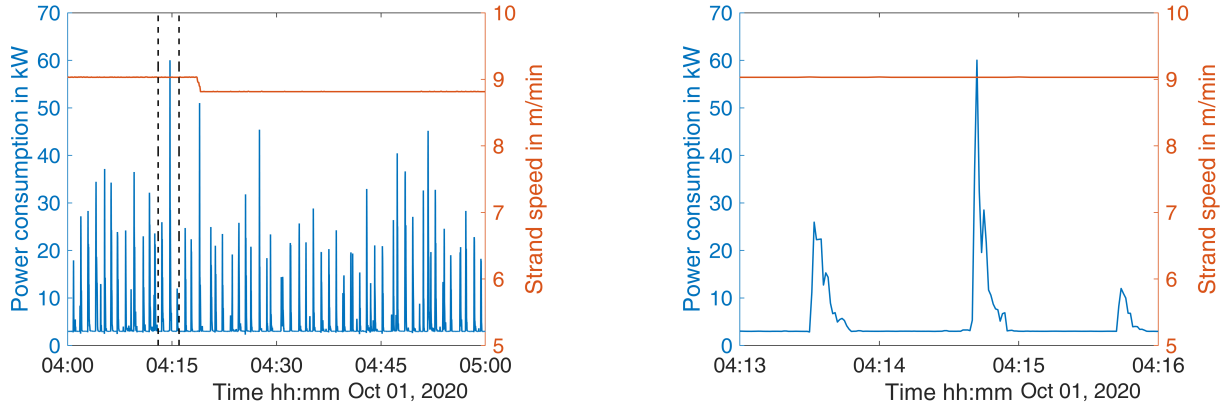


Figure 4.2: Power consumption of the DK hot crusher (sample rate 1 Hz). Left: 1 h overview Right: 3 minutes detail view

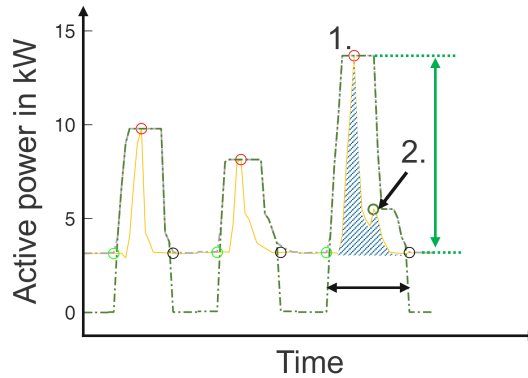


Figure 4.3: Calculation of the hot crusher power consumption KPIs, 1. maximum power peak (= peak height) 2. 2nd power peak, peak duration, blue area = peak area (peak energy)

Key Performance Indicators (KPI) (power peak in kW and energy in kW) are shown in Figure 4.4 for a randomly selected time over a period of 10 hours. The power peak value represents the maximum power rate achieved during a sinter discharge sequence, while the energy value additionally considers all subpeaks and the peak duration (Figure 4.3). Both values show a good accordance (cf. Figure 4.4). As observed during MinSiDeg [1], the HC energy values and $x \leq 5 \text{ mm}$ sinter fraction measured by the online PSD system (described in Section 4.1.2) and the CRF mass flow from VASD sinter plant depicted in Figure 4.5, showed a negative linear correlation of $\rho = -0.44$ between CRF and HC Energy and slightly higher negative correlation of $\rho = -0.67$ for the fraction $x \leq 5 \text{ mm}$ and HC Energy. In this case, the RT of the sinter between the HC at the end of the SM and the CRF and online PSD measuring position (Figure 4.1) had to be estimated first to combine both values (described in Section 4.3). The values depicted in Figure 4.5 are based on an estimated RT corresponding to 5.5 sinter cooler rotations ($\hat{R}_{SC}$). The correlation

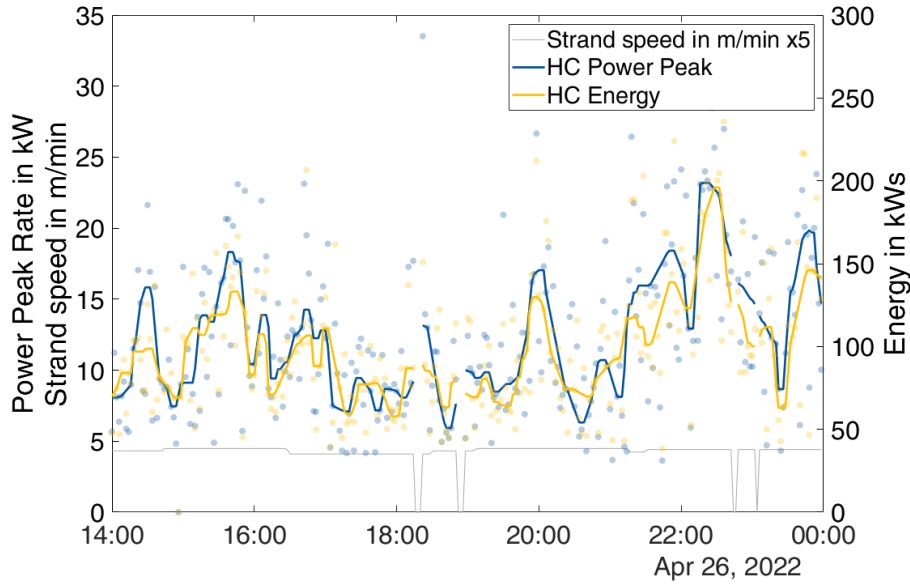


Figure 4.4: Exemplary power peak (kW) and energy (kW) values after pre-processing of hot crusher raw values, DK sinter plant

behaviour indicates that with increased energy consumption of the hot crusher, fewer fines are produced during sinter production and vice versa. The hypothesis proposed above is

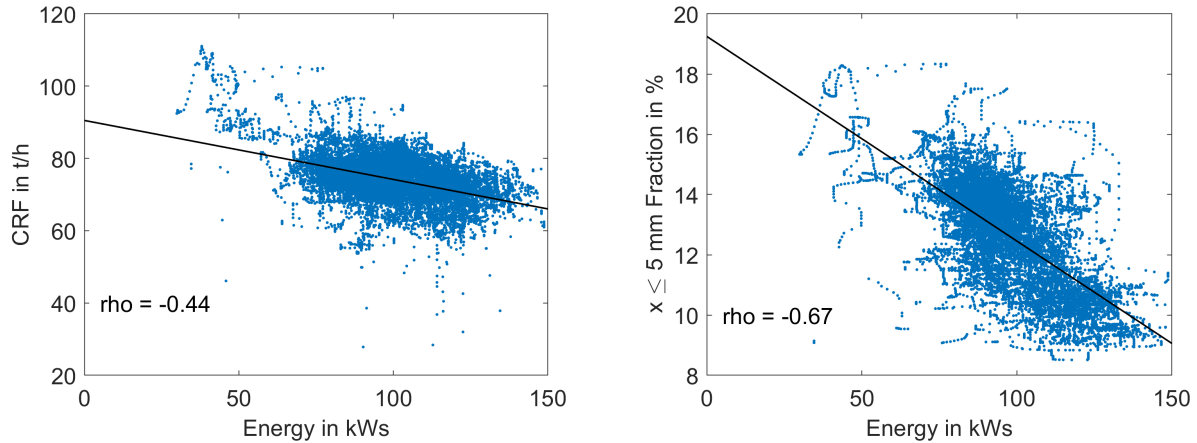


Figure 4.5: Linear correlation of possible target variables (response). The data are aligned based on $\hat{R}_{SC} = 5.5$ Sinter Cooler (SC) rotations. Left: Between CRF and hot crusher energy consumption. Right: Between $x \leq 5 \text{ mm}$ fraction (online PSD) and hot crusher energy consumption.

confirmed by the observation that increased energy consumption of the hot crusher results in a lower quantity of fine particles $x \leq 5 \text{ mm}$ and thus in sinter with high strength. Weak sinter, on the other hand, requires less work from the hot crusher and produces more fines. During MinSiDeg [1], it could also be proven that a drop in hot crusher power is also recognisable in the manual laboratory screening analysis and that a lower TI and a higher AI were observed during a measuring campaign at the DK sinter plant [1].

4.1.2 Online PSD Measurement

Two different commercial online PSD measurement methods were evaluated at the sinter plants of DK and VASD. At DK sinter plant the acoustic measuring device, the so-called "GeoScanner", was installed in front of the conventional sampling position. At VASD, an optical PSD measuring system called "VisioRock" was tested. However, as the "VisioRock" and "GeoScanner" systems were unable to determine the PSD of sinter moving on a standard conveyor belt, an alternative method for online PSD detection based on a different principle was found by VASD. The tests with the new online PSD (VASD, in-house-developed) optical system were more successful and were used for further analyses of VASD data during MinSiDeg and in this thesis. The device was calibrated on standard sinter particles. The evaluation software is able to analyse every image at a frame rate of 0.6 seconds (100s screening time $\approx$ 160 pictures and $\approx$ 3.5 tons of screened sinter) and calculate the PSD for each screening interval [1]. Unfortunately, no robust online and continuous PSD measurement system could be implemented at the DK sinter plant. Therefore, the datasets in the present work are based on the VASD sinter plant values.

The optical detection system was placed by VASD in front of the last screen, removing the CRF from the finished sinter. Due to the high level of dust development at the online PSD detection position at the end of the sinter plant (Figure 4.1), the continuous measurement system, which is based on optical detection of the sinter flow, could not be operated over longer time intervals without maintenance. This resulted in the decision to use the continuous CRF quantity, the mass flow measured in tons per hour (t/h) using a conveyor belt scale after the online PSD measuring position (Figure 4.1) as a continuous sinter quality index [61, 57, 36], delivering more values for the development of the RTE model. The first dataset from June 2022 contains data from 31 days including both online PSD and CRF values. The second dataset from May 2023 contains data from 66 days including only the CRF values.

4.2 Data Aggregation

The data values gained from the approaches described in Section 4.1, including HC power consumption and CRF, should help to get additional continuous information to estimate and validate sinter quality indices and the RTE method. Another key component of the database is the process and operating data from the sinter plant, generated during sinter production.

Historical data were provided by VASD for a period of approximately 3 months for the EU RFCS MinSiDeg project, which were also used for this work. The development of the new measurement techniques presented in [1, 35, 36] was also based on DK sinter plant process data of about 6 months generated and collected during the project. The unprocessed datasets contain 77 attributes (Table B.1, Appendix B) of raw data of the VASD sinter plant with one-second to ten-second sampling intervals, mainly ten-second sampling intervals (0.1 Hz). The provided datasets are used for the development of the RTE approach and the prediction of the sinter quality (CRF) by implementing the new RT method based on machine learning (ML) approaches.

To access large quantities from different data sources, the data were transferred directly from the data-acquisition and archiving databases of the sinter plants to a transfer server at

the VDEh-Betriebsforschungsinstitut GmbH (BFI). A BFI co-worker established the data acquisition setup, while the pre-processing setup was implemented throughout the project by the author of this thesis. Data transfer and aggregation were realised according to the data flow diagrams in Figure 4.6 for the sinter plants of VASD (top) and DK (bottom). In the case of VASD, operational data from the sinter plant were accessed directly from the plant database (DB) and buffered in a local PostgreSQL DB at VASD, from which the data packages could be transferred to the BFI IT infrastructure via a Virtual Private Network (VPN) connection. During data development (top part of Figure 4.6), the data were exported manually and sent to the BFI Database DB. At the end of the project, the developed CRF prediction model approach was implemented as an online application on the VASD plant infrastructure on a local computer, but could only be realised for a limited number of test runs (cf. Outlook in Chapter 6). In the case of DK, the sinter

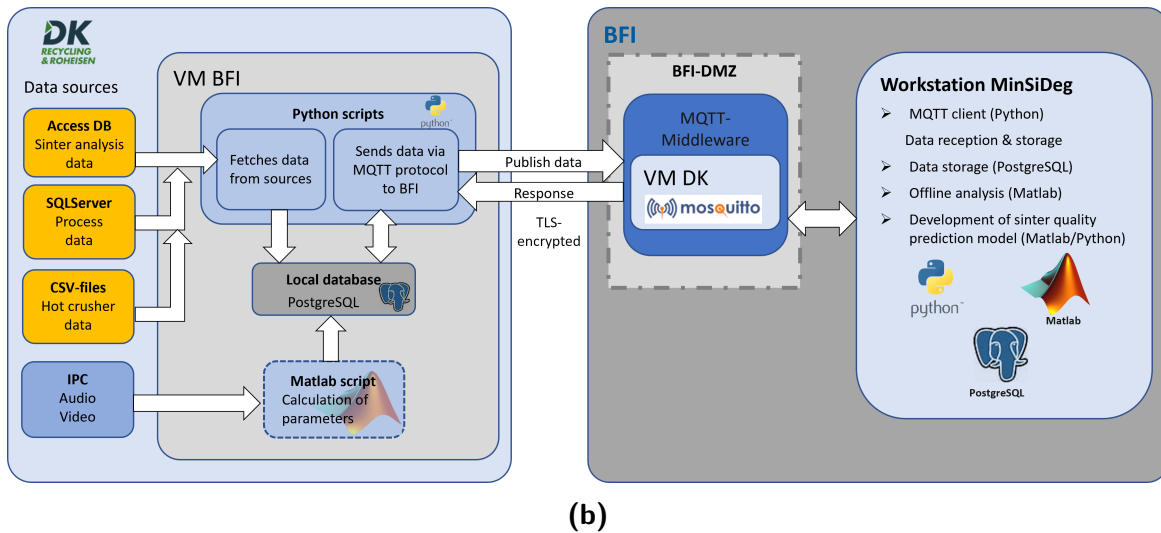
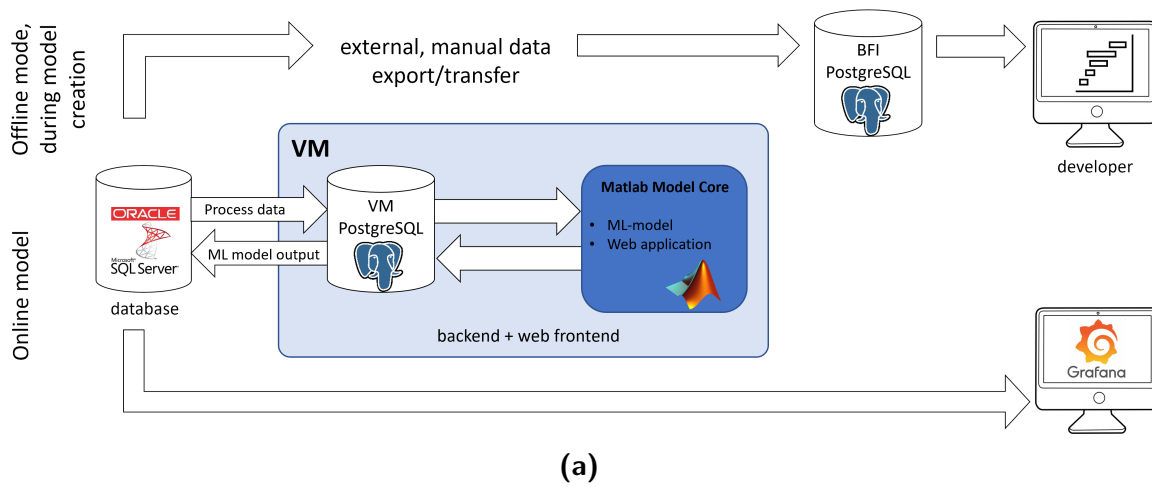


Figure 4.6: Data Flow Diagram for offline and online data transfer, (a) VASD and (b) DK

plant operating data were imported directly from the plant database via a local buffer DB. The values of the power consumption from the hot crusher with a sampling rate of 1 Hz had to be accessed in a bypass by manual import in weekly data packages (CSV files), as the highest possible sampling rate provided by DK DB was 1/120 Hz (2-minute

period). The data for the new online measurements were pre-processed in real-time by the filter procedures presented in [1, 35, 36] and buffered together with the operational data from the DK DB in a local PostgreSQL DB (Figure 4.6, bottom, left side). From that location, the data were sent via the Message Queuing Telemetry Transport (MQTT) protocol in real time to a mirror PostgreSQL DB located at the BFI Network. From there, the data processing took place. Raw data aggregation and parts of the online data pre-processing were implemented directly at the DK data infrastructure, as mentioned before. During this procedure, the evaluation algorithm for the HC data processing from DK was developed and subsequently adapted and applied to VASD data. The first step after data aggregation from the different data sources was data pre-processing, which includes outlier removal, filtration, smoothing and truncation of unplausible signals to enhance the data quality for data-driven approaches [109, 110, 117]. The first step to exclude unplausible data regions from the raw datasets was performed by searching time regions where the sinter plant interrupts the sinter production process. The sinter strand speed was used as an indicator for production stops. The value fluctuates only slightly during normal operation, and as soon as the value drops to approx. 0 m/min, the other conveyor belts in the entire plant are stopped simultaneously, since the sinter process is a continuous process and there is no possibility to buffer the sinter mass during production stops. In this thesis, those time regions were marked with a lead-in of 5 minutes and a lead-out time of 8 minutes (Figure 4.7) to include values during transient start and stop effects. After calculating the dynamic RT (Section 4.3) at the SM, all marked data were removed from the raw datasets. Each variable (attribute) from Table B.1 (Appendix B)

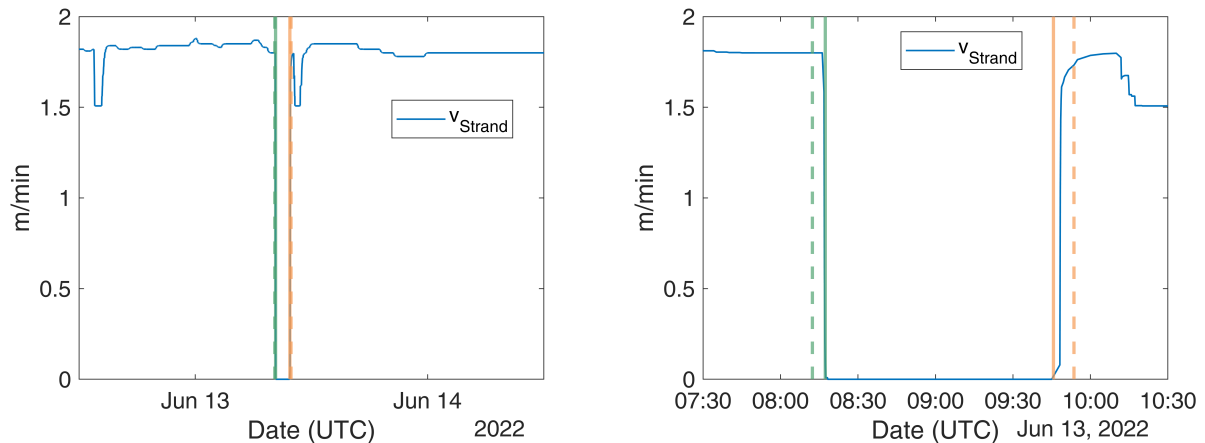


Figure 4.7: Left: Example for detection of sinter production stoppages with 0 m/min strand speed. Right: Detailed view to show cut-off region of lead-in 5 minutes and lead-out 8 minutes.

was filtered and smoothed by applying the DWMTM-filter (Equation (3.9) or application of the moving median filter (Equation (3.4) with different range of q_t (Equation (3.8))), depending on the individual fluctuation of the values from each variable. The filtering and truncation approach of operational raw data from the sinter plant and its success is sketched exemplarily in Figure 4.8. The first figure shows a selection of exemplary raw data of incoming raw material mass flows, raw sinter mixture mass flow, raw sinter humidity (water amount), and strand speed after dynamic time synchronisation (Section 4.3). Especially the value AM22 (mass flow of raw sinter mixture) needs attention due to the enormous

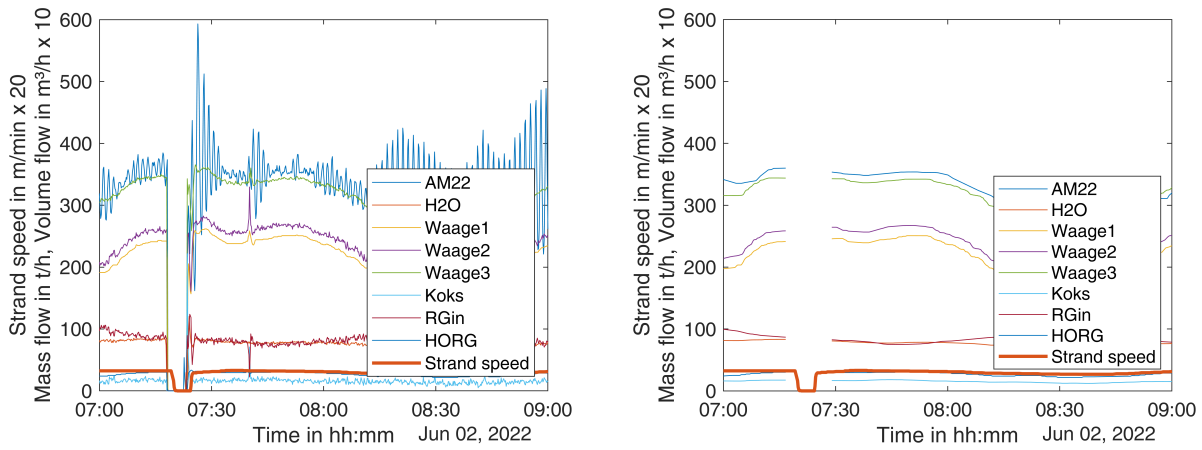


Figure 4.8: Left: Exemplary raw data (incoming raw materials). Right: Data after filtering, smoothing and truncation of unplausible regions.

fluctuation of the values caused by a strongly oscillating belt weigher. The result of the pre-processing is shown in Figure 4.8. Obviously, the noise and fluctuations in the data are significantly improved, and unstable sections before and after a short stoppage are removed. The remaining data from the sinter plant are treated individually, according to their specific values and the required processing. Via the large number of different measurements and measured variables, tailored approaches are needed instead of a "one for all approach" [111, 118, 120].

Due to the different units of the used data, the entire dataset is standardised using z -score normalisation (Section 3.1, Equation (3.15)). Even after pre-processing, some outliers or implausible values may remain; the impact of such values can be reduced through z -score normalisation [133], which is a more robust approach than minimum-maximum (min.-max.) scaling, a common method for re-scaling.

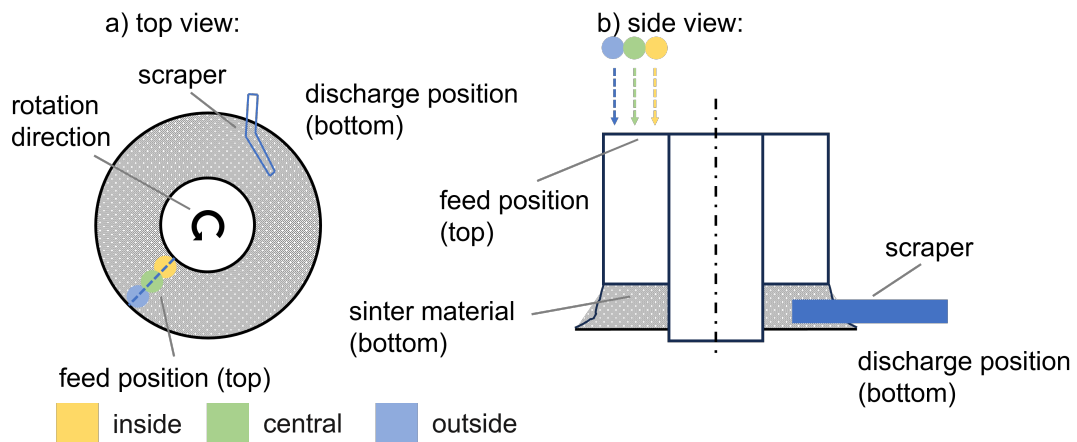
After pre-processing all datasets, they are available as potential predictor and response variables for developing the RTE method (Chapter 5) and later to be applied to data-driven ML approach to predict the CRF amount. Due to different designs of the examined sinter plants and the available measuring systems at the sinter plants of DK and VASD, some important limitations arise for the data processing and possibilities of data usage depending on the respective sinter plant in this work. Table 4.1 summarises the specifications of the sinter plant of DK and VASD. For the DK sinter plant, no reliable target variable was available to describe the continuous sinter quality indices. The used online PSD measurement system "Geoscanner" yields no reliable values describing the continuous PSD [1]. The usage of conventional screening analysis from daily bulk sample would lead to an unbalanced dataset [130, 132] with more predictors (X_p) but less observations (x_t, y_t). Also, no continuous return fines measurement was available at the sinter plant of DK. Hence, missing target variable or insufficient sample resolution make ML methods uncertain and inaccurate [109, 110] for the given setup of the DK sinter plant. In the case of VASD, an online PDS measuring system could be implemented at the sinter plant. However, online PSD values were only provided for the first of the two datasets from June 2022. In addition, continuous measurement of the CRF mass flow is available as a potential target variable, which is also known as the common sinter quality index [64].

Table 4.1: General plant attributes and measuring values from DK and VASD sinter plants

General data	DK Recycling und Roheisen GmbH	voestalpine Stahl Donawitz GmbH
Strip length, - width	32 m, 2.5 m	46 m, 3 m
Wind box (total number)	16	11
Sinter cooler	horizontal belt cooler	cylindrical shaft cooler
Measuring:		
Hot Crusher power rate	yes	yes
CMOS/Laser	yes	no
Acoustic	yes	no
Online PSD	no	yes

The absence of the target variable at the DK sinter plant has led to a decision to focus on the VASD datasets, as previously outlined in Section 4.1, for the utilisation and integration of ML methodologies within this work.

The VASD sinter plant uses a cylindrical shaft sinter cooler (Table 4.1), as shown schematically in Figure 4.9 and introduced in Section 2.1.4. The hot sinter material is charged by a chute on the top of the cylindrical SC and discharged from the bottom by a scraper. The sinter material (particle) flow cannot be observed from the outside. Still, from Section 2.3 it is known that the particle movement is subjected to different influences like sifting, segregation and asymmetrical discharge, which affect the particle flow, resulting in irregular material flow.

**Figure 4.9:** Schematic illustration of the VASD sinter cooler

VASD investigations have shown that:

- Material feeding and discharge is inhomogeneous. Partial mixing of sinter material from different pallets occurs during feeding and during passing the SC (sifting).
- Due to vibrations within the SC, segregation is intensified (percolation).
- The particle size of the sinter material influences mixing speed and RT.
- Different RTs were observed depending on the feed position (inside-central-outside).
- According to VASD, it takes 5.5–19.5 rotations ≈ 1 to 3 hours for particles $x > 100\text{ mm}$ to pass the SC. The timings were obtained from tracer experiments with coloured sinter particles (particle size $x > 100\text{ mm}$). Small particles should tend to descend faster, resulting in shorter RTs.

Finally, determining the RT in the SC is complex and transient due to insufficient information about the geometry, feed and discharge position, sifting, percolation, and segregation effects, but the actual rotation speed (revolution per minute, rpm) of the cooler is known. As already mentioned in this work in Section 2.4 and in [18], the temporal alignment of the measurement data with the sinter material is of enormous importance to obtain models of sufficient quality and significance. Without sufficient knowledge of the RT of the sinter in the sinter cooler, the measured values obtained upstream of the cooler will be biased when combined with the measured values downstream of the SC. The values (up- and downstream of the SC) will be randomly connected without knowledge of the RT in the SC. The data are "lost", or rather, mixed or superimposed in the sinter cooler analogue to the mixed sinter, resulting in inaccurate information and connections. In order to apply ML models, it is necessary to determine or estimate the RT. This is required to assign the response signals of the downstream measurement series to suitable measurement periods of the predictor signals from upstream measurements. The RT before and after the sinter cooler can be approximated using the strand and conveyor speeds, without regarding segregation effects (simplification), by determining the static and dynamic RTs as outlined in the Section 4.3. For the estimation of the RT in dependence of the sinter cooler rotations, a method was developed in this thesis and is introduced in Chapter 5.

4.3 Material Tracking

After data aggregation (Section 4.2) the data were used to determine the RT (material tracking, labelling) for the first part of values, which include positions of measuring devices upstream of the SC. The upstream SC material tracking is presented in this section. The second part, which measures the position downstream of the SC, is presented in Section 5.1. The RT before the SC can be represented by the combination of static and dynamic RTs. The leading operational conditions which require this approach are described below. The RT after the SC is affected by the (unknown) RT in the SC and the downstream paths with static RTs to the specific measuring points (downstream SC) as depicted in Figure 4.10. The data pre-processing (Section 4.2) was done in parallel to the time alignment as depicted in Figure 4.10 to keep the time periods with plant stoppages, which are important to calculate the RTs. If the sinter plant stops production (no complete shutdown), the sinter

strand stops moving ($v = 0 \text{ m/min}$), as well as all other conveyors, but the sinter on the strand that has already passed the ignition hood and has been ignited will continue to burn through unless the air suction (wind boxes) is switched off or reduced. The sinter cake section in the ignition hood is particularly affected, as this is usually powered down after a few minutes and continues to heat the sinter in an uncontrolled manner. In these cases, the sinter process continues under unstable conditions, resulting in unfavourable sinter properties. The process time is not interrupted at the same time as the strand speed stops (production stoppages). In these cases, the RT of the sinter is longer than under normal production conditions, as the sinter mass remains at the same place, but the process continues uncontrolled. These conditions (sinter material) must be tracked until the sinter mass leaves the sinter plant. Each measuring value at the sinter plant is recorded

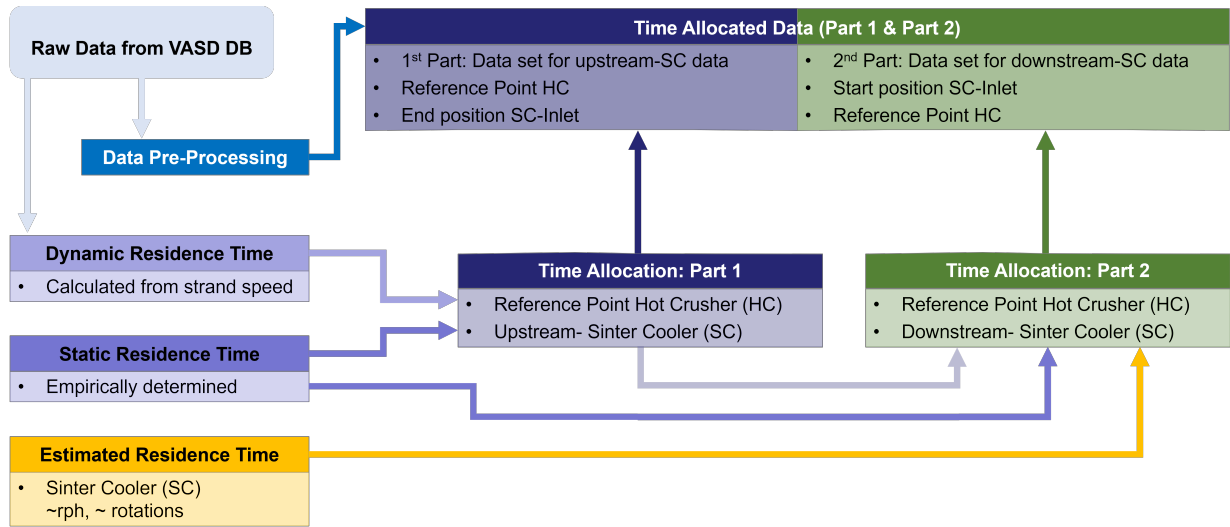


Figure 4.10: Schematic procedure for Residence Time determination for the VASD sinter plant data, upstream (Part 1)- and downstream (Part 2)- sinter cooler

simultaneously at the same actual local measuring time and individual measuring position and stored in the plant DB, but is not linked to the sinter mass. The usage of this data would result in a random connection of process parameters, signals, and changes in the sinter mass composition. This results in a random connection of all predictor variables values and a random connection to the response variables.

Time alignment of the data is essential for sinter (material) tracking throughout the plant and for accurate data-driven (ML) approaches to be able to associate all considered measuring points (predictor and response values) with the sinter mass (bulk material) at each measurement position with the best achievable time resolution and time shift, as described in Section 2.4 and in [18]. To generalise the data and decouple it from temporal misalignment, it is necessary to establish a connection between the observed changes in the signals and the specific sinter mass. This is precisely the basic requirement of any data-based approach: being able to link the data to a discrete product unit at any point in the process.

Sinter mass is composed of loose particles and is subject to several different and superimposed effects influencing the particle flow, including sifting, segregation and percolation, which is influenced by multiple impacts (vibration, transfer points, core flow, cf. Section 2.3). It is also not possible to mark the sinter with barcodes. For test measurements,

it is possible to mark and trace the sinter mass with paint or use an RFID tracer. But this procedure is only suitable for individual short measurement campaigns and not feasible for continuous monitoring of the sinter mass flow. The colouring of the sinter only produces results for large sinter particles ($x > 100\text{ mm}$), as these can be identified as they pass through the plant. In contrast, smaller particle fractions are lost in the mass and therefore cannot be detected again, which makes it impossible to trace the tracer particle. The use of RFID tracers is expensive as they must withstand the rough operating conditions in the sinter flow (temperatures up to 1450°C , abrasion). However, selected plant sections can be analysed in this way.

For this reason, the measured data of the sinter plant have no adequate time alignment (no continuous labelled data) to the sinter mass when passing the individual process steps and measuring positions inside the sinter plant, which was confirmed in the work of [6, 9, 18, 15, 20, 30, 31, 32, 33] and outlined as a challenge for the usage of ML models. A change in the composition of the raw material or the process parameters, and the subsequent feedback in the measuring data, can only be tracked with a high degree of imprecision when the specific section of sinter mass that has been affected passes the sinter plant.

In the context of daily practice for short-term cases, the sinter mass on the sinter strand can be tracked by the observation of the sinter pallets. Nevertheless, this is not a solution that can be applied continuously for continuous labelling of sinter mass. Consequently, the "passing strand length in meters [m]" was identified as a suitable alternative for dynamic sinter tracking.

To address the missing label for the sinter mass, three RT approaches were used in this thesis: static, dynamic, and estimated RTs. All considered variables from Table B.1 (Appendix B) and boundary conditions for time synchronisation are shown in Figure 4.11.

4.3.1 Dynamic Residence Time

In the direct area of the SM, the actual strand speed was used to determine the dynamic Residence Time (RT) (green dashed frame, Figure 4.11) of the sinter mass and is assumed to be equal for all particle sizes. The sinter mass is connected to the sinter strand position "sinter strand - meter, [m]". Together with the specific distances between the measuring points (wind boxes, ignition hood) and the actual strand speed v_{strand} in m/min the RT can be calculated in relation to the reference position, which was set to the position of the HC at the end of the SM. The sinter strand consists of several pallets connected in series, which are linked together in a closed circuit and rotate in an infinite loop (Figure 4.12). This has the advantage that the strand speed can be considered to be equal at all measuring positions along the sinter strand. The resulting RT is the time needed to pass the discrete distance at the actual speed of the strand. This approach leads to acceptable results even when the sinter strand is stopped during stoppages of the sinter production. By this procedure, all dynamic RTs can be calculated for all measuring points at the SM. This includes all wind box temperatures and pressures, values from the ignition hood and the values measured at the sinter discharge position at the end of the SM. At the SM, the primary sinter process occurs. The sinter process should be reflected in the sinter strand (wind box) measurements (wind box temperatures and pressure drop). It should be influenced by parameters of the ignition hood (temperature, gas volume flow, specific energy). These values are of considerable importance, as they provide direct information about the sinter process and can contain patterns which bear quality information [6, 34]. Furthermore, their temporal

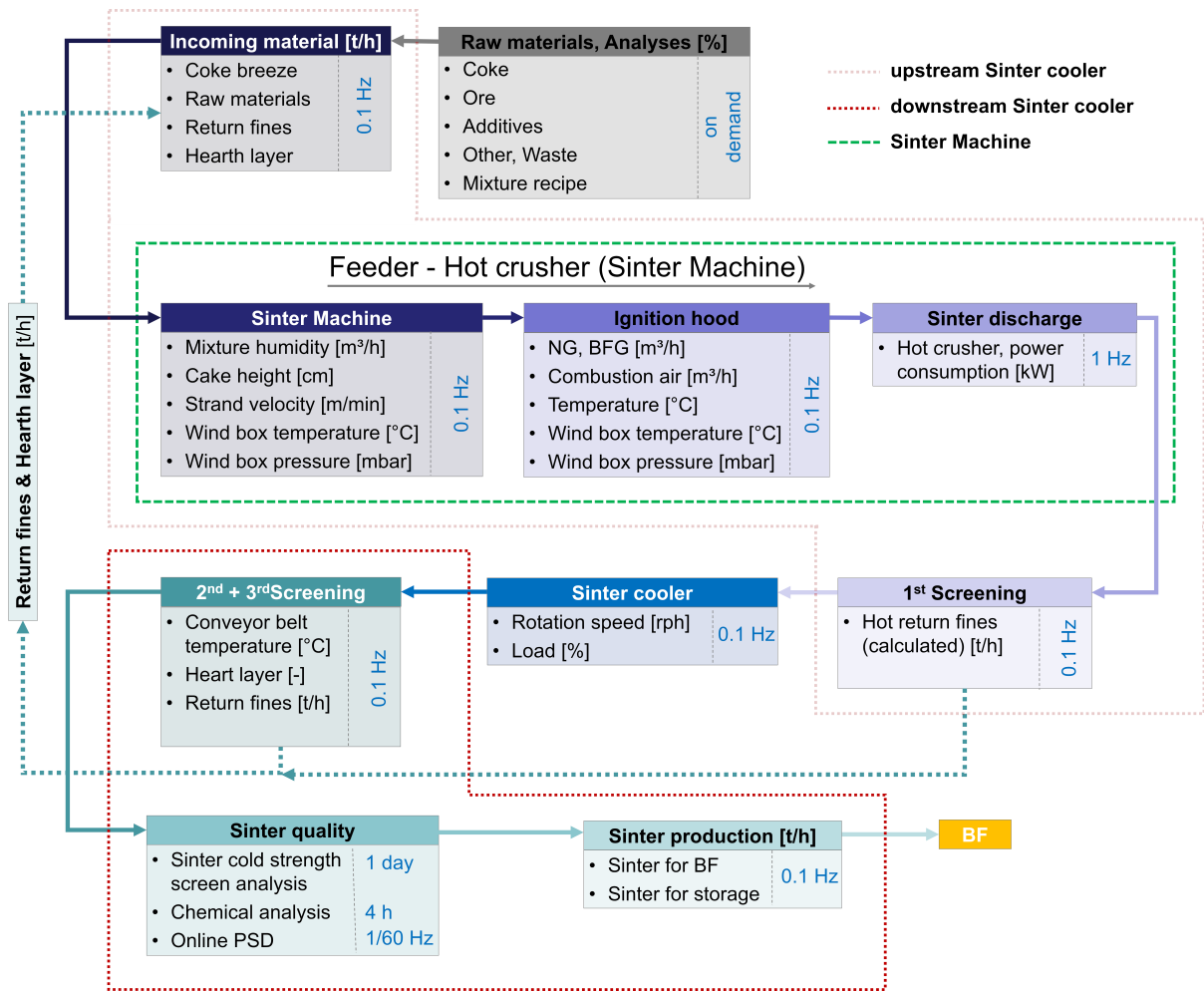


Figure 4.11: Data flow diagram of VASD sinter plant, SM : dynamic RT, upstream SC: dynamic + static RT (Part 1), downstream SC: estimated + static RT (Part 2)

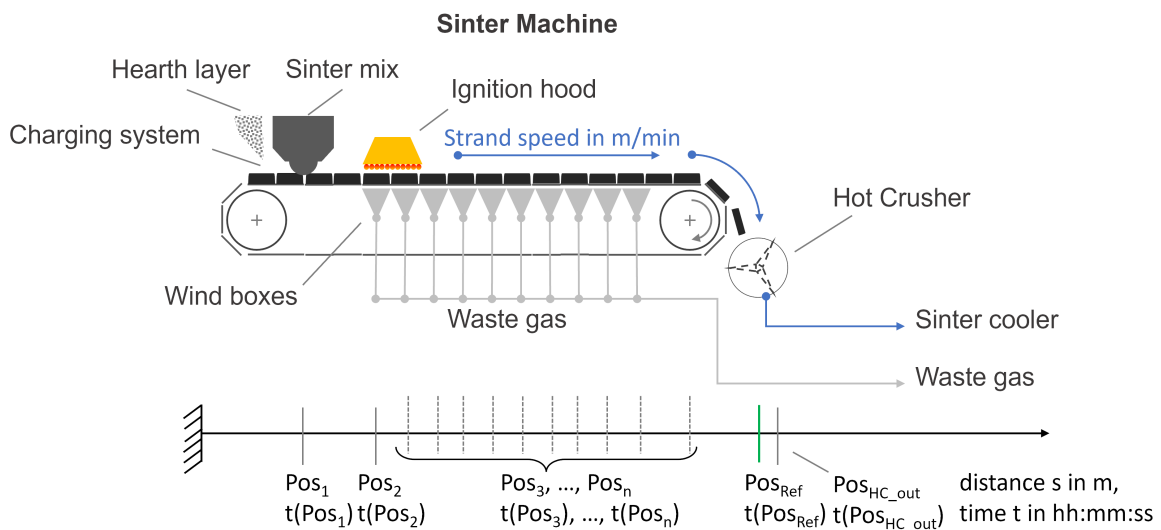


Figure 4.12: Distances between the positions at the SM

assignment to the sinter mass is of significant importance. This should enable connecting these values and patterns to the quality values at the end of the sinter plant. When these values can be labelled, the connection should be possible. This was the motivation for developing a dynamic sinter-tracking approach at the SM. Suppose the assignment of the data collected at the SM to the finished sinter product at the sinter outlet of the sinter plant is successful. In that case, it should enable the implementation of model approaches that accurately predict the quality variables by combining the predictor (SM values) with the response values (quality indices, CRF) and by matching the present pattern in the data of both the predictor matrix and the output vector. The chemical composition of the raw materials is also essential for the sinter process. Still, this information is usually not available due to a lack of traceability and was therefore not considered in this work. The mass flow rate of the raw material is known and has been considered. The dynamic RT calculation ensures that all predictor variables at the SM are aligned with the reference position. This is achieved by time alignment of the measured values with respect to a reference position, to the same sample portion of sinter material, i.e. all associated measuring values at the SM, for example, for wind box #1 (Pos. 2, Figure 4.12) at the start of the SM. This is done by reconstructing the travel route of the sinter material and calculating the RT from a position of a measured value to a reference position at which a sinter quality value shall be modelled. For example, the measured value at Pos. 2 was previously measured before the sinter portion arrived at the reference position. The elapsed time, which characterises this delay, represents the period required for the sinter mass to reach the reference position. The elapsed time, referred to as RT, is calculated by the dynamic RT procedure presented in the next section. For instance, if the sinter mass arrives at the reference position at 1:00 PM and the RT to Pos. 2 is 40 minutes, the measured value of Pos. 2 at 12:20 PM is temporally aligned with the measured value of the reference position at 1:00 PM, which belongs to the identical portion of the sinter material. In Figure 4.13, the RTs of the wind box #1, #8, #10 and #11, temperatures are exemplarily indicated as arrows in the diagram and extracted for two sample times for 3:12 PM and 3:46 PM, Table 4.2. The temperature value of wind box #1 (first wind box)

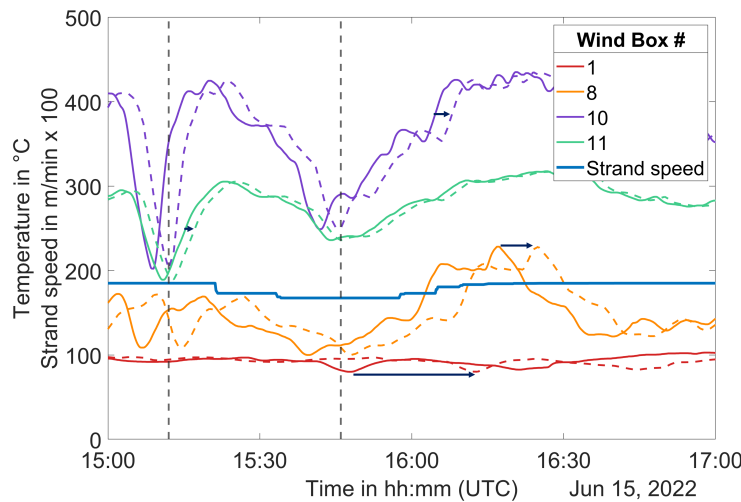


Figure 4.13: Example of time alignment of SM values, wind box temperatures; solid lines represent the raw data, dashed lines represent the values after time alignment

is positioned at the beginning of the SM and shows the longest RT in contrast to the value of wind box #11 (last wind box) which is positioned close to the reference position (HC) at the end of the SM and therefore results in the shortest RT, cf. Table 4.2. In Figure 4.14,

Table 4.2: Exemplary Residence Time in mm:ss
for WB #1, #8, #10, #11

Sample Time in hh:mm	15:12	15:46
Strand Speed in m/min	1.85	1.67
WB #1	23:20	25:20
WB #8	7:40	8:30
WB #10	3:20	3:40
WB #11	1:50	2:00

the wind box temperature profiles are shown for the two extracted sample times, 3:12 PM and 3:46 PM, from Figure 4.13, where the solid lines represent the values of the raw data and the dashed lines show the temperature values after time alignment of the values. The dashed line represents the temperature profile of the sinter mass aligned to the HC reference position, i.e. the temperature course of the same sinter mass production unit (same sinter pallet or sinter batch) as it passes the SM. In this randomly chosen example, it is evident that the temperature profile differs from the raw values, especially at wind box #10 and #11, resulting in different connections of sample time and sinter material. In this instance, the data for BTP and BTP temperature would diverge, resulting in incorrect input values for the ML model. The example is intended to underline the importance of correct time shift allocation, which can be achieved by determining the RT to connect the measuring values to the same batch of sinter mass (production unit).

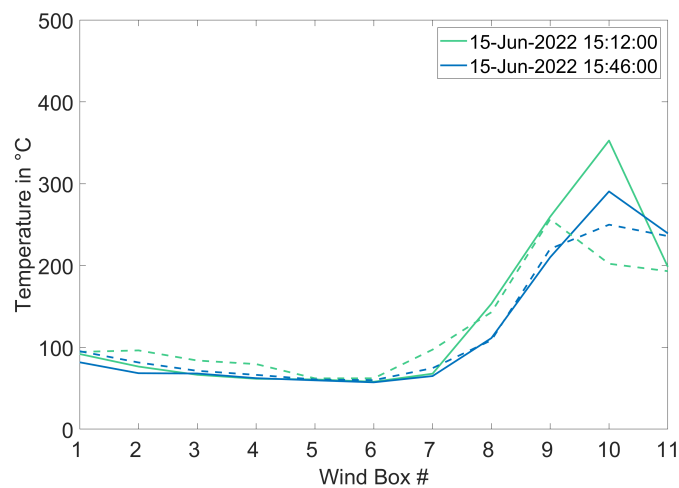


Figure 4.14: Exemplary sinter temperature profiles, for two sample times, raw data: all wind box temperatures at the same time and different sinter production units (solid line), temporal aligned data: wind box temperatures at different sample times for the same sinter production unit (dashed lines)

The dynamic RT calculation at the VASD SM was calculated in two parts. The calculation of the passed sinter in meters on the sinter strand by Equation (4.2) and the calculation of the dynamic RT in the format: hh:mm:ss by Equation (4.7), which corresponds to the duration to reach the reference point (cf. Section 3.5.3). The reference position was defined as the discharge position at the end of the SM (Figure 4.12). This has the advantage that the power consumption values have an RT of zero, and the dynamic RT approach can temporally align all SM values.

For better readability, the time t is indexed by i for the dynamic RT calculation. Thus, a time vector $\mathbf{t}$ containing the measuring times t_i , $i = 1, 2, \dots, n$ is introduced to calculate the dynamic RT. Each time t_i corresponds to x_{ij} variables in a $(n \times p)$ matrix:

$$\mathbf{X} = \begin{pmatrix} t_1 & x_{11} & x_{12} & \cdots & x_{1p} \\ t_2 & x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ t_n & x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix} \quad \mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \quad (4.1)$$

where:

- $\mathbf{t}$: is the time vector containing discrete times points t_i
- $\mathbf{X}$: is the data matrix containing all predictor $j = 1, 2, \dots, p$ (columns) and observation $i = 1, 2, \dots, n$ (rows), cf. Equation (3.11)
- $\mathbf{y}$: is the response vector containing corresponding y_i values

1) The dynamic RT calculation starts by calculating the approximated cumulative sinter strand length S_i for every measuring time t_i , cf. Section 3.5.3:

$$S_i = \int_{t_1}^{t_a} v(t) dt \approx \sum_{i=1}^a (t_s \cdot v_i), \quad a = 1, 2, \dots, n \quad (4.2)$$

where:

- t_s : is the sample period ($t_{i+1} - t_i$) in s
- v_i : is the strand velocity in m/s at time t_i
- S_i : is the cumulative sum of strand length in m up to time t_i

The sampling period of the raw data used in this thesis is recorded in 10 second intervals. Consequently, the calculated approximate distance is discretised over time intervals of 10 seconds.

2) Calculation of the dynamic RT:

First, the specific distances for the sinter machine (SM) are determined in meters and stored in scalar vector $\mathbf{d}$. The scalar vector $\mathbf{d}$ contain the distances from each measurement position Pos_n to the reference position Pos_{Ref} :

$$\mathbf{d} = \begin{pmatrix} \Delta Pos_1 \\ \Delta Pos_2 \\ \vdots \\ \Delta Pos_n \end{pmatrix} \quad (4.3)$$

where:

- ΔPos_n : are the distances from the measuring positions from $Pos_1, Pos_2, \dots, Pos_n$ along the SM till $Pos_{Ref.}$ in m
- $\mathbf{d}$: is the scalar vector containing ΔPos_n the distances from the SM in m

Then the cumulative strand length S_{1+off} in m at the time t_{1+off} is assigned to the reference position $Pos_{Ref.}$ (cf. Section 3.5.3). The time offset off is used to shift the start of the new aligned dataset. This time offset off is necessary because the first aligned values, corresponding to the same sinter segment, are in the past relative to the reference time, as shown in the example in Figure 4.15:

$$S_{1+off} \mapsto Pos_{Ref.}(S_{1+off}) \quad (4.4)$$

where:

- S_{1+off} : is the cumulative sum of strand length in m at time t_{1+off}
- off : is the time offset where the aligned dataset begins
- $Pos_{Ref.}(S_{1+off})$: is the cumulative sum of strand length at the time t_{1+off} assigned to $Pos_{Ref.}$

The time t_{1+off} represents the first time t'_1 (reference time assigned to the reference position) in the new aligned dataset. In the next step, the cumulative strand length value at time t_{1+off} at the reference position $Pos_{Ref.}(S_{1+off})$ is subtracted by the distance scalar vector $\mathbf{d}$ from Equation (4.3) to get the corresponding strand length differences to the measuring positions Pos_1 to Pos_n :

$$\mathbf{ds} = Pos_{Ref.}(S_{1+off}) - \mathbf{d} \quad (4.5)$$

where:

- $\mathbf{d}$: is the distance scalar vector, cf. Equation (4.3)
- $Pos_{Ref.}(S_{1+off})$: is the cumulative sum of strand length at time $t_{1+off} = t'_1$ assigned to $Pos_{Ref.}$
- $\mathbf{ds}$: is the strand length vector (differences), for the measuring positions $(Pos_1, Pos_2, \dots, Pos_n)$ in m

The strand length differences in $\mathbf{ds}$ correspond to the distances travelled at the strand speed v (discretised over the sampling time t_s) from the measurement positions $(Pos_1, Pos_2, \dots, Pos_n)$ to the reference position $Pos_{Ref.}$. Given the known values for the sinter strand speed v and the distance from the measuring position ($\mathbf{d}$) to the reference position, the strand segment ($\mathbf{ds}$) in m that was at the respective measuring position at the time t'' can be determined by subtracting the distance to the measuring position ($\mathbf{d}$) from the strand position (cumulative strand length S_{1+off}) at the reference position $Pos_{Ref.}$ Equation (4.5). The corresponding measurement variable, e.g. to Pos_1 : wind box #1 temperature x_{i1} and wind box #1 pressure x_{i2} at t'' is shifted to t' in the data matrix $\mathbf{X}$ and corresponds to the same sinter material segment. The time difference between these two instants, i.e. $t_{1+off} - t''$ or $(t'_1 - t'')$, can then be used to calculate the dynamic RT by Equation (4.7). Each variable x_j corresponding to its measurement position Pos_n is aligned for each reference time $t'_1, t'_2, \dots, t'_n$ using this method.

The spatio-temporal quantification is performed at a mean strand velocity of 1.83 m/min ($\sigma_v = 0.13 \text{ m/min}$) and the given sampling rate of 10 s corresponding to 0.305 m passed strand length at a total strand length (fed position – HC) of 49.9 m to an error of 0.61% for the determined time (RT) and location (distance). For comparison, one sinter pallet corresponds approximately to a sinter mass of 3.06 tons. The presented dynamic RT improves the considered sinter mass segment to a discretisation of 0.89 t (for 0.305 m strand length). This corresponds to an improvement in spatio-temporal quantification of around 71% compared to the usage of sinter pallets. At a mean production rate of 392 t/h raw sinter mass of the SM (in June 2022), the improvement amounts to a reduction in error from 0.78% (sinter pallets) to 0.23% (dynamic RT), based on raw sinter mass. Nevertheless, the sinter pallets are not tracked during regular sinter plant operation; instead, they are used as a theoretical reference for the dynamic RT.

To demonstrate the calculation of the dynamic RT, a short example is given in Figure 4.15 with fictional values. The positions Pos_n can represent measuring positions along the sinter strand, as shown in Figure 4.12. Table a) in Figure 4.15 shows the distances

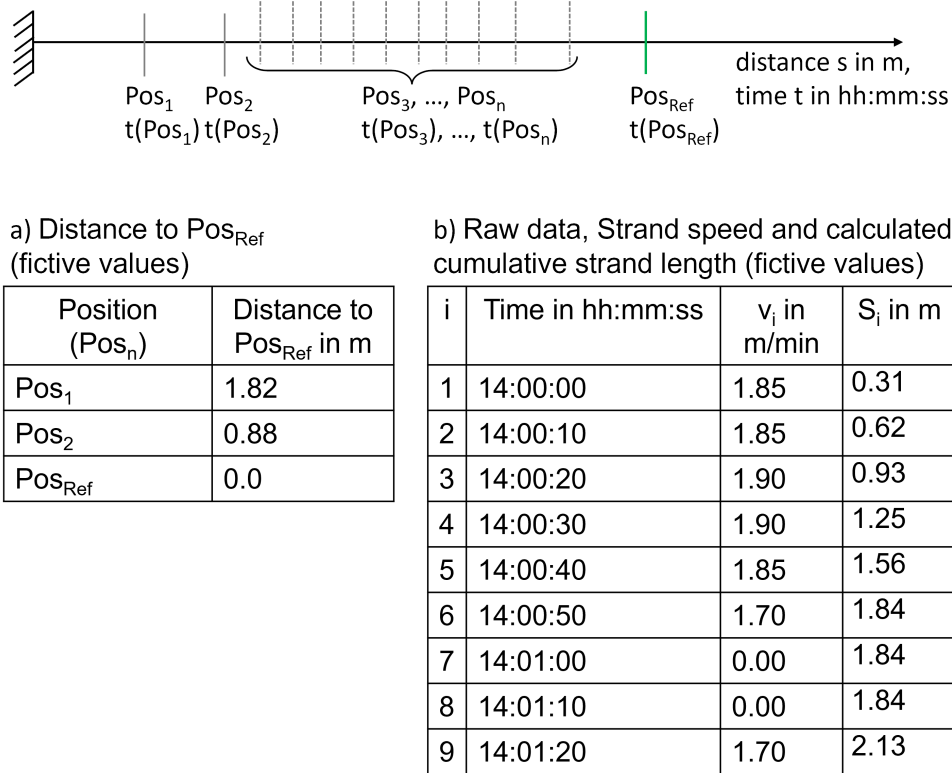


Figure 4.15: Example of determination of the dynamic Residence Time. a) Distance information b) Calculation of cumulative strand length for Residence Time calculation

from the positions Pos_n to the reference position Pos_{Ref} . In table b) in Figure 4.15, the cumulative strand length S_i is calculated for a sample period t_s of 10 seconds. The introduced Δs , Δt approach in Equations (4.5) and (4.7) stands for Δ distance, Δ time introduced in Section 3.5.3. For example, the dynamic RT should be determined for the reference time 14:01:20 (Figure 4.15 b)) for the values from Pos_1 and Pos_2 . In that case, the offset is $off = 8$ and $Pos_{Ref}(S_{1+off})$ is 2.13 m, and $\mathbf{d} = \begin{pmatrix} 1.82 \\ 0.88 \end{pmatrix} \text{ m}$,

resulting in $\mathbf{ds} = \begin{pmatrix} 0.31 \\ 1.25 \end{pmatrix} m$. The corresponding times are given by the reference time $t'_1 = 14:01:20$ and $\mathbf{t}''(\mathbf{ds}) = \begin{pmatrix} 14:00:00 \\ 14:00:30 \end{pmatrix}$ resulting by Equation (4.7) to the RTs $\mathbf{dt}_{RT}(Pos_n) = \begin{pmatrix} 00:01:20 \\ 00:00:50 \end{pmatrix}$ or in other words, the RT for Pos_1 is 1 minute and 20 seconds and for Pos_2 50 seconds. For the datasets from VASD, this algorithm is repeated for every reference time $t'_1, t'_2, \dots, t'_n$ (aligned dataset time). The algorithm can handle plant stoppages, such as at the times 14:01:00 and 14:01.10, cf. Figure 4.15 b). In the event that the $\mathbf{ds}$ algorithm from Equation (4.5) encounters an area during a plant stoppage with equal cumulative strand lengths S , the latest time of the batch with equal strand length S (which corresponds to one time unit before the sinter plant restarts after a stoppage) is selected. The algorithm for the dynamic RT calculation was written in MATLAB, the selection of the corresponding times of the $\mathbf{ds}$ strand lengths is realized by a custom search function with a tolerance range, because the resulting $\mathbf{ds}$ difference lengths do not always match exactly the cumulative band length due to the 10 s sampling time, as given in the example in Figure 4.15. The spatio-temporal quantification is realised through the identification of the corresponding time vector $\mathbf{t}''$ to the strand length differences in $\mathbf{ds} \mapsto \mathbf{t}'' = \{t_1, t_2, \dots, t_n\}$:

$$\mathbf{t}''(\mathbf{ds}) \xrightarrow{\text{search for}} \{S_i - \mathbf{ds} < h\} \mapsto \mathbf{t}'' = \{t_1, t_2, \dots, t_n\} \quad (4.6)$$

where:

$\mathbf{ds}$: is the strand length vector (differences), containing the ΔS distances, cf.

Equation (4.5)

S_i : is the cumulative sum of strand lengths, cf. Equation (4.2)

h : is the tolerance variable, set to $h = 0.2 m$

$\mathbf{t}''$: is the corresponding time vector to the strand length vector (differences, ΔS)

In the latest version, the algorithm was optimised by calculating linearly interpolated times between the matching distances. To avoid problems during stoppages with constant cumulative strand lengths, a small value, realised by a factorised infinitesimal small value "eps" (next larger double-precision number) [150], was added to the cumulative strand length to ensure that the linear interpolation always works with monotonically increasing values and to avoid falsification of the resulting strand lengths by adding a too large offset. The $\mathbf{d}$ scalar vector is constant for each sinter plant. It contains the distances $\Delta Pos_1, \Delta Pos_2, \dots, \Delta Pos_n$ from every measuring point $Pos_1, Pos_2, \dots, Pos_n$ to the reference position Pos_{Ref} . The $\mathbf{ds}$ column vector contains the corresponding passed cumulative strand length from each measurement position to the reference point for each measuring time t'_i .

The dynamic RT given as $\mathbf{dt}_{RT}(Pos_n)$ at the SM is calculated by the time difference Δt between t'_i (assigned to the reference position) and the corresponding times from $\mathbf{t}''_i(\mathbf{ds})$:

$$\mathbf{dt}_{RT}(Pos_n) = t'_i - \mathbf{t}''(\mathbf{ds}) \quad (4.7)$$

where:

- t'_i : is the time (t'_i) at reference position, temporal aligned dataset
- $t''(ds)$: is the corresponding time vector to strand length ds , cf. Equation (4.5)
- $dt_{RT}(Pos_n)$: is the Residence Time vector between measurement position and reference position in hh:mm:ss

The time $t''(ds)$ is determined by searching for the corresponding time t'' to the matching ds length from the cumulative strand length S_i as mentioned in the example. The developed algorithm was realised with MATLAB.

The ds distance vector automatically adapts to the actual strand speeds v_i at time t_i . The procedure is repeated for each reference time $t'_1, t'_2, \dots, t'_n$ of the aligned dataset.

4.3.2 Static Residence Time

The conveyor belt speed upstream and downstream of the SM (red dashed frames, Figure 4.11) is typically not recorded, and thus the calculation of the dynamic RT is not possible. Instead, the static RT between the raw material bunker and the charging system, as well as from the Hot Crusher (HC) to the inlet of the Sinter Cooler (SC) and from the outlet of the sinter cooler to the measuring positions at the plant outlets (finished sinter) was measured by the plant operators during test series under normal production conditions of the sinter plant.

However, the RT determination for bunker, drum mixer, transfer points, screens, or the sinter cooler is subject to factors such as segregation, which significantly affects the particle flow (Section 2.3). Consequently, the empirical approach is inaccurate when the static RT approach is used for these plant aggregates. This was demonstrated by VASD investigations at the sinter cooler for particles with diameters of $x > 100 \text{ mm}$ (Table 4.3, SC (row 10–11)), which yielded RT values from 55 minutes (minimum) to 195 minutes (maximum). To minimise the quantity of bunkers or similar aggregates in the sinter path and at the measuring points, a compromise was therefore made. In this work, sinter tracking begins after the raw material belt weigher at the inlet of the sinter plant, excluding the raw material bunker. However, the static RT includes the conveyors' transport, transfer, and screen retention times. In addition, material tracking is divided into two parts, upstream of the SC (Part 1) and downstream of the SC (Part 2) as depicted in Figure 4.10. Thus, the impact of the Sinter Cooler RT can be examined separately. However, the sinter passes through a drum mixer (including water addition) and then into the raw mix bunker, directly before the SM. According to the plant operator, these are operated in such a way that they cause only minor RT fluctuations in the raw sinter mixture. The SC, however, causes considerable RT fluctuations, which influence the SC- downstream RT and are therefore considered separately in this work (Part 2, Section 5.1) as mentioned before.

It should be noted that the static RTs determined are only indicative values, as they are only valid for a constant operational condition (constant bunker loadings, conveyor belt speed, and screen loadings) at the sinter plant and is assumed to be equal for all particle sizes. Furthermore, they do not accurately reflect the actual RT when the conveyor belt speed is adjusted by the plant operator, and particularly during start-up and shutdown. The static RT used in this thesis for the upstream and downstream measurement positions of the SM are summarised in Table 4.3.

Table 4.3: Empirically determined static RT of VASD sinter plant

No.	Start Point	Via	End Point	Duration in mm:ss
1	RM1	–	CB	0:20
2	CB	–	IRF	0:20
3	IRF	–	BF_RF	0:20
4	BF-RF	–	RM2	0:20
5	RM2	–	DM	0:20
6	DM	DM, Water	RMH	2:00
7	RMH	Raw Mix bunker	Feed_SM	3:00
8	Feed_SM	SM, IG, WB #1–#11	HC	28 minutes ²
9	HC_out	HRF_Screen	SC_in	00:25
10	SC	–	5.5 rounds ³	55 minutes
11	SC	–	19.5 rounds ⁴	195 minutes
12	SC_out	HL_Screen	HL_out	0:58
13	SC_out	HL_Screen	PSD	1:12
14	SC_out	HL_Screen, PSD	CRF_out	1:43
15	SC_out	HL_Screen, CRF_Screen	CRF	2:17
16	SC_out	HL_Screen, PSD, CRF_Screen	FS	2:44

Legend:	
RM1	Raw mix, including iron ore
CB	RM1 + coke breeze
IRF	RM1 + CB + internal RF
BF-RF	RM1 + CB + IRF + BF-RF
RM2	RM1 + CB + IRF + BF-RF
DM	Drum mixer, water
RMH	Raw mix bunker
Feed_SM	Feeder sinter strand
HC	Hot crusher
HRF_Screen	Hot return screen
SC	Sinter cooler
SC_in/out	Inlet/Outlet SC

HL_Screen	Hearth layer screen
HL_out	Outlet hearth layer screen
PSD	Online PSD
CRF_out	Outlet cold return screen
CRF	Cold return fines
FS	Finished sinter or BF-Sinter
Color Legend:	
Upstream SM	
SM	
Downstream SM/Upstream SC	
SC	
Downstream SC	

²Average sinter time under normal operating conditions.³Minimum rotations to pass the SC for particles $x > 100\text{ mm}$, determined by VASD trials.⁴Maximum rotations to pass the SC for particles $x > 100\text{ mm}$, determined by VASD trials.

The total RT of the sinter is calculated as the sum of the dynamic RT (Equation (4.7)) and the static RT (Table 4.3) upstream and downstream of the SM, as follows:

Upstream SM:

$$-dt_{total\ RT, upstream\ SM} = dt_{RT}(Pos_{Feeder}) + dt(\sum Pos_{static}) \quad (4.8)$$

where:

$dt_{RT}(Pos_{Feeder})$: is the Residence Time from Equation (4.7) for feeder position (charging system)

$dt(\sum Pos_{static})$: is the sum of measured static Residence Time between upstream SM position of interest and feeder position as duration from Table 4.3

$-dt_{total\ RT, upstream\ SM}$: is the total Residence Time for upstream SM positions

Downstream SM to SC inlet ($Pos_{SC.in}$):

$$dt_{total\ RT, downstream\ SM} = dt_{RT}(Pos_{HC.out}) + dt_{total, HC.out-SC.in} \quad (4.9)$$

where:

$dt_{RT}(Pos_{HC.out})$: is the Residence Time from Equation (4.7) for hot crusher position (SM discharge position)

$dt_{total, HC.out-SC.in}$: is the sum of measured static Residence Time between HC.out and SC.in position (Table 4.3)

$dt_{total\ RT, downstream\ SM}$: is the total Residence Time for downstream SM positions

The time-varying RTs between a measurement position and the reference position (hot crusher outlet) are defined as negative for upstream measurement positions and positive for downstream measurement positions. With these RTs, the time alignment of the measurement time series is achieved correctly, pairing measured process values from the reference position at times t'_i with those from the upstream or downstream measurement positions at the respective times $t'_i \pm dt_{total\ RT}$. The RT, using both dynamic and static calculation methods, can be performed up to the SC inlet. Thus, the RT over the SC is unknown and will be calculated based on estimates in Section 5.1.1 and estimated in Section 5.1.3.

The result is a time-aligned dataset as matrix $\mathbf{M}_{Set, upstream\ SC}$ ($n \times p$) and time vector $\mathbf{t}$ where for each measuring time t'_i (from the reference position) corresponding x_i values (rows) are represented for each upstream SC variable X_j (columns). Due to the use of empirical static RTs, which are valid only for a constant belt speed, the total RT obtained using the time-alignment approach is only an estimate of the real RT for the sinter processes. The resulting dataset $\mathbf{M}_{Set, upstream\ SC}$ is limited to all positions from the raw mix conveyor weigher to the sinter cooler inlet position (SC.in, Table 4.3, Figure 4.10 (Part 1) and Figure 4.11). Downstream the inlet position of the Sinter Cooler (SC), the RT are calculated by the new RTE approach (Chapter 5) and summation of the static RT downstream of the SC (Table 4.3 and Figure 4.10 (Part 2)).

The calculated (static) RTs from Equation (4.8) and (4.9) have a higher accuracy in the case of "normal" process conditions at the sinter plant, where the conveyor speeds correspond to the conveyor speed at the time of the measurement campaigns. For conveyor speeds

that exceed the "normal" plant conditions, the accuracy decreases, since the actual conveyor speed can be faster or slower, resulting in different RT, to minimise the effect of start and shutdown effect, the values t_i were excluded from the data matrix $\mathbf{M}_{Set, upstream\ SC}$ 5 minutes before and 8 minutes (Figure 4.7) after sinter production stoppages (including the values during the stoppage), where the sinter conveyor speeds are known to be transient and, hence, deviate from the constant empirical value. The values measured directly at the SM reflect the actual strand speed (as recorded), thereby ensuring greater accuracy in determining (dynamic) RT. However, the total RT is the sum of the dynamic and static RTs, which may ultimately reduce the accuracy of the total RT. Nevertheless, this approach represents a satisfactory compromise for the RT of the collected data upstream and downstream of the SM until the sinter reaches the SC. The calculated static and dynamic RTs do not account for segregation, mixing, or other influences on particle movement and assume that the sinter is a static mixture and moves at the same speed as the conveyor. The real particle movement is omitted in this observation, which does not reflect the real situation. During conveying, at transfer points, and at screens, the sinter particles are subject to segregation, mixing, and percolation. Additionally, sifting can occur, as described in Section 2.3. These circumstances make the calculated (static and dynamic) RTs even less accurate, because the methods cannot consider the real particle movement, as it would exceed the effort required to measure these effects, as stated in [63], so they have to be seen as approximations of the real RT. One way to validate the accuracy of the determined static and dynamic RTs is the use of cross-correlation (Section 3.2) at process periods with known process changes, like stoppages, which can be used to track the sinter property changes through the sinter plant system presented in Section 5.1.

4.3.3 Estimated Residence Time (Sinter Cooler)

As previously stated, calculating the Residence Time (RT) becomes more challenging when the sinter passes through a bunker or other transient process steps with varying RTs. Due to the segregation and mixing effects (cf. Section 2.3), the sinter material of different sinter segments (even sinter pallets) is mixed, resulting in RTs with high variance. Consequently, it is only possible to determine the exact RT with a high degree of uncertainty, as the RT is distributed over the particle size. Therefore, the time-aligned dataset $\mathbf{M}_{Set, upstream\ SC}$ is used as the initial dataset (Part 1) together with the unaligned dataset containing the response variables (downstream SC) to estimate the RT at the SC for sinter particles with a particle size $x < 5\text{ mm}$ (CRF). The detailed approach is presented in the next chapter (Chapter 5).

5 Results and Discussion

Historical data from the VASD sinter plant were provided during the EU RFCS project MinSiDeg to develop a data-based approach for predicting sinter quality. As previously discussed in Section 2.4, the temporal alignment is of enormous importance for developing reliable models by connecting the measured values with the sinter material. In Section 4.3, the procedure for calculating the Residence Time (RT) of the sinter material based on both static and dynamic RTs was presented.

Due to transient segregation effects as common for bulk material (sinter) described in Section 2.3, it is difficult to estimate the exact RT over the Sinter Cooler (SC) since the RT depends on particle size, rotations and feed position on the SC as demonstrated in tracer experiments of VASD (section 4.3). To approximate the unknown RT at the SC, a data-driven approach was developed to estimate the RT using a Residence Time Estimation (RTE) method.

The present situation at the VASD sinter plant can therefore be divided into two parts with different RT conditions: measuring positions upstream of the SC (Part 1) and measuring positions downstream of the SC (Part 2), both connected by the SC with unknown RTs. The RT of the Part 2 is directly influenced by the RT of the SC as depicted in Figure 5.1. To adjust the static and dynamic RTs from Table 4.3 and Equation (4.7) between two

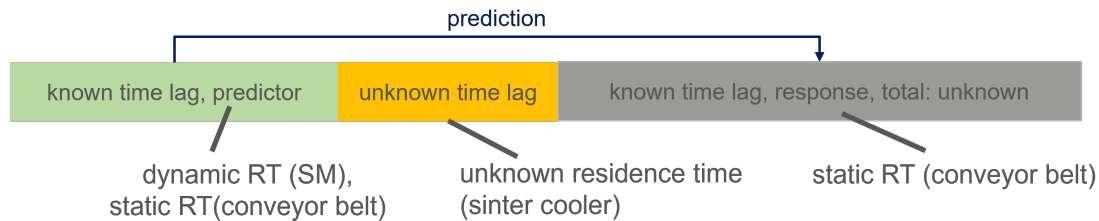


Figure 5.1: Schematic overview of the Residence Times of the dataset, upstream-, downstream-, estimated RT sections

individual variables the cross-correlation Equation (3.26) was used.

The static RTs are valid for "specific" normal operation conditions of the sinter plant. They may vary over operation time or if the plant operator makes manual changes, resulting in different conveyor speeds and, consequently, different RTs. By validating the RT using cross-correlation, the specified RTs can be approved, adjusted, or even estimated for unknown time lags. To demonstrate the cross-correlation according to Equation (3.26), the unknown time lag between the strand speed changes and fuel gas volume flow (power rate) adjustments from the ignition hood will be determined exemplarily. Under "normal" plant conditions, the fuel rate of the ignition hood is adjusted to ensure optimum ignition of the sinter mix; for example, the BTP must be reached before the end of the SM. Increasing the strand speed reduces the required ignition time (RT of sinter in IG) because the sinter passes the IG more rapidly. To ensure optimal ignition, the fuel rate is usually

linked to the strand speed. For example, the fuel rate is increased after the strand speed is raised to deliver more ignition energy to the top surface of the sinter cake. To determine the unknown time lag between changes in strand speed and the IG's fuel gas rate, cross-correlation is applied. In line with the subsequent objective of predicting sinter quality based on the CRF amount, it is hypothesised that the IG fuel rate will play an essential role, along with time alignment, as no information on the time lag from the VASD sinter plant is available. The values of the strand speed thus serve as a reference to determine the dynamic RT for the wind box temperatures and pressures. Cross-correlation is used to align the IG and SM values by matching the gas volume flow (IG) and strand speed (SM). The RT is thereby calculated by the dynamic RT approach introduced in Section 4.3 for the SM. The ignition hood is located at the sinter strand (SM) over wind box #1. Thereby, it is sufficient to determine the time lag of the fuel gas volume flow to the sinter strand speed and then use the dynamic RT from the measuring position of wind box #1 and add or subtract the time lag to the IG. Since the time lag between the strand speed and the fuel gas flow can be positive or negative, Equation (3.25) considers positive and negative lag values. Given that the reference variable is the strand speed, it will be represented as x_t values, while the fuel gas volume flow will be represented as y_t values. To determine the term $c_{x,y}(\tau)$ from Equation (3.25) for each positive and negative lag, it is first necessary to calculate the mean $\bar{x}$ and $\bar{y}$ of all x_t and y_t values, Equation (3.25):

$$c_{x,y}(\tau) = \begin{cases} \frac{1}{n} \sum_{t=1}^{n-\tau} (x_t - \bar{x})(y_{t+\tau} - \bar{y}); & \tau = 0, +1, +2, \dots \\ \frac{1}{n} \sum_{t=1}^{n+\tau} (y_t - \bar{y})(x_{t-\tau} - \bar{x}); & \tau = 0, -1, -2, \dots \end{cases}$$

where:

- τ : is the lag between x_t and y_t
- x_t : are the x variable values
- y_t : are the y variable values
- $x_{t-\tau}$: are the x variable values with lag τ
- $y_{t+\tau}$: are the y variable values with lag τ
- $\bar{x}$: is the mean of x value
- $\bar{y}$: is the mean of y values

In this example, the lag assumes values in the range of $\tau = \pm 50$. For each lag value, the Equation (3.25) is executed. Together with the standard deviation of x and y according to Equation (3.27)

$$\sigma_x = \sqrt{\text{var}(X)}, \sigma_y = \sqrt{\text{var}(Y)}$$

the cross-correlation of Equation (3.26)

$$\rho_{x,y}(\tau) = \frac{c_{x,y}(\tau)}{\sigma_x \sigma_y}; \quad \tau = 0, \pm 1, \pm 2, \dots, \pm 50$$

can be solved, and the solution for each lag is noted. In Figure 5.2, the values of the sample cross-correlation are displayed between the strand speed (SM) and fuel gas volume flow values from the ignition hood. The vertical axis represents the cross-correlation of each lag, and the horizontal axis depicts the lag in the range of $\tau = \pm 50$. The course of

the correlation between both values can be analysed in this way. By searching the highest correlation from Equation (3.26) [79] as noted in Equation (3.28)

$$rho_{max.}(\tau) = \arg \max \frac{c_{x,y}(\tau)}{\sigma_x \sigma_y}$$

the lag with the highest correlation value can be identified, and thus the lag between the y_t variable (fuel gas volume flow) and the x_t variable (strand speed). In this case, the values of the fuel gas volume flow exhibit a positive lag of the lag parameter, designed as $\tau = 8$, with the highest correlation coefficient being $rho_{x,y}(8) = 0.9595$. With a given sample period of 10 seconds, this corresponds to a time lag of 80 seconds. By shifting the time stamps of the fuel gas volume flow by 80 seconds, the two values are, hence, reasonably aligned, resulting in maximum correlation. Now the fuel gas flow values can be directly

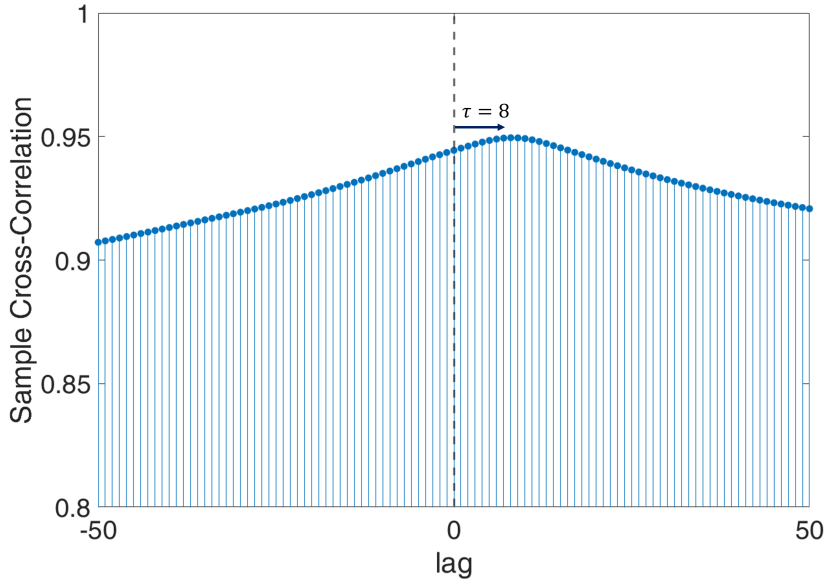


Figure 5.2: Sample Cross-Correlation ($rho_{x,y}(\tau)$) between strand speed and fuel gas volume flow (Ignition hood), $\tau = 8 \rightarrow 80$ seconds

connected to the RT of the position of the wind box #1 by addition¹ of 80 seconds to the RT, $-(dt_{RT}(Pos_{WB\#1}) + 80 \text{ seconds})$. As previously stated, this is possible because the IG is positioned over wind box #1. Further, the positive time lag reveals that the power rate (fuel gas volume flow) of the IG burner is adjusted before the strand speed is adjusted. Also, the positive correlation ($rho_{x,y}(8) = 0.9595$) indicates that the values of strand speed and fuel gas flow are positively correlated (i.e., increase or decrease at the same time). The cross-correlation function, as demonstrated in the provided example, is implemented in MATLAB (Version: R2024a, 1994–2025 The MathWorks, Inc.) as the "crosscorr" function. It was used during the development of this thesis.

The correlation between all predictor and response variables can be examined by constructing a correlation matrix that includes all 77 attributes. Between the response variable (CRF) and all predictors, the result of the correlation yields a lower degree of accordance (lower accuracy) when only individual variables are considered, even when the best

¹Referred from the reference position.

matching estimated RT for the rotation estimate $\hat{R}_{SC} = 5.5$ SC rotations is considered (cf. Section 5.1.3). The maximum linear correlation ($\rho = -0.52$, dataset June 2022) of all predictors yields the wind box #11 temperature (TWB11) and CRF according Equation (3.23) compared with the maximum correlation of the MLR model with $\rho = 0.75$ (dataset June 2022, Figure 5.8). The response value (CRF) is influenced by multiple factors, represented as multiple predictor variables. This has motivated the use of a quality function (kernel) that accounts for several input variables, rather than relying on traditional cross-correlation, which only measures the correlation between two variables as a function of lag. Machine learning methods meet these requirements and can serve as quality functions. In this thesis, an MLR model (Section 3.3) was selected to describe this relationship. As demonstrated, incorporating multiple variables yields a higher correlation than conventional cross-correlation, which considers only two variables. However, as previously mentioned, accuracy is affected by the time alignment of the values.

5.1 Sinter Residence Time Estimation

In the VASD sinter plant data, one section (upstream SC) has determinable Residence Time (RT) (Part 1) consisting of dynamic and static RTs, while another midsection has an unknown RT, and a second section has static RT region that is influenced by the RT of the SC (Part 2) as depicted in Figure 5.1. In this case, the matching accuracy of the predictor and response (from up- and downstream SC data) depends on the RT of the SC. If the RT matches the real (unknown) RT, the accuracy of the prediction of MLR or any ML model (quality function) should be higher. The developed approach connects both parts (Part 1 and Part 2), using different RT estimates $\hat{\tau}$ and measures the degree of agreement. The range of potential RT may be constrained by physical or known system limits, facilitating the identification of an optimal RT and resulting in high correlation or a low error rate. The ML quality function identifies connections between patterns in predictor variables (upstream SC) and patterns in response variables (downstream SC). These patterns result from the sintering process, including reactions linked to the specific sinter mass. They should be recognisable in the response as the same sinter mass production unit reaches the downstream SC measurement positions. It is assumed that changes in process data and measuring values before the SC should be detectable in the measurement values after the SC.

The method utilises ML techniques to identify these patterns in the predictor and response variables. As the sinter mass needs a specific time (RT) to pass through the upstream and downstream SC positions, the degree of matching patterns depends on RT. By varying the RT between the predictor and the response, it is possible to determine the optimal fit of the predictor and response patterns in dependence on the RT. The ML model training is therefore carried out on multiple $1, 2, \dots, n$ datasets with different RTs estimates $\hat{\tau}_1, \hat{\tau}_2, \dots, \hat{\tau}_n$ as illustrated in Figure 5.3.

In the case of the VASD data, new datasets are constructed containing the upstream SC data (Part 1), aligned by the dynamic and static RTs and combinations with different time lags $x_{t+\hat{\tau}}$ ($\hat{\tau} = \tau + a_1, \tau + a_2, \dots, \tau + a_n$) representing the range of unknown RTs estimates for the SC and thus for all downstream SC measurement positions (Part 2, Figure 4.10 and Figure 4.11). The dataset creation scheme is shown in Figure 5.3. As the feeding and discharge positions are on opposite sides of the round SC, the minimum possible RT

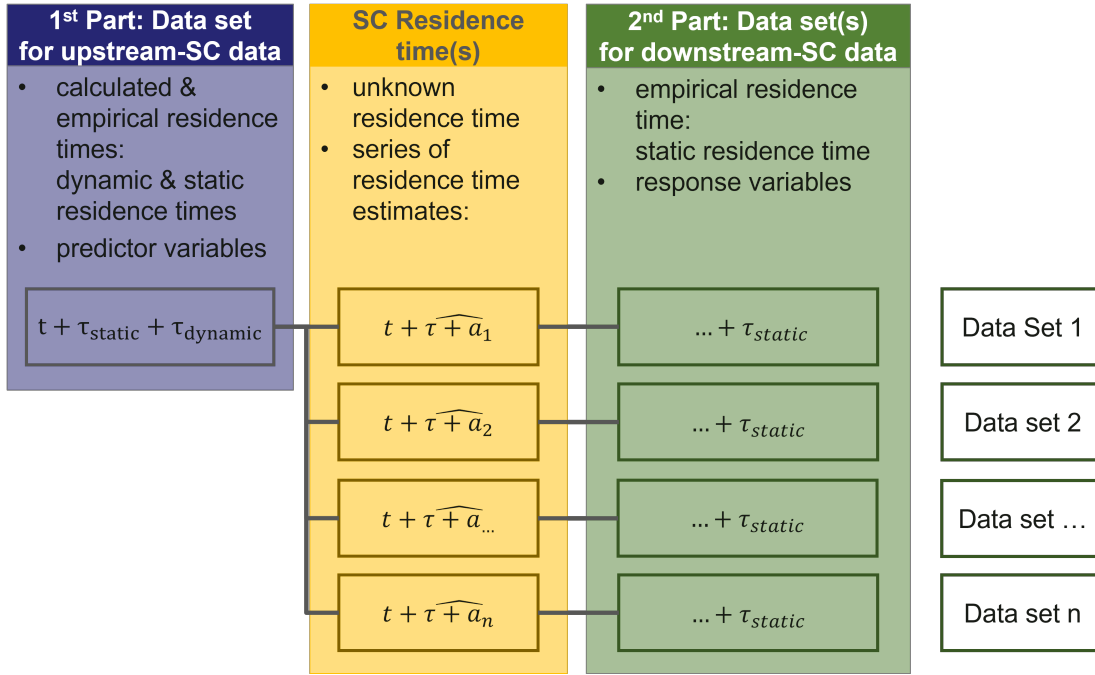


Figure 5.3: Dataset creation for Residence Time Estimation (RTE)

is the required time for 0.5 rotations of the SC, depending on the rotational speed of the cooler (average rotational speed 0.1 rpm). To optimize the range of RT the minimum and maximum RT were determined by trials from VASD for sinter particle of a size of $x > 100\text{ mm}$ as empirical values (Table 4.3) and can be used to set the initial range of time lags $\hat{\tau} = 55, 65, \dots, 195$ minutes e.g. every full rotation of the SC. The optimal RT can be identified by determining the prediction accuracy of each "combined dataset", which includes different RTs estimates $x_{t+\hat{\tau}}$ for the SC (and Part 2). This is achieved by comparing the results of the correlation function from each n dataset, as indicated by e.g., R^2 -statistic by Equation (3.21), or the minimum error rate, e.g., MSE by Equation (3.20). The correlation function in this procedure can be any supervised ML method that does not internally adjust or optimise the time alignment to match the predictor with the response variable. In such a case, the significance of the result would be reduced, as the ML method would yield almost identical results for each dataset (with different RTs) by optimising the predictor to the response by adjusting the RT (internal regulation) [6, 18, 15, 31, 34]. For that reason, supervised ML methods should be preferred with no enhanced internal regulatory capacity ("self-optimising") using back propagation as Neural Network (NN), Long Short-Term Memory (LSTM) or Recurrent Neural Network (RNN) methods as it was proposed in the approach in [6, 18, 15, 31, 34] to eliminate the lag in the detection time of composition in sinter. In the case of unregulated ML methods, the prediction accuracy should be higher for RTs when the optimal combination of predictor and response (optimal match) can be achieved in dependence on the used RT estimates $\hat{\tau}$. In other words, estimates of $\hat{\tau}$ that are closer to the real RT yield higher model accuracy. For that reason, a simple MLR model was used, which ensures no internal self-regulation (Section 3.3.1). The general formulation of this new data-driven method for RTE is presented in Section 5.2, which was used in this work to estimate the RT of the sinter in the SC presented in the next section. The timely aligned data obtained by the method are utilised in a use case to

predict the mass flow of CRF in Section 5.3.

The workflow to estimate the RT at the SC is outlined in this section:

Data aggregation from the plant IT infrastructure, as well as the pre-processing, is documented in detail in Section 4.2. The determination of the static and dynamic RT from the Part 1 of the data series for upstream SC measurement positions (Figure 4.10 and Figure 5.1) is handled in Section 4.3. A brief outlook on Part 2 concerning downstream SC measurement positions (Figure 4.10 and Figure 5.1) is provided at the beginning of this section. The following section will present the procedure for the data-based RTE method. As a supervised ML method, MLR is used because it is one of the fundamental ML methods. The concept of the MLR model is described in Section 3.3. For the first initial MLR model creation the RT for the SC was selected (estimated) based on VASD trials with sinter trace particles of a size of $x > 100 \text{ mm}$ which show an acceptable throughput of 66.46% passed sinter particles in dependence of the radial feed position (inside/central/outside) of the tracer particles after 9.5 rotations of the SC (Figure 5.4). This particular dataset, with 9.5 SC rotations, will be used for initial MLR model development, including predictor selection by the RRelief algorithm [33, 134] and collinearity examination. These steps do not involve estimating RT; instead, they focus on building a general MLR model that will later be applied to different datasets containing various RT estimates.

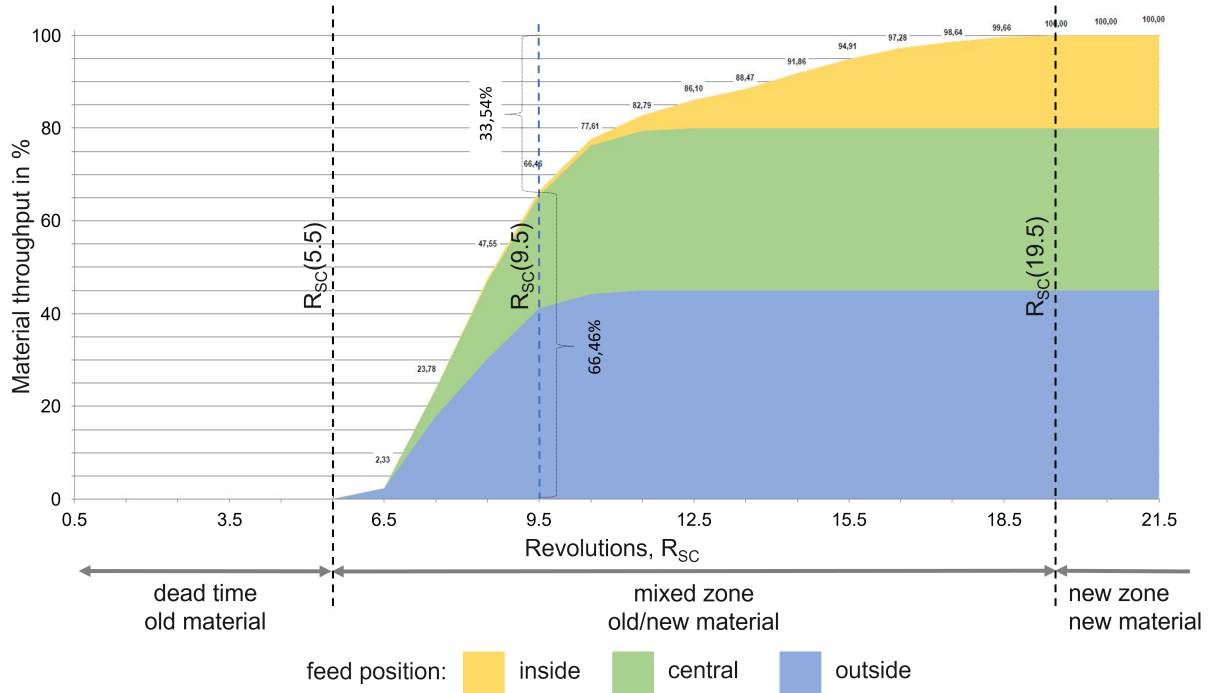


Figure 5.4: Material throughput over SC rotations in dependence on the feeding position (inside/central/outside), results based on VASD trials for $x > 100 \text{ mm}$ tracer particles [1, 105]

5.1.1 Dynamic Residence Time of the Sinter Cooler

The individual RT estimates for the sinter is calculated based on the actual rotation speed in rpm of the SC and the time needed to absolve the estimated rotations $\hat{R}_{SC}$ in the range from 5.5 to 19.5 rotations (Figure 5.4), including the initial dataset with $\hat{R}_{SC} = 9.5$

SC rotation. System knowledge helps limit the range of freely selected RT estimates in this method. The SC input time is gained by Equation (4.9) for the SC_in position (Table 4.3). The rotation speed of the SC determines the time required to complete the assumed number of rotations. The SC is not operated at a constant rotational speed. The charged and discharged volumes of sinter may vary, resulting in different rotation speeds to ensure a constant filling level.

The calculation of the dynamic RT for each rotation estimate over the SC is performed analogously to the dynamic RT calculation at the SM (Section 4.3). First the cumulative sum of rotations $R_{SC}(t_i)$ for each sample time t_i is approximated:

$$R_{SC,i} = \int_{t_1}^{t_a} r_{SC}(t) dt \approx \sum_{i=1}^a (t_s \cdot r_{SC,i}), \quad a = 1, 2, \dots, n \quad (5.1)$$

where:

- t_s : is the sample period = $(t_{i+1} - t_i)$ in s
- $r_{SC,i}$: is the SC rotational speed in rpm at time t_i
- $R_{SC,i}$: is the cumulative sum of rotations at time t_i

In the second step, the calculation of the SC RT estimates (dependent of the SC rotation) is performed by subtracting the time when the rotation estimates $\hat{R}_{SC}$ are absolved $t(R_{SC,i}(t_{SC_in}) + \hat{R}_{SC})$ from the SC input time t_{SC_in} . According to Equation (4.9) the SC input time t_{SC_in} can be calculated in two steps:

$$\begin{aligned} dt_{total, downstream SM} &= dt_{RT}(Pos_{HC_out}) + dt_{total, HC_out-SC_in} \\ t_{SC_in} &= t'_i + dt_{total, downstream SM} \end{aligned} \quad (5.2)$$

where:

- t_{SC_in} : is the SC input time
- t'_i : is the reference time at reference position cf. Section 4.3.1
- $dt_{RT}(Pos_{HC_out})$: is the Residence Time from Equation (4.7) for hot crusher position (SM discharge position)
- dt_{total, HC_out-SC_in} : is the sum of measured Residence Time between HC_out and SC_in position (Table 4.3)

The RT $dt_{RT}(\hat{R}_{SC})$ at the SC_out position is calculated as follow:

$$dt_{RT}(\hat{R}_{SC}) = t(R_{SC,i}(t_{SC_in}) + \hat{R}_{SC}) - t_{SC_in} \quad (5.3)$$

where:

- t_{SC_in} : is the time at the SC_in position from Equation (5.2)
- $R_{SC,i}(t_{SC_in})$: is the cumulative sum of rotations at time t_{SC_in} , cf. Equation (5.1)
- $\hat{R}_{SC}$: is the rotation estimate
- $t(R_{SC,i}(t_{SC_in}) + \hat{R}_{SC})$: is the corresponding time to absolve the $\hat{R}_{SC}$ rotations
- $dt_{RT}(\hat{R}_{SC})$: is the Residence Time between SC_in and SC_out, to absolve $\hat{R}_{SC}$ rotations

The corresponding time for $t(R_{SC,i}(t_{SC.in}) + \hat{R}_{SC})$ is determined by searching the rotation amount of the sum $R_{SC,i}(t_{SC.in}) + \hat{R}_{SC}$ in the cumulative sum of rotations $R_{SC,i}$ from Equation 5.1 which point to the searched time, analogous to the dynamic RT approach in Section 4.3.1. The Equations 5.2 and 5.3 are repeated for every $t' = t'_1, t'_2, \dots, t'_n$ reference time. The result $dt_{RT}(\hat{R}_{SC})$ represents the Residence Time Distribution (RTD) estimates at the SC in accordance with the selected rotations estimates $\hat{R}_{SC}$, as shown in Figure 5.5 for $\hat{R}_{SC} = 9.5$ SC rotations. As the RT at the SC is dependent on the number of rotations and rotation speed, the different RTs $x_{t+\hat{\tau}}$ can be represented as $x_{t+\hat{\tau}} \rightarrow x_{t+dt_{RT}(\hat{R}_{SC})}$ in the case of the VASD SC. The RTs (estimates) downstream of the SM, including the SC (based

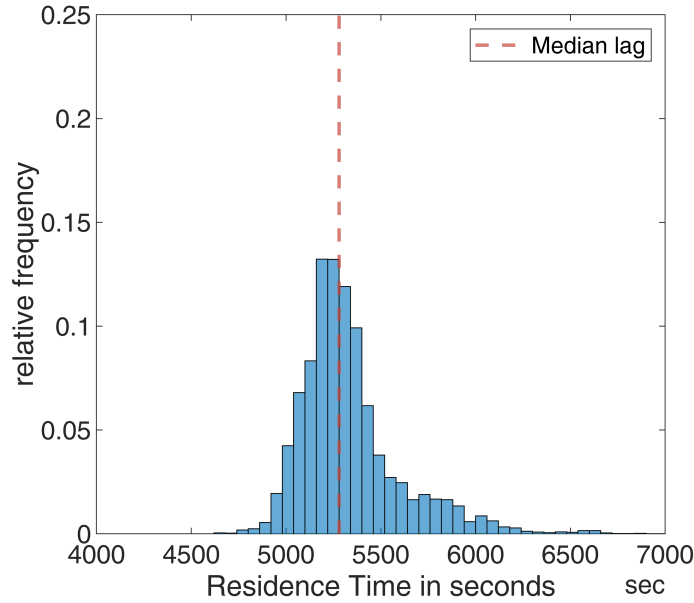


Figure 5.5: Estimated RTD between HC and Cold Return Fines measuring position (CRF) in seconds for $\hat{R}_{SC}(9.5)$, median Residence Time: 88 minutes

on estimates), can be obtained by adding the static RTs from Table 4.3 for downstream SC positions:

$$dt_{total, downstream\ SC} = dt_{total, HC.out-SC.in} + dt_{RT}(\hat{R}_{SC}) + dt(\sum Pos_{static}) \quad (5.4)$$

where:

$dt_{total, HC.out-SC.in}$: is the Residence Time between HC (reference position) and the SC.in position from Equation (4.9)

$dt_{RT}(\hat{R}_{SC})$: is the Residence Time estimate at the SC, from Equation (5.3)

$dt(\sum Pos_{static})$: is the sum of measured Residence Time between SC.out and downstream SC position (Table 4.3)

The total RT between HC and CRF measuring position is depicted in Figure 5.5 for $\hat{R}_{SC} = 9.5$ SC rotations. For each rotation value $\hat{R}_{SC}$ a new dataset containing dynamic and static RTs (Part1) and dynamic RTs dependent on SC rotation speed (Part2) is created for the multiple $1, 2, \dots, n$ datasets for the RTE method, Figure 5.3.

5.1.2 Initial MLR Model Development

The initial MLR model development is performed for a single $\hat{R}_{SC}$ case with 9.5 SC rotations. It includes predictor selection based on the RRelief approach and collinearity examination using the Variance Decomposition Index (Belsley collinearity diagnostic [138]). The complete dataset with 77 attributes (Table B.1) and temporal alignment for upstream and downstream SC values and pre-selected $\hat{R}_{SC} = 9.5$ (cf. Figure 5.4) for the SC rotations was used for the initial model development.

The response value was already identified by correlation measurements and data availability in Section 4.1. From both available sinter quality index CRF mass flow [42, 48, 61, 57] and online-measured percentages of $x < 5\text{ mm}$ fraction size, which is measured online at VASD before CRF screening, the CRF amount was selected as the response value. Given the greater availability of the CRF amount compared to the online PSD measurement values, which have a slightly higher correlation, the CRF amount was selected as the response variable. The CRF amount is measured with sufficient sample resolution (equal to the predictor sampling rate, 0.1 Hz) to obtain a balanced dataset of observations for both the predictor and response variables during model training. It has better availability than the online PSD-measuring values, which were affected by measurement failures caused by dust contamination of the optical measuring devices.

Predictor Selection

To identify the most relevant predictors affecting the response (CRF) from all available 77 attributes (Table B.1, Appendix B) only the variables located upstream of the SC which reduce the size of attributes to 53, a RRelief algorithm was utilized, as described in earlier work from [33] in their analysis of sinter plant data.

Selecting all variables would include those that do not enhance model accuracy (contain no additional information) and would only increase computation time. On the other hand, removing significant variables from the model will reduce its overall accuracy, especially concerning the impact of those variables. The goal of predictor selection is to find the most important or influential variables that best predict the response variable [6, 33]. For this purpose, an RReliefF algorithm was used to rank the predictors. The RReliefF algorithm can handle noisy continuous-time series and help select important variables for regression approaches [134]. RReliefF uses a k -nearest neighbour approach to weight the predictor variables in connection to the response [134, 151]. RReliefF penalises the predictors that give different values to neighbours with the identical response values, and rewards predictors that provide different values to neighbours with varying values of response. However, RReliefF uses intermediate weights to compute the final predictor weights. The results are presented in a ranked predictor list, sorted by the relative importance of all examined predictors influencing the response, as illustrated in Figure 5.6. 27 estimated predictors (Table B.2, Appendix B) from Figure 5.6 of the initial 53² predictor variables were pre-selected according to their importance weight as input variables for the ML model. The results were discussed with the plant operator during MinSiDeg and confirmed as important parameters (variables) in the sinter process. To avoid collinearity as described in Section 3.3, the variance decomposition proportions (Belsley collinearity diagnostics) were

²53 predictor of 77 attributes, only SC upstream attributes were considered

opment of the RTE method. The plant operators identified the gas volume flow (IG_Gas) from the ignition hood and the wind box #3 temperature (TWB003) as unreliable measurements, so they were dropped, too. For ignition hood energy consumption, the specific energy was reported to be more dependable, so this value was preferred.

Table 5.1: Final selected predictor:

No.	Attribute	Unit	Description
1	BF_RF	t/h	BF Return Fines
2	BTP_Pos	m	Burn through point in m
3	BTP_Temp	°C	Burn through point temp.
4	Coke	t/h	Coke breeze
5	H ₂₀	m ³ /h	Water amount
6	IG_kWh	kWh/m ²	Specific energy consumption IG
7	kWm ³	kW/m ³	Specific power consumption HC
8	kWsm ³	kWs/m ³	Specific energy consumption HC
9	peakarea	kWs	Combustion air volume flow
10	PeakmaxPower	kW	Maximum Power Peak HC
11	IRF (RF_in)	t/h	Internal return fines
12	TWB001	°C	Wind box #1 temp.
13	TWB008	°C	Wind box #8 temp.
14	TWB009	°C	Wind box #9 temp.
15	TWB010	°C	Wind box #10 temp.
16	TWB011	°C	Wind box #11 temp.
17	TWB020	°C	Wind box #20 temp.
18	TWB027	°C	Wind box #27 temp.
19	TWB040	°C	Wind box #40 temp.

5.1.3 Residence Time Estimation

The Residence Time (RT) is proportional to the number of absolved Sinter Cooler (SC) revolutions and is expressed as R_{SC} . The estimated rotations are thereby referred as $\widehat{RT}_{SC} \sim \hat{R}_{SC}$. With the time-aligned values from the finally selected predictors from Table 5.1 datasets for $n = 10$ different $\hat{R}_{SC}$ combination were generated with $\hat{R}_{SC} = [1.5, 3.5, 5.5, 7.5, 9.5, 11.5, 13.5, 15.5, 17.5, 19.5]$ for the data from June 2022 and for $n = 8$ additional $\hat{R}_{SC}$ combinations with $\hat{R}_{SC} = [1.5, 3.5, 5.5, 7.5, 9.5, 11.5, 13.5, 15.5]$ for the data from May 2023 were created according to Figure 5.3 with the pre-selected predictor and response variables. All datasets were used as training sets to train MLR models based on the different estimated $\hat{R}_{SC}$ mentioned. The MLR model was trained in MATLAB.

Interaction between variables and quadratic extensions (Section 3.3.1) was allowed during model training. After MLR model training, only the model training error of each dataset with different $\hat{RT}$ expressed as $\hat{R}_{SC}$ was observed, and the development was plotted in Figure 5.8 and Figure 5.10. It is not necessary to apply the model to a test set with fresh data that were not used during training, particularly for Residence Time Estimation (RTE). The ML training is primarily used by the ML quality function to acquire the RT, rather than to predict the response variable. It should be noted that the RT for values outside the time range of the data used for RTE estimation may differ from that estimated for the RTE dataset and thus may not be valid for those values. As the RT in the SC is distributed over the particle size, the estimated RT is only valid for sinter particles with a size of $x < 5\text{ mm}$, reflecting the amount of CRF (target variable). As the In Section 5.3, training and test datasets are defined, which are within the data used for the RTE, to predict the CRF amount. As training error, the MSE, linear correlation (ρ) and R^2 -statistic (R -squared) were considered from all datasets. The graphical representation of the results obtained from the dataset collected in June 2022 is presented in Figure 5.8, while the dataset gathered in May 2023 is illustrated in Figure 5.10, analogous to the cross-correlation shown in Figure 5.2.

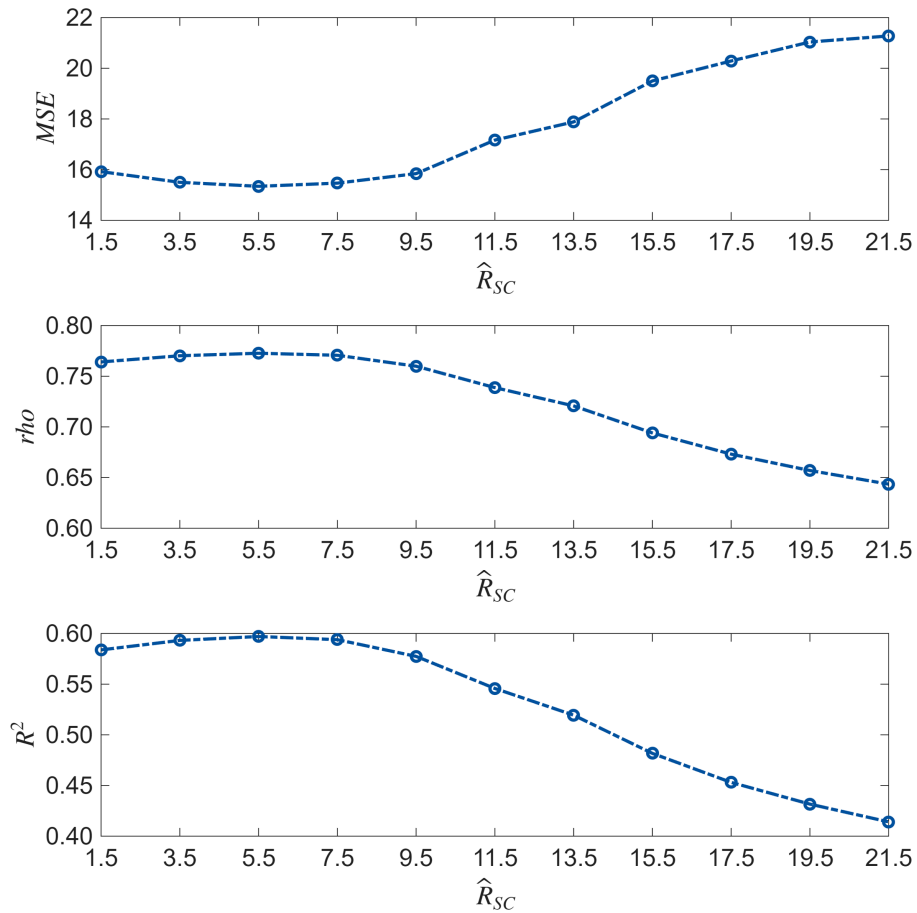


Figure 5.8: Development of MSE , linear correlation ρ and R^2 over $\hat{R}_{SC}$, for $\hat{R}_{SC} = [1.5, 3.5, 5.5, 7.5, 9.5, 11.5, 13.5, 15.5, 17.5, 19.5]$, Dataset June 2022, 23,244 Observations

By determining the $\arg \max_{corr}(\hat{R}_{SC})$ or $\arg \min_{MSE}(\hat{R}_{SC})$, the optimal dataset can be identified, which corresponds to the dataset with the best matching estimated RT. Thus,

the optimal RT, expressed as the $\hat{R}_{SC}$ value, can be identified. The best fit for the June 2022 dataset is found for $\arg \max_{corr}(\hat{R}_{SC})$ at $\hat{R}_{SC} = 5.5$ SC rotations with the lowest $MSE = 15.34$ and highest $\rho = 0.77$ and $R^2 = 0.60$. The maximum correlation and minimum error rate point to the dataset with the best matching combination of predictor and response values. The combination of SC upstream data (predictor) with SC downstream values (response), connected by the estimated RT, resulted in an optimal fit, thereby reflecting the pattern observed in the SC upstream data in the SC downstream data. As the SC is not operated with a constant rotation speed, the corresponding estimated RT can be represented as a distribution in a histogram showing the relative frequency of the estimated RTD (Figure 5.9). The estimated median RT for the dataset from June 2022 with 23,244 observations lies at 52 minutes regarding Figure 5.9. Based on the estimated $\hat{R}_{SC}$ the RT is calculated as a measure of the time (sum of static and dynamic RT) required for the sinter to be conveyed from the reference position (HC) at the SM over the SC to the measuring point of the CRF quantity. By increasing the resolution of RT estimates, in this

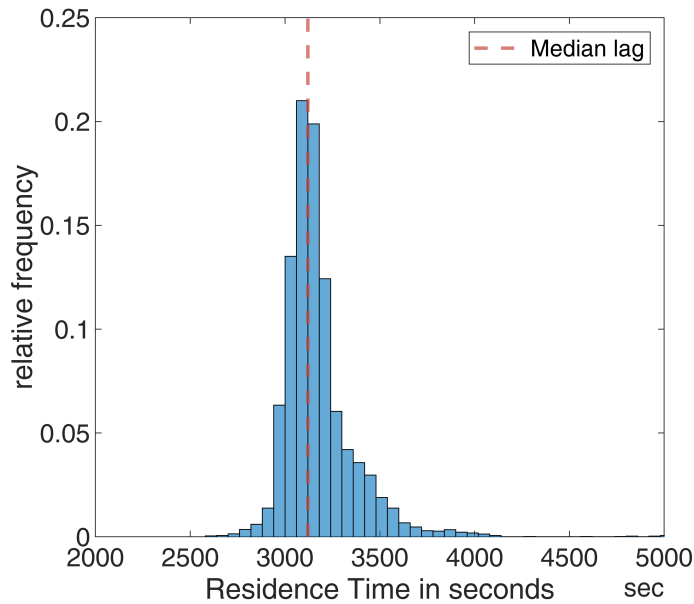


Figure 5.9: Estimated RTD for $\hat{R}_{SC} = 5.5$, median 52 minutes

case between $\hat{R}_{SC} = 3.5$ to 7.5 SC rotations, the location of the $\arg \max_{corr}(\hat{R}_{SC})$ could be enhanced; however, this was not investigated in this study due to time constraints.

The range of $\hat{R}_{SC}$ values was limited to maximum $\hat{R}_{SC} = 15.5$ SC rotations for the dataset from May 2023 (Figure 5.10) as the minimum MSE and maximum correlation, was expected to be in lower SC rotations regarding the results from the data from June 2022 (Figure 5.8). The development of MSE , ρ and R^2 over the $\hat{R}_{SC}$ estimates is depicted in Figure 5.10. The dataset from May 2023 indicated a best fit at $\hat{R}_{SC} = 7.5$ SC rotations, with the lowest $MSE = 12.14$, and the highest $\rho = 0.80$ and $R^2 = 0.63$. The corresponding RTD for $\hat{R}_{SC} = 7.5$ SC rotations led to a median RT of 73 minutes as shown in Figure 5.11 and is 21 minutes (corresponding to two SC rotations) longer compared to the estimated RT for the set from 2022. The estimated $\hat{R}_{SC} = 7.5$ SC are in accordance compared with the estimated rotations of the June 2022 data, which showed the best fit at $\hat{R}_{SC} = 5.5$ SC rotations (Figure 5.8). The results from the dataset from June 2022 ($MSE = 15.34$,

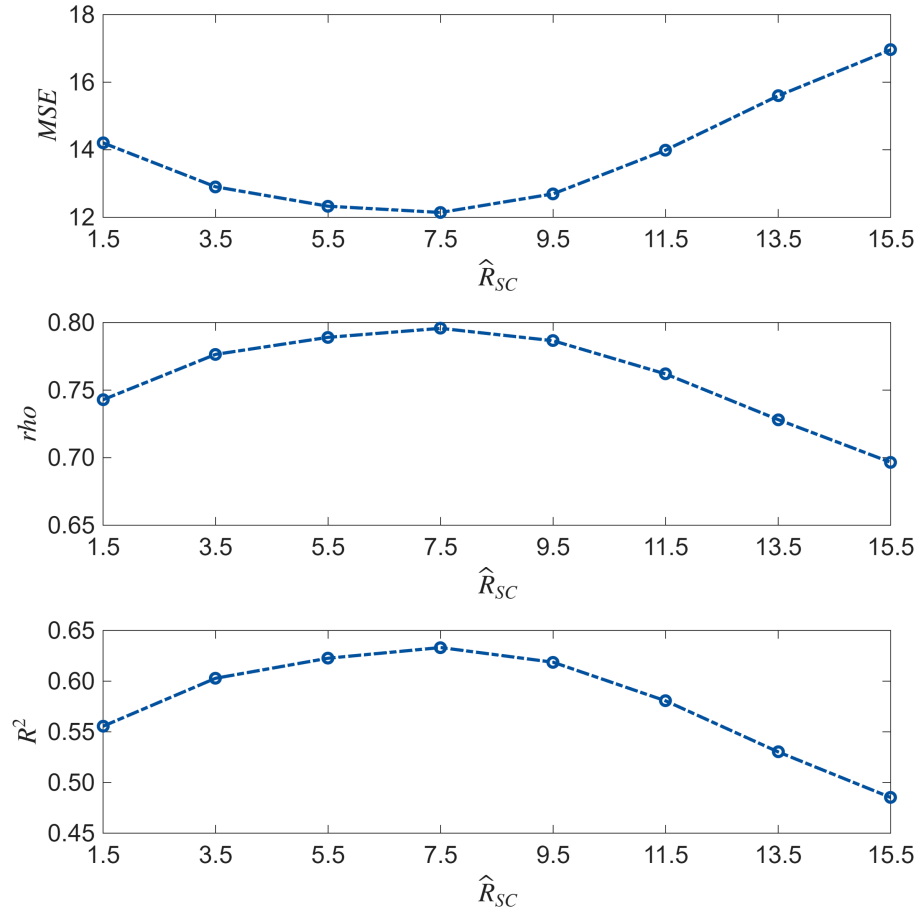


Figure 5.10: Development of MSE , linear correlation ρ and R^2 over $\hat{R}_{SC}$, for $\hat{R}_{SC} = [1.5, 3.5, 5.5, 7.5, 9.5, 11.5, 13.5, 15.5]$, Dataset May 2023, 89,068 Observations

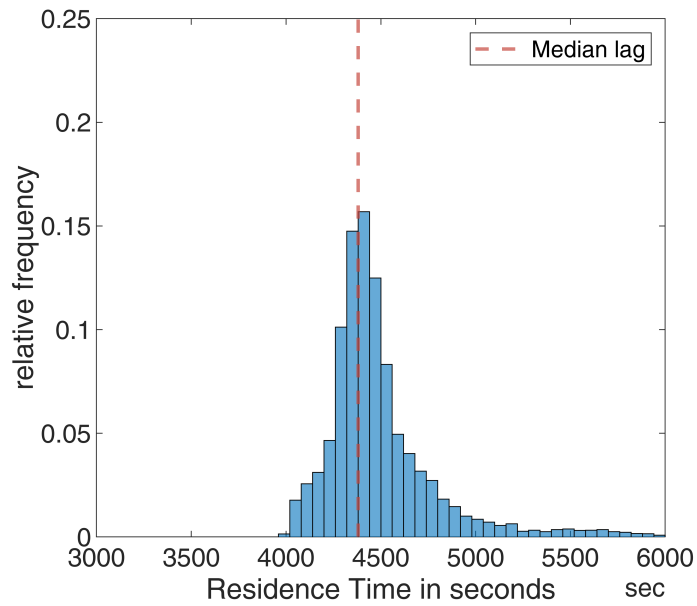


Figure 5.11: Estimated RTD for $\hat{R}_{SC} = 7.5$, median 73 minutes

$\rho = 0.773$, $R^2 = 0.60$) showed only a quite better accuracy for $\hat{R}_{SC} = 5.5$ compared with $\hat{R}_{SC} = 7.5$, with $MSE = 15.46$, $\rho = 0.770$ and $R^2 = 0.59$. VASD determined 9.5 SC rotations for tracer particle (coloured sinter lumps) with $x > 100\text{ mm}$ at a throughput of 66.46% sinter to pass the SC (Figure 5.4). The estimated RT for the CRF position reflects the quantity of sinter particles with $x < 5\text{ mm}$. The lower number of SC rotations to pass the SC for the smaller fraction size $x < 5\text{ mm}$ compared to particle sizes of $x > 100\text{ mm}$ can be explained by the effect that the smaller sinter particles slip through the voids between the coarse particles (percolation) as described in Section 2.3 by [63] and thereby can pass the SC faster as coarser particles like the tracer particle with $x > 100\text{ mm}$ used by VASD and need less rotation of the SC. The movement of smaller particles, driven by segregation due to percolation, can be enhanced by vibrations induced by the rotation of the SC, in addition to gravity. This phenomenon is particularly evident at relatively small particle size differences, with a ratio of 1:1.3 [63, 72]. In the SC, the sinter particles have a ratio of approximately 1:20, with most particles $< 5\text{ mm}$ and the largest over 100 mm . Additional effects, such as segregation due to different trajectories of the sinter particles during feeding (chute, Figure 2.11) at the SC charge position and the influence of the scrapper at the sinter outlet of the SC, can result in the formation of dead zones and eccentric flow zone at the outer cooler wall witch can also cause sifting in the SC. These effects are challenging to prove with the applied method, but are commonly observed in the literature [63] and contribute to the instability of the material flow within the SC. As a consequence of the factors outlined above, it is challenging to determine the exact RT with precision. The method presented shows at least an average RT in the range of the applied data.

The June 2022 dataset, with 23,244 observations, is smaller than the May 2023 dataset, which has 89,068 observations and is approximately 3.83 times larger. The RT at the various times of the datasets can be different, or the smaller dataset (June 2022) may include more periods with a longer RT caused by possibly different CRF amounts or other possible influences. Figure 5.12 show the different CRF amount distribution of the dataset from June 2022 and May 2023. The June 2022 data have a lower median CRF of 4.8 t/h, confirming the assumption of different CRF values across the datasets. In [1, 38], it was observed that coarse particles flow significantly better than fine material during bunker discharge. This would lead to the assumption that a lower quantity of smaller particles (CRF) can pass the SC more quickly, driven by the above-mentioned segregation effects. Consequently, a reduction in the amount of CRF would result in a decrease in RT, as evidenced by the data collected in June 2022 with lower (74.3 t/h) and May 2023 with higher (79.1 t/h) CRF amounts and explain the higher estimated median RT for the May 2023 dataset of 73 minutes compared to the shorter median RT of 52 minutes of the June 2022 dataset. The result for the VASD data indicates that $\hat{R}_{SC} = 5.5$ (June 2022 dataset) and $\hat{R}_{SC} = 7.5$ (May 2023 dataset) leads to the optimal matching combination of patterns indicated by predictor and response connected by the RT resulting from $\hat{R}_{SC} = 5.5$ SC rotations resulting in 52 minutes (median) RT and 7.5 SC rotations resulting in 73 minutes (median) RT.

To determine the (estimated) RT, only the training error was considered, as it reflected the match of the known patterns in the applied dataset between the input and output variables. In this case, the test error of different datasets (outside the examined dataset, unknown data to the previously trained MLR model) would lead to uncertainty as the RT can differ from the selected data series used for RTE.

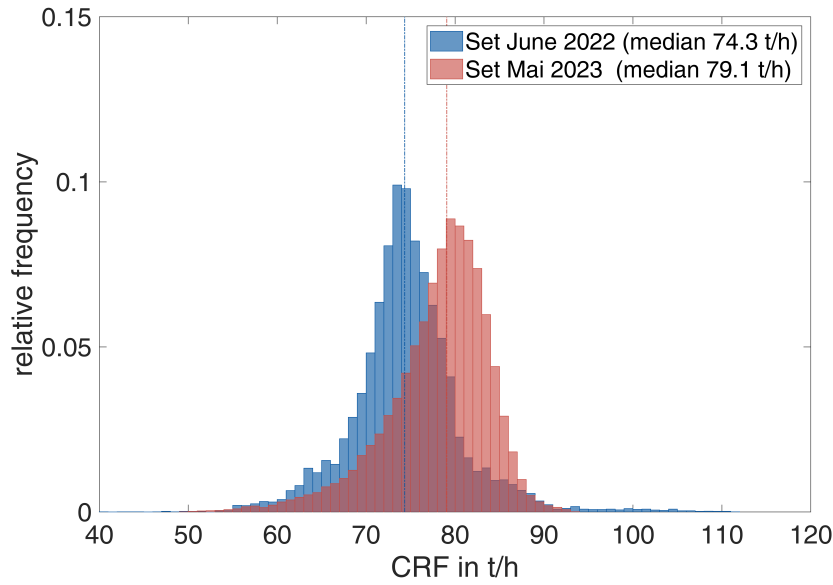


Figure 5.12: Cold Return Fines (CRF) distribution of June 2022 and May 2023 dataset

The determined RT resulting from $\hat{R}_{SC} = 5.5$ and 7.5 SC rotations and the corresponding dataset can further be used to predict the CRF amount in which the RT was determined by dividing the dataset into a training and test set and applying an ML method of choice, including new model training. In Section 5.3, a fundamental ML method is utilised in a use case to forecast the CRF amount for the formerly employed datasets.

Further examinations of the RTE approach were undertaken to analyse the influence of operational parameters, including CRF quantities, the SC rotation speed, and coke content in the raw sinter mix. The impact of different CRF quantities on RT was examined by analysing specific operational conditions at the sinter plant. This was conducted to evaluate the sensitivity of the introduced RTE method and to confirm the influence of particle size on RT (particle flow speed).

For both sets (June 2022 and May 2023) production periods with high (larger median) and low (smaller median) CRF amounts were extracted from the complete dataset, and small datasets (subsets) were generated for the defined conditions. To enhance the quality of the datasets, only temporally related data were extracted to ensure continuity. Figure 5.13 (June 2022) and Figure 5.15 (May 2023) show the different CRF distributions of every selected subset. For each subset, the RTE procedure for all $\hat{R}_{SC}$ estimates ($n = 10$ and $n = 8$ datasets) was applied. The development of the accuracy is depicted in Figure 5.14 for the data from June 2022 and the subsets. The procedure was repeated for the May 2023 set. Figure 5.16 shows the development of the determined accuracy for the May 2023 set, including the subsets with different (smaller and larger median) CRF amounts. For the reference set (complete set) as well as for all subsets, the median CRF amounts were determined and are indicated in the figures to simplify the assignment (readability) of the examined sets. The findings presented in Figure 5.14 support the hypothesis that an increase in fines amount results in a corresponding increase in estimated RT. The development of the accuracy of the subsets shows increased fluctuations; this may be explained by the relatively small datasets with 1,318 observations (min. CRF set) and 1,664 observations (max. CRF set) compared to the reference set with 23,244 observations.

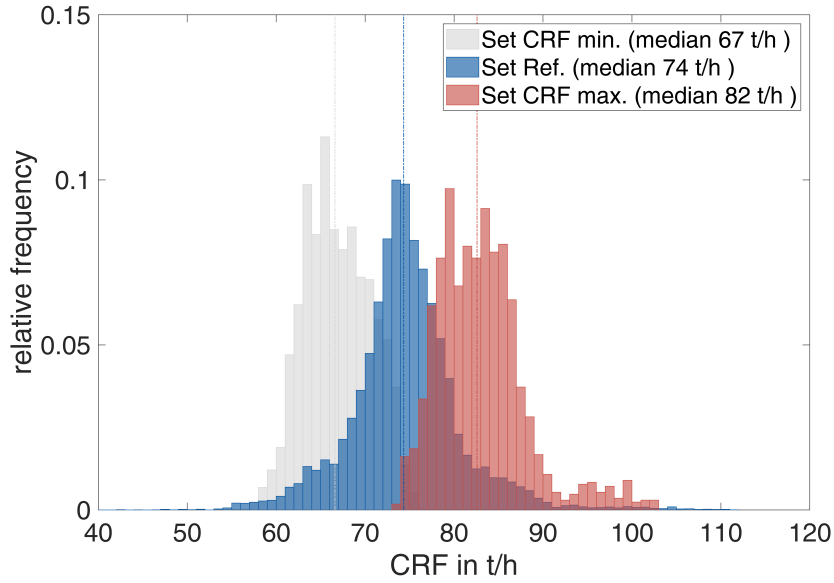


Figure 5.13: Examination of different CRF amounts, min.: smaller median; max.: larger median; CRF values; Ref.: complete dataset, June 2022

The quality of the generated MLR model becomes unstable trying to fit the data, resulting in lower MSE (4.01;7.26;15.34³), and higher ρ (0.86;0.88;0.77) and R^2 (0.73;0.77;0.60) values. The small number of observations leads to unbalanced datasets, resulting in high variability in the least-squares fit and overfitting, and higher accuracy of the MLR model in the training mode. Still, worse predictions in the test modus, as stated in [130, 132]. Nevertheless, to enhance the readability of the figures the quality values on the vertical axis were rescaled between 0 and 1. Despite a reduction or increase in accuracy compared to the reference set, the trend of the accuracy is well recognisable.

The minimum and maximum error rate for correlation of the subsets point for lower CRF amounts (median 67 t/h) to $\hat{R}_{SC} = 7.5$ SC rotations and for higher CRF generation periods (median 82 t/h) to $\hat{R}_{SC} = 9.5$ SC, resulting in increased estimated RT of two SC rotations (Figure 5.14), 70 minutes (66.7 t/h CRF) and 89 minutes (81.7 t/h CRF) median RT respectively as summarised in Table 5.2. The results confirm the hypothesis that an increase in CRF amount is associated with increased RT. The reference dataset, with a median of 74 t/h CRF generation, results in $\hat{R}_{SC} = 5.5$ SC rotations (median RT of 52 minutes); this value contradicts the values of the subsets. It should, as expected, generate an $\hat{R}_{SC}$ value between the values of the subsets ($\hat{R}_{SC} = 7.5\text{--}9.5$). The results indicate the potential for other influences to affect the RT, which were not considered in this analysis. It should be noted that the dataset sizes of the reference and subsets are not identical, which can lead to overfitting, as previously mentioned. This can lead to inaccurate results. To clarify this aspect, it would be beneficial to repeat this study with a comparable number of observations. However, it is challenging to find conditions that are similar and comparable in industrial plants, as boundary conditions change constantly [9, 31]. The outcomes of the May 2023 data and subsets indicate a comparable tendency to that observed in the June 2022 datasets, thereby confirming the hypothesis that low CRF quantities result in

³(min. CRF; max. CRF; Reference Set)

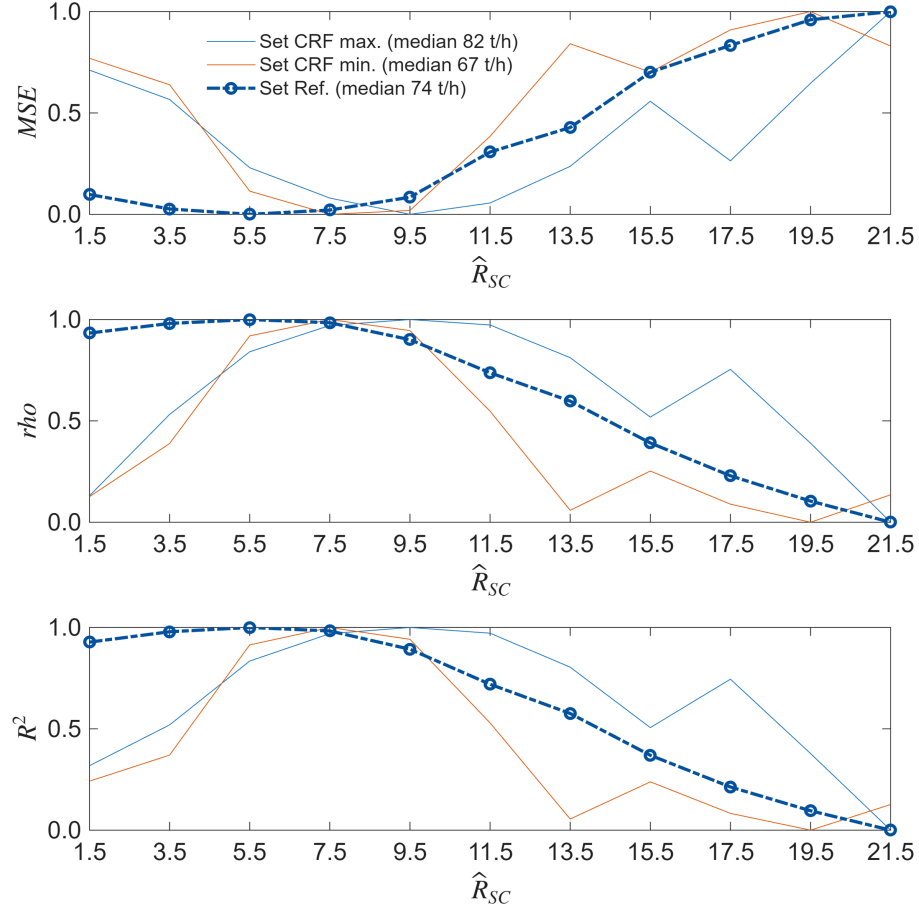


Figure 5.14: Correlation development for different CRF amounts: min. Set: 1,318 observations; max. Set: 1,664 observations; Ref. Set: 23,244 observations, Set June 2022

a reduction in RT and that elevated CRF quantities lead to an increase in RT regarding the RT of CRF.

The minimum and maximum error rates and correlation of the May 2023 subsets as depicted in Figure 5.16 point for lower CRF amounts (median 72 t/h) to $\hat{R}_{SC} = 5.5$ SC rotations and for higher CRF generation periods (median 83 t/h) to $\hat{R}_{SC} = 7.5$ SC, resulting in an increased estimated RT of two SC rotations, 56 minutes (72.1 t/h CRF) and 73 minutes (82.7 t/h CRF) median RT respectively as summarised in Table 5.2. The reference dataset, with a median of 79 t/h CRF generation results in $\hat{R}_{SC} = 7.5$ SC rotations and has the same rotation value as the subset with a median of 83 t/h CRF generation but results in a median RT of 73 minutes which lies between the median RT of the subsets. The difference in the fines production of $\Delta 4$ t/h is thereby recognisable in the RT for the May 2023 dataset. The size of the subsets (min. CRF Set: 9,034 observations; max. CRF Set: 10,536 observations) is much larger than that of the June 2022 datasets, but is still lower than the reference dataset with 89,068 observations. It is therefore also not possible to exclude the influence of the set size on the results to obtain comparability and reliability, as mentioned before. Furthermore, it is not possible to exclude the influence of other parameters in the May 2023 datasets on the RT. As previously stated, the finding of comparable plant conditions poses a challenge and could be mitigated by including additional data periods. However, no further datasets were available for this work.

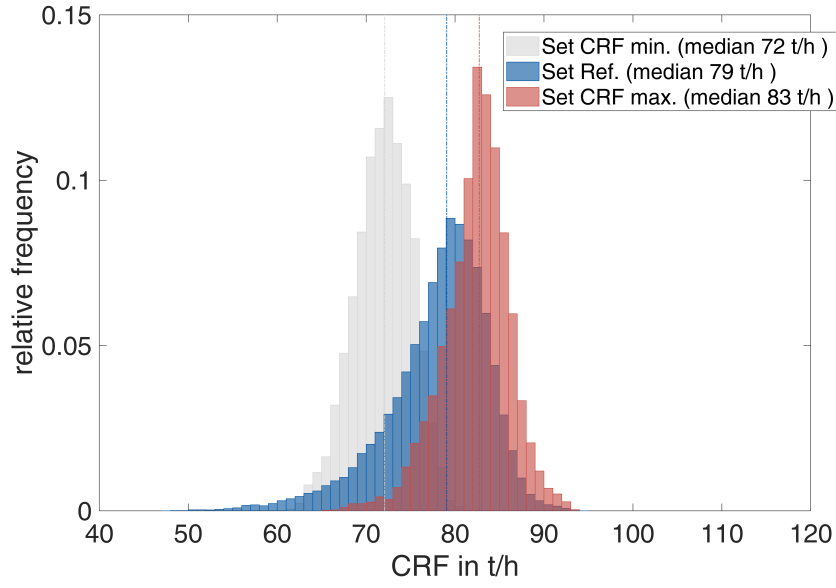


Figure 5.15: Examination of different CRF amounts, min.: smaller median; max.: larger median; CRF values; Ref.: complete dataset, May 2023

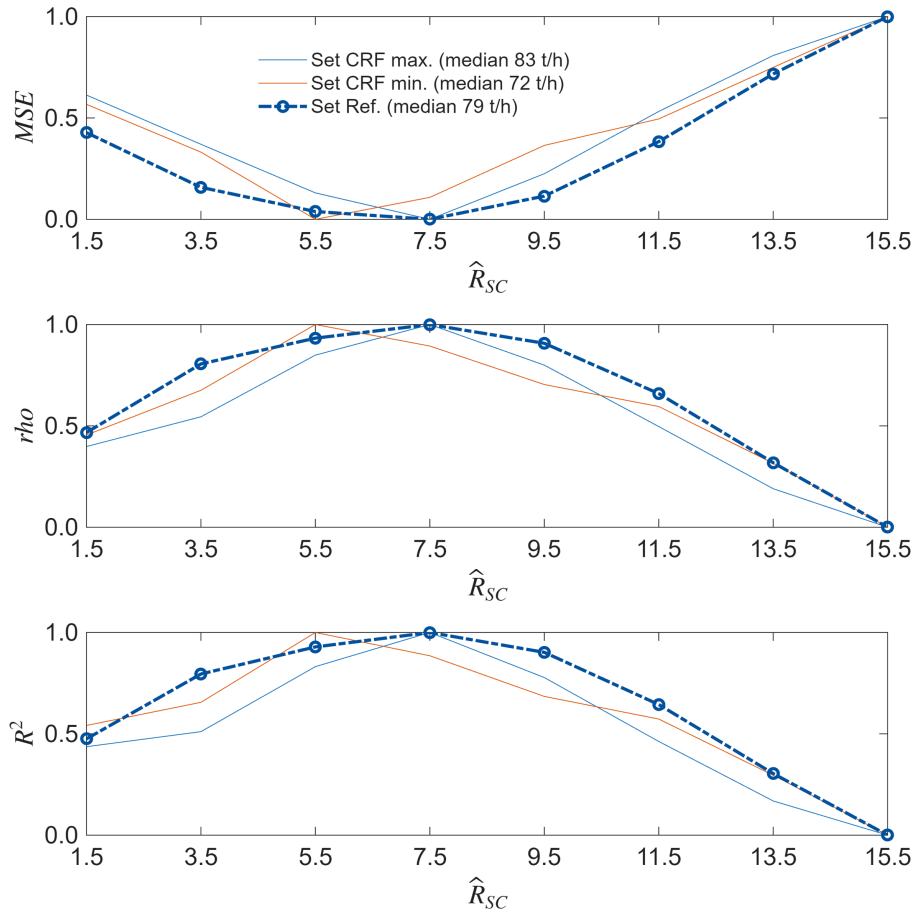


Figure 5.16: Correlation development for different CRF amounts: min. Set: 9,034 observations; max. Set: 10,536 observations; Ref. Set: 89,068 observations, Set May 2023

The subsets examined with different CRF quantities revealed that an increase in the production of both $\Delta 15 \text{ t/h}$ (June 2022) and $\Delta 11 \text{ t/h}$ of fines resulted in an increase of 2 SC rotations, corresponding to a 19 and 17 minutes increase in the median RT (cf. Table 5.2). Low amounts of CRF lead to shorter RT and excessive amounts of fines lead to longer RTs, vice versa. This finding corroborates the hypothesis that lower amounts of fines can pass the SC at a faster rate than larger particles (VASD trails). The enhanced particle movement can be attributed to the utilisation of the voids between the larger particles by the smaller particle [63, 72]. This effect will be slowed by increasing the amount of fines, which are unable to utilise the already occupied voids (filled with fines) between the larger particles, resulting in increased RT [1, 38]. As illustrated in the results in Figure 5.14 and Figure 5.16. The introduced RTE method is therefore capable of detecting changes in RT introduced by different amounts of fines, depending on the corresponding dataset and set size. However, it remains constrained by the size of the applied datasets (number of observations) to ensure the reliability of the results. By the usage of larger datasets with statistically sufficient observations, care must be taken to maintain the significance of short-term effects (temporal RT fluctuations). Otherwise, the method will provide an estimated average RT across the dataset, as illustrated in Figure 5.8 and Figure 5.10. This can be optimised by increasing the sample rate and generating sufficient observations for the ML model.

In the next section, the influence of the SC rotation speed (revolution per hour, rph) on the RT was examined. Due to the relatively limited size of the datasets resulting from the June 2023 Set (min. rph set: 485 observations and max. rph set: 555 observations) and the associated low quality of the results, the analysis was conducted only on the May 2023 dataset. Figure 5.17 presents the data for the different regions of revolution speed per hour (rph), analogous to the examination of the different CRF amounts. The data were selected from the reference dataset (May 2023) based on lower and higher median rotation speeds per hour. Two regions were identified, characterised by smaller (5.9 rph) and larger (6.8 rph) medians, respectively. Additionally, the reference dataset with a median of 6.4 rph is depicted. In Figure 5.18, the corresponding CRF amounts were shown for the selected region from the data defined in Figure 5.17. Regarding Figure 5.18, it is evident that the median values and distributions of the respective datasets are close to each other with 72 t/h (min. rph), 79 t/h (Ref.), 80 t/h (max. rph). After applying the RTE method on the subsets for the different rotation speed regions, the development of the error rate (MSE), correlation ρ and R^2 are illustrated in Figure 5.19. The $\arg \max_{corr}(\hat{R}_{SC})$ and $\arg \min_{MSE}(\hat{R}_{SC})$ of the error and correlation curve point to $\hat{R}_{SC} = 7.5$ SC rotations regardless of which rotation speed is considered (min. 5.9; Ref. 6.4; max. 6.8 rph). However, when comparing the median RTs of the investigated subsets with an identical number of estimated rotations $\hat{R}_{SC}$, but different median RT values result (cf. Figure A.1). The subset with a slower rotation speed of 5.89 rph resulted in a median RT of 79 minutes (cf. Table 5.2). In contrast, the subset with a faster rotation speed of 6.82 rph led to a median RT of 68 minutes (cf. Table 5.2), which is 11 minutes faster and corresponds to the duration of one SC rotation. This corresponds to the difference in rotation speed between the two subsets that are examined. Regarding the CRF amounts of the min./max. rph subsets, the dataset with the faster rph value has a CRF amount of 79.8 t/h, which is 7.3 t/h more than the slower subset. As demonstrated in the preceding section, increasing the CRF amount increases RT. The previously mentioned effect is compensated by the increased rotation speed at max. rph subset. It is evident that the CRF amount increases

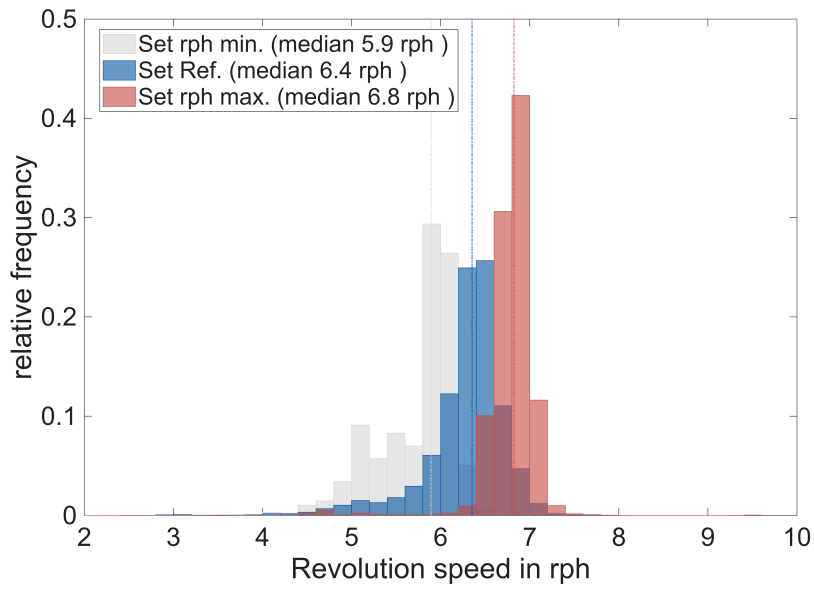


Figure 5.17: Examination of different SC rotation speeds (rph), min.: smaller median; max.: larger median; Ref.: complete dataset, Set May 2023

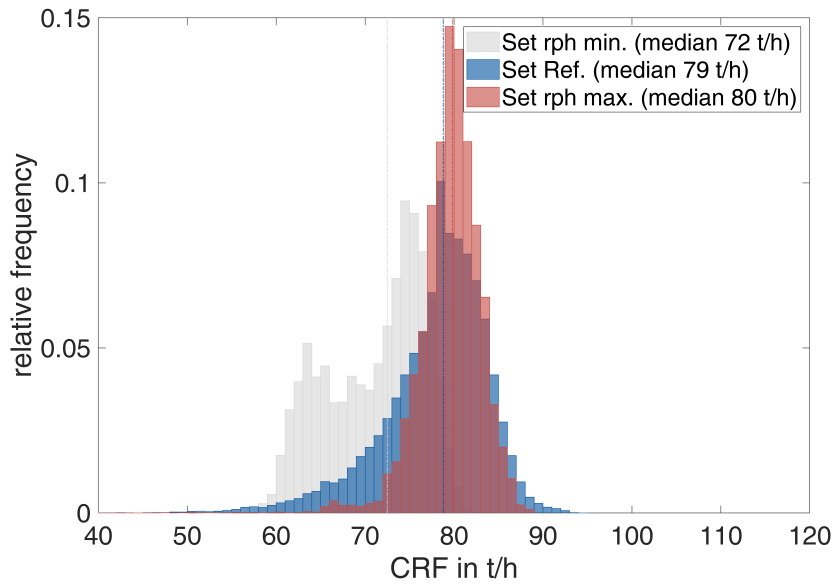


Figure 5.18: corresponding CRF amounts in t/h for: min. rph, max. rph, Ref. datasets, Set May 2023

by 7.3 t/h. In such cases, a longer RT is expected; however, this is compensated by the higher median rotation speed of 6.82 rph and the same estimated rotation estimate of $\hat{R}_{SC}$ of 7.5, which was also estimated for the min. rph subset, but with a lower CRF amount of 72.5 t/h. The findings indicate that the rotation estimates $\hat{R}_{SC}$ can be similar but rely on different RTs, and that the RT depends on the rotation speed. The rotation speed directly affects the RT. A higher revolution speed leads to shorter RT and a lower rotation speed to higher RT, as shown for the RTD in Figure A.1 for the different min. and max.

rph datasets, as the rotation is performed at a higher or slower rotational velocity. The motivation for the examination was that an increase in rotational speed may intensify vibrations, thereby amplifying the impact of segregation through percolation, resulting in shorter RTs. Due to the vibration, the fine fraction (CRF) should slip faster through the voids between coarser sinter particles. The findings of the actual examination verify this effect. Increasing rotation speed resulted in shorter RT even when the fines amount (CRF) increased. The usage of RTE method on two dataset from the sinter plant of VASD

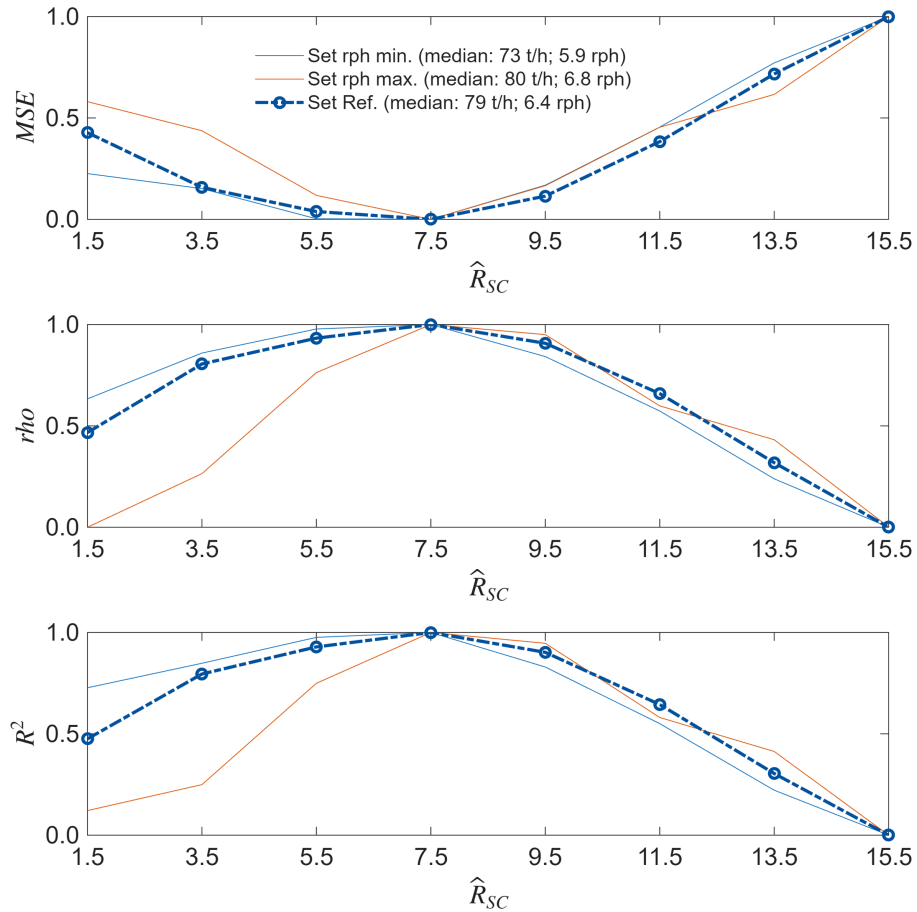


Figure 5.19: Correlation development for different rph values: min. Set: 4,220 observations; max. Set: 6,514 observations; Ref. Set: 89,068 observations, Set May 2023

revealed for the dataset from June 2022 a required number of $\hat{R}_{SC} = 5.5$ SC rotations to pass the SC in case of fines ($x < 5\text{ mm}$) which correspond to a median RT 52 minutes to reach the CRF belt weigher from the HC. The dataset from May 2023 needed $\hat{R}_{SC} = 7.5$ SC rotation that result in a median RT 73 minutes.

Additional examination of periods with higher and lower generated CRF amounts revealed that, with increasing CRF amount, the RT increases caused by the slowing-down effects of segregation by percolation (the capacity limit of voids between larger sinter particles). In contrast, lower CRF amounts lead to decreasing RT, since the smaller particles can better use the voids between the larger particles to pass the SC (segregation by percolation). The actual work indicated for an increase of $\Delta 15\text{ t/h}$ (June 2022) and $\Delta 11\text{ t/h}$ (May 2023) of fines resulted in an increase of 2 SC rotations, corresponding to a 17–19 minute increase in the median RT. The examination of the SC rotation speed indicates that the RT is

influenced by it. The higher vibration of the SC favours the passage of the fines through the coarse particles (percolation) even at higher fines (CRF) rates. However, the sinter requires a shorter duration to complete the estimated number of rotations at higher rotation speeds and a longer duration at lower rotation speeds, which results in the RTD.

As described in [61], the productivity of the sinter process is related to the amount of return fines. A higher proportion of fines indicates a lower proportion of raw materials agglomerated, caused by a lack of coke in the sinter mix, irregular combustion, and moisture changes in the sinter mix, leading to decreased sinter plant productivity. This suggests that periods with higher RT and greater CRF amounts are associated with lower plant productivity. In contrast, a reduction of the return fines percentage means an increase in the strength of the sinter product as a result of low sinter strand speed and high coke content in the mix, resulting in increasing productivity of the sinter plant [61]. This suggests that shorter RT periods lead to higher productivity in the sinter plant.

A comparison of the two datasets analysed indicates that the June 2022 dataset, which resulted in estimated median RT of 52 minutes and (median 74 t/h CRF), would have a higher productivity than the May 2022 dataset, which resulted in longer estimated median RT of 73 minutes (79 t/h CRF).

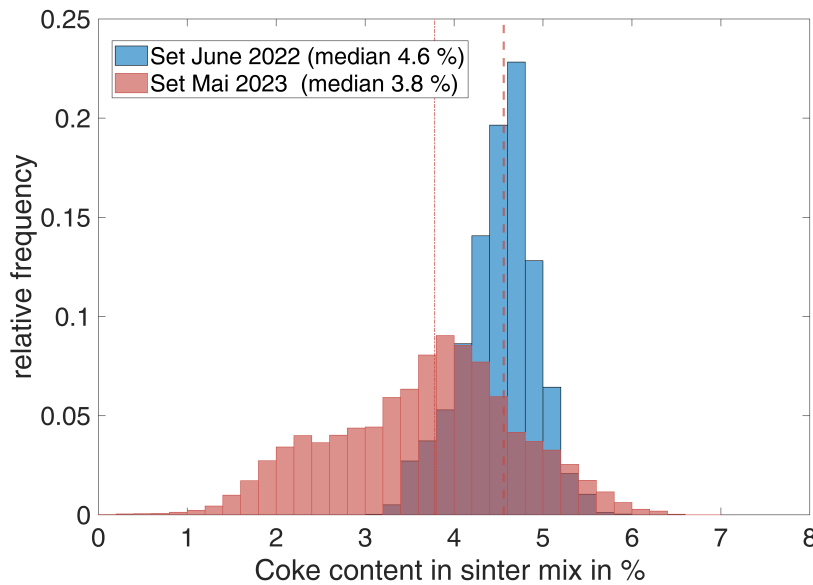


Figure 5.20: Histogram of coke content in the sinter mix of June 2022 and May 2023 dataset

The coke rates for both datasets (June 2022 and May 2023) support the hypothesis that the coke rate was higher during the June 2022 data, regarding Figure 5.20, as indicated by the lower estimated RT. The June 2022 data show a notable reduction in the variability of the coke rate in comparison to the corresponding dataset from May 2023, which is indicative of a more stable coke rate during June 2022 sinter production. The examinations of the subsets for periods with increased and decreased CRF amount underline the findings. Periods with increased CRF generation have lower coke content in the sinter mix, and periods with decreased CRF production show higher coke rates, as depicted in Figure 5.21 for the June 2022 subsets and in Figure 5.22 for the May 2023 subsets.

The investigation of the rotational speed demonstrated that it affects the RT and RTD. In

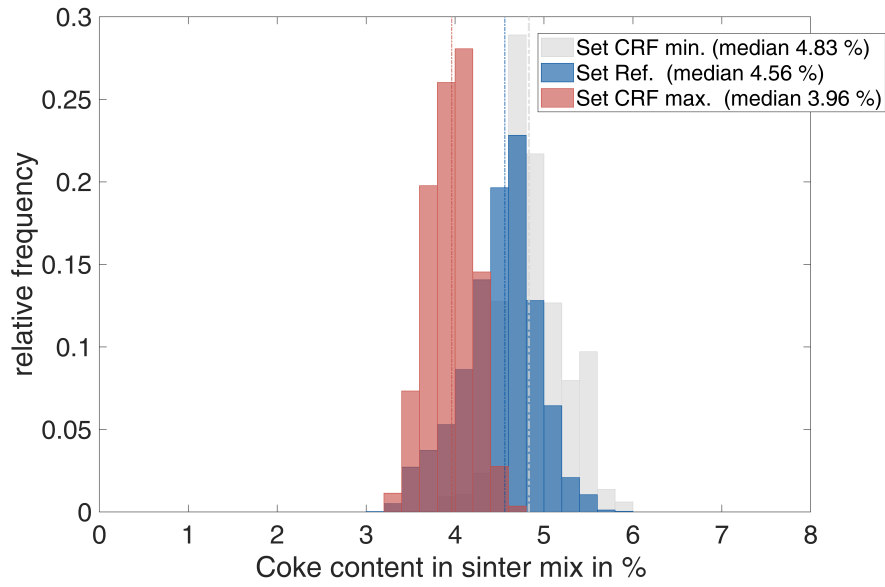


Figure 5.21: Histogram of coke content in the sinter mix of June 2022, subsets CRF min./max.

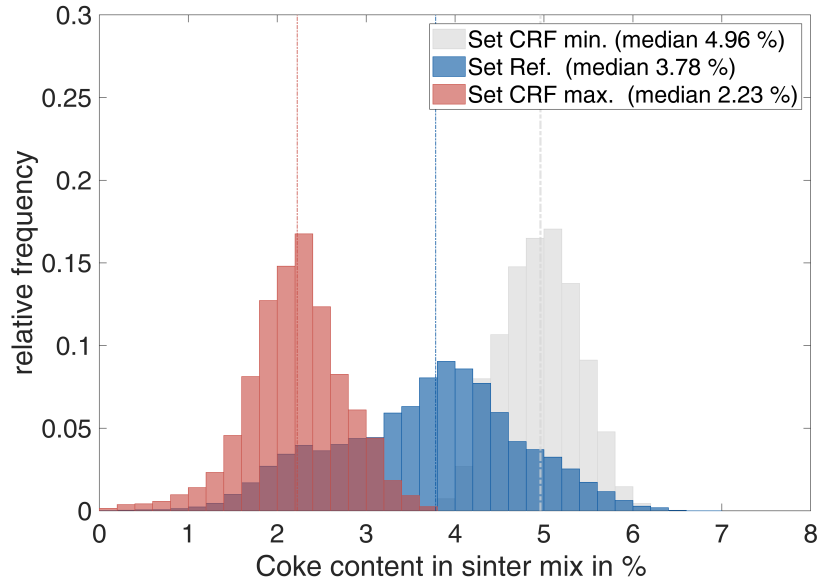


Figure 5.22: Histogram of coke content in the sinter mix of May 2023, subsets CRF min./max.

this thesis, the number of SC rotation estimates is the control variable ($\hat{R}_{SC}$, cf. beginning of Section 5.1) to vary the total RT. The rotation speed of the SC has a direct influence on the RT of the sinter. At higher rotation speeds, the RT is shorter because rotations are completed faster; at lower rotation speeds, the RT increases because it takes longer to complete the rotations to pass the SC. This effect is generally valid and addresses the velocity-dependent effects of the SC, where the RT is directly proportional to the rotation speed. The fluctuation of the actual rotation speed of the SC leads to the RTD, as demonstrated in the results of (Section 5.1.3) with shorter and longer RTs depending on the actual SC rotation speed. Furthermore, the total RTD is also influenced by the rotation

speed; higher rotational velocity of the SC leads to increased vibrations, which emphasise the effect of percolation, resulting in shorter RTs and shifting the RTD to shorter times, which is characterised by a shorter median RT. The sinter fines (e.g. CRF) can pass the voids faster due to enhanced percolation. The main results of this section are summarised in Table 5.2. Due to the relatively small dataset size (< 600 observations), the training was not conducted on the subsets of min./max. rotation speed (rph) in June 2022.

Table 5.2: Main results of sinter Residence Time Estimation (RTE)

Set Name	$\hat{R}_{SC}$	MSE	ρ	R^2	RT ^{4,5}	Observations	Particle Size	CRF ⁵	Revolu- tion Speed ⁵	Coke Rate ⁵
Unit	—	—	—	—	min	—	mm	t/h	rph	%
June 2022 Set	5.5	15.34	0.77	0.60	52	23,244	< 5	74.3	6.69	4.56
May 2023 Set	7.5	12.14	0.80	0.63	73	89,068	< 5	79.1	6.35	3.78
June 2022 min. CRF	7.5	7.26	0.86	0.73	70	1,318	< 5	66.7	6.68	4.83
June 2022 max. CRF	9.5	4.01	0.88	0.77	89	1,664	< 5	81.7	6.58	3.96
May 2023 min. CRF	5.5	6.10	0.63	0.40	56	9,034	< 5	72.1	6.09	4.97
May 2023 max. CRF	7.5	9.35	0.57	0.33	73	10,536	< 5	82.7	6.40	2.23
June 2022 min. rph	—	—	—	—	59	485	< 5	65.0	6.00	4.57
June 2022 max. rph	—	—	—	—	49	555	< 5	73.9	7.06	4.41
May 2023 min. rph	7.5	5.12	0.69	0.48	79	4,220	< 5	72.5	5.89	3.57
May 2023 max. rph	7.5	8.04	0.85	0.73	68	6,514	< 5	79.8	6.82	5.16
Reference (VASD)	9.5	—	—	—	88	—	>100	—	—	—

⁴estimated Residence Time (RT)

⁵median values

5.2 Formulation of Residence Time Estimation Algorithm

The data-driven algorithm for Residence Time Estimation (RTE) introduced in the previous chapter is presented in the following section.

For a given time series situation where the predictor variables have a known RT and are connected to the response variable by a section of unknown RT, the introduced RTE method can be applied to identify an optimal connection between the "in values" and "out values" in dependence of the (unknown) RT "time lag" (Figure 5.23). The resulting estimated RT can be considered the average RT, valid for the time series (dataset) examined. The method applicable to time series in which multidimensional input variables (predictors) are used to predict one or more dependent variables with an unknown time lag. Ordinary cross-correlation (cf. Section 3.4) can be used to align one-dimensional variables in time to the outcome variable.



Figure 5.23: Time series situation with given RT for incoming data; multiple predictor (in), unknown RT (time lag), one or more dimensional response variable (out)

The data-driven algorithm for RTE is formulated as follows:

Resident Time Algorithm:

1. *Data pre-processing of the dataset.*
2. *ML method ("ML-Kernel") selection and model creation on dataset including known and initial RT estimate (e.g., system knowledge, physical limits, RT from trials).*
3. *Generation of multiple n datasets including predictor (known resident time) and series of RT estimates, for section of unknown RT:
 $x_{t+\hat{\tau}}$ with $\hat{\tau} = \tau + a_1, \tau + a_2, \dots, \tau + a_n = \hat{\tau}_1, \hat{\tau}_2, \dots, \hat{\tau}_n$
and response variable according Figure 5.24, for data interval of interest (searched RT).*
4. *Application of ML-Kernel from step (2) to train the multiple datasets from step (3).*
5. *Determine training error rate and/or correlation (e.g., MSE, R^2).*
6. *Find $\arg \min_{MSE}(\tau)/\arg \max_{corr}(\tau)$ of correlation function ("ML-Kernel") in dependence of lag $\hat{\tau}$ estimates (datasets from step (3)). $\rightarrow$ dataset with minimum error rate or maximum correlation value reflects optimal estimated RT.*
7. *Optional: Run ML Model with estimated RT from step (6) or corresponding dataset, apply on training and test set in the data region of valid RT (range from step (3)). Step (7) can be performed with "any" ML method, after model development.*

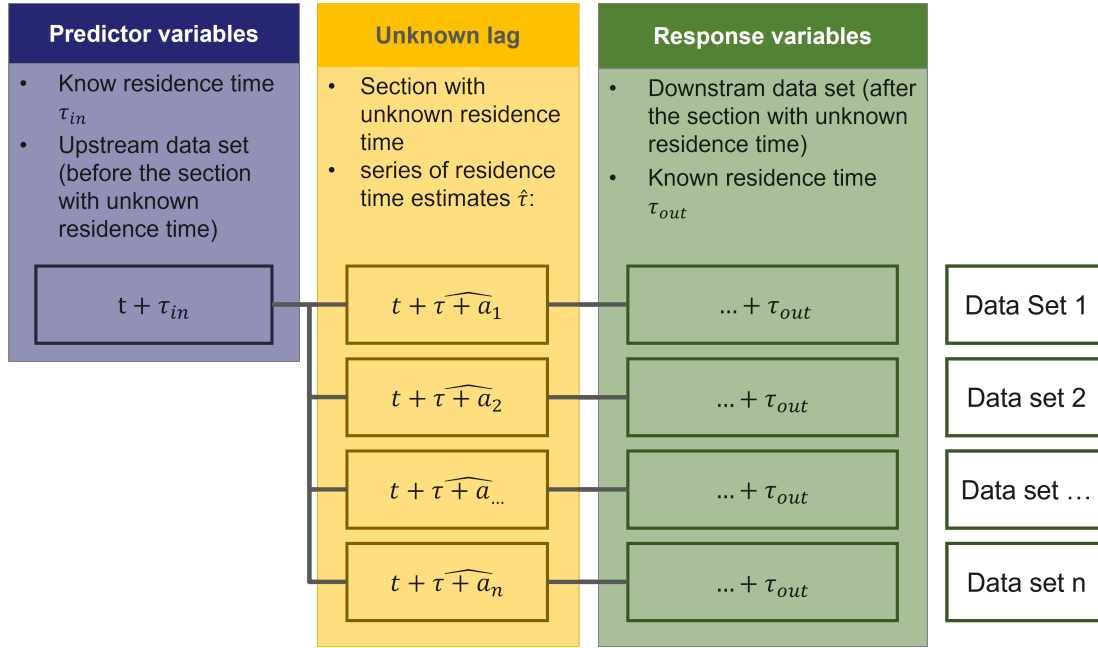


Figure 5.24: Dataset generation based on Residence Time estimates τ

The method is unable to estimate short-term changes in RT within the examined dataset. With sufficient observations and resolution, the method can be restricted to sections with different RTs, providing average RT information for each section. In general, the specifications of the selected ML method (ML-Kernel) determine the required data properties. The correlation function (ML-Kernel) in the presented procedure can be any supervised ML method that does not internally adjust or optimise the time alignment to fit the predictor to the response variable. In such a case, the significance of the result would be reduced, as the ML method would provide almost identical results for each dataset (even applied on different RTs) by attempting to optimise the predictor to the response by adjusting the RT (internal regulation) as reported in [6, 18, 15, 31, 34]. For this reason, supervised ML methods should be preferred with almost no internal regulatory capacity ("self-optimising") using back propagation as an artificial neural network (NN), Long Short-Term Memory (LSTM) or Recurrent Neural Network(RNN) methods, as it was proposed in the approach from [6, 18, 15, 31, 34]. In the case of unregulated ML methods, the prediction accuracy should be higher for RTs when the optimal combination of predictor and response (optimal match) can be achieved in dependence on the used RT estimates $\hat{\tau}$. In the presence of multimodal correlation distributions, it is necessary to intensify the analysis of the data in order to identify the source of each peak. In general, the introduced method performs adequately when a unimodal correlation distribution is present (in the dataset of interest).

5.3 Application on Sinter Plant for Sinter Quality Estimation

Based on the two datasets from Section 5.1 from June 2022 with 44,200 observations (30 days, raw data) and from May 2023 with 94,540 observations (65 days, raw data) an MLR model was trained as a use case on defined training datasets and applied on test

datasets. The total observations of each set were reduced after eliminating data from non-stable plant operating periods and pre-processing to 23,244 observations for the dataset from June 2022 and 89,068 observations from the dataset from May 2023, containing 19 predictor attributes and one response variable (CRF).

The datasets were selected based on the previously determined estimated RT based on $\hat{R}_{SC} = 5.5$ SC rotations (best match, June 2022 data) and $\hat{R}_{SC} = 7.5$ SC rotations (best match, May 2023 data). The dataset from June 2022 was divided into a training set containing 18,465 observations (Figure 5.25) and used to predict the CRF amount of a test set containing 4,779 observations (Figure 5.27), with a 80:20 ratio of training to test set observations, fulfilling the proposed ratio from [132] (training set $\geq 50\%$ observations). The dataset from May 2023 was also divided into a training set containing 60,862 observations (Figure 5.26) and used to predict the CRF amount of a test set containing 28,206 observations (Figure 5.28, with a 70:30 ratio of training to test set observations. The training and test results of each dataset are presented in tabular form in Table 5.3 (dataset June 2022) and Table 5.4 (dataset May 2023). The values of p -value and F -statistic indicate that the null hypothesis H_0 can be rejected. The values suggest that the model explains a considerable proportion of the variation of the CRF data. Both datasets (June 2022 and May 2023) included periods of sinter plant stoppages, and the June 2022 dataset contained a region with unplausible data. All these regions were removed from the datasets.

Table 5.3: Best Fit Set June 2022, based on $\hat{R}_{SC} = 5.5$ rotations (MinSiDeg)

	Training Set ⁶	Test Set
MSE	16.26	12.8
ρ	0.75	0.78
R^2	0.57	0.60
Observations	18,465	4779
Root Mean Squared Error	4.03	—
Adjusted R -Squared	0.567	—
F -statistic	1,330	—
p -val	0	—

The training dataset (June 2022) is shown in Figure 5.25, including the pre-processed raw values and predicted training values for the CRF amount. The areas with missing values in Figure 5.25 represent time periods when variables or response data were missing from the training dataset due to truncation resulting from pre-processing or plant stoppages, hence no prediction was possible. The three missing passages exhibit no data for 172 hours and 45 minutes in the dataset. The first and last passages are instances of sinter plant stoppages. The period from 13 June to 16 June contains implausible values, which were thus removed.

⁶Include stoppage of 19:20 (hh:mm), unplausible data 66:46 (hh:mm), stoppage 86:39 (hh:mm)

⁷Include stoppage of 41:10 (hh:mm)

Table 5.4: Best Fit Set May 2023, based on $\hat{R}_{SC} = 7.5$ rotations

	Training Set	Test Set ⁷
MSE	10.95	33.19
ρ	0.78	0.79
R^2	0.61	0.09
Observations	60,862	28,206
Root Mean Squared Error	3.3	—
Adjusted R -Squared	0.612	—
F -statistic	5,330	—
p -val	0	—

The linear correlation coefficient ($\rho = 0.75$) and the R^2 -statistics ($R^2 = 0.57$) show acceptable results for the trained MLR method. During the training phase, interactions between the predictor and quadratic extensions were permitted. Although sintering is a non-linear process, the outcome of the linear fit (with quadratic extensions and interaction terms) was able to reproduce the trend in the CRF values. This may be attributed to the temporal alignment of the variables and the sintering material by the RTE method developed in this thesis.

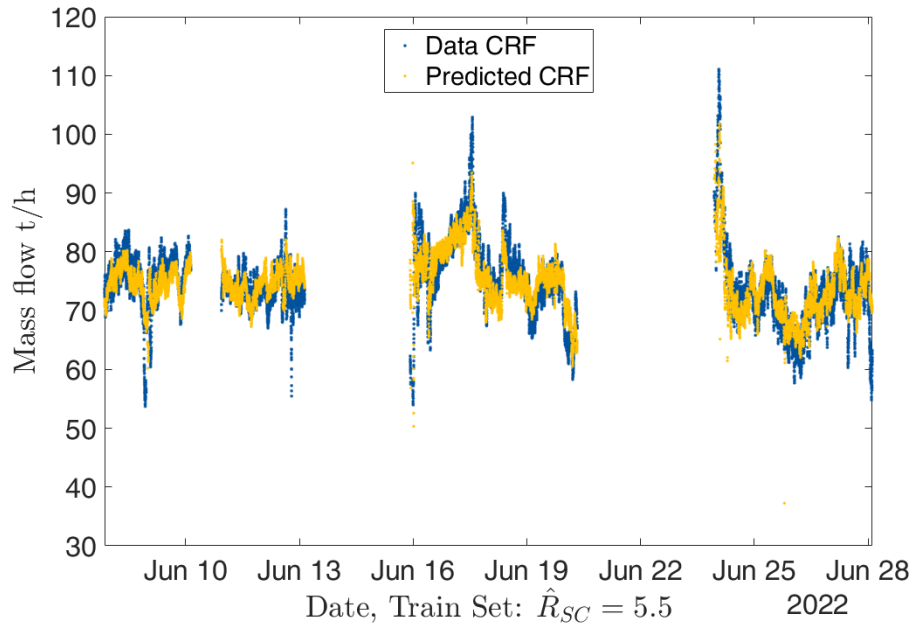


Figure 5.25: Training dataset (June 2022), $\hat{R}_{SC} = 5.5$, $n = 18,465$ observations, $MSE = 16.26$, $\rho = 0.75$, $R^2 = 0.57$

The training dataset (May 2023) is shown in Figure 5.26, including the pre-processed raw values and predicted training values for the CRF amount. The training dataset includes no

stoppages or implausible data periods. The linear correlation coefficient ($\rho = 0.78$) and the R^2 -statistics ($R^2 = 0.61$) show acceptable results for the trained MLR method. The level of accuracy regarding the linear correlation coefficient and R^2 -statistic is somewhat superior to that observed in the June 2022 datasets. This can be attributed to the absence of sinter plant stoppages in the training data, suggesting that the sinter process is generally more stable during the May 2023 period than during the June 2022 period (based on the training datasets). It should be noted that the training set size is not identical. That of the May set is 42,397 observations larger, which may also contribute to the improved generalisation of the results. Nevertheless, sintering is a non-linear and complex process [9, 31]. The linear fit (with quadratic extensions and interaction terms) reproduced the trend in the CRF values. The accuracy could be improved by using non-linear ML methods, but this would extend the scope of this thesis. The test set from the June 2022 data is

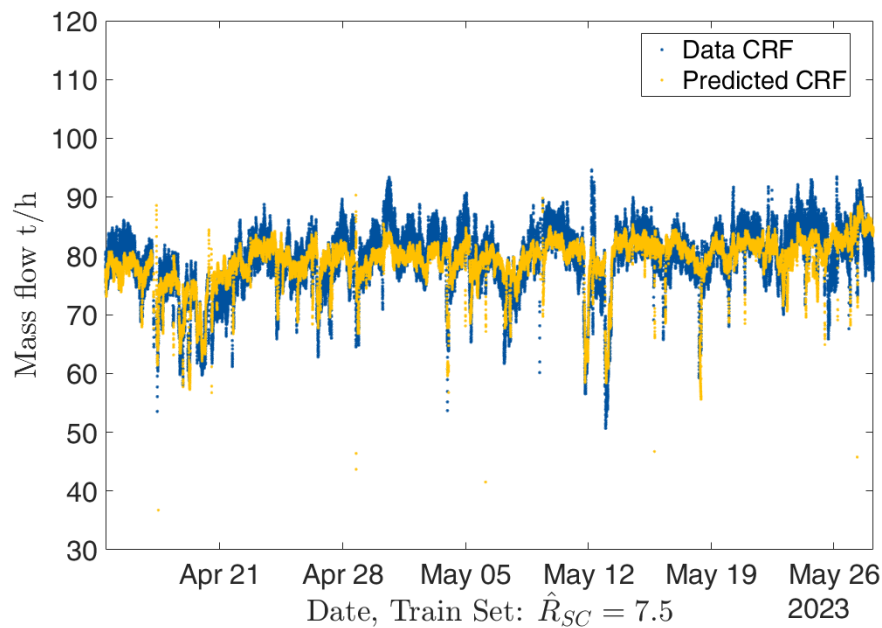


Figure 5.26: Training dataset (May 2023), $\hat{R}_{SC} = 7.5$, $n = 60,862$ observations, $MSE = 10.95$, $\rho = 0.78$, $R^2 = 0.61$

shown in Figure 5.27 and for the May 2023 data in Figure 5.28. The predictions of the test set in Figure 5.27 (June 2022 data) show a good agreement with the pre-processed measured values. The linear correlation demonstrates a prediction accuracy of $\rho = 0.78$, and an R^2 -statistic of 0.60. The values are even slightly higher than those obtained from the training dataset ($\rho = 0.75$, $R^2 = 0.57$). The observed tendency towards marginal better performance can be explained by the application of the MLR model to a time series in which the predictor can randomly fluctuate due to the non-linear, complex sinter process. Consequently, the potential for optimal matching of predictor variables between the training and test datasets may enhance accuracy, as observed in this work, but could also decrease it. Additionally, the occurrence of production disruptions and the associated fluctuations in production parameters in the June 2022 training set will result in a reduction in the accuracy of the predictions made in that dataset, in contrast to the predictions made in the corresponding test set, which was free from significant irregularities (Figure 5.27, Table 11). The prediction of the test set associated with the dataset from May 2023 is

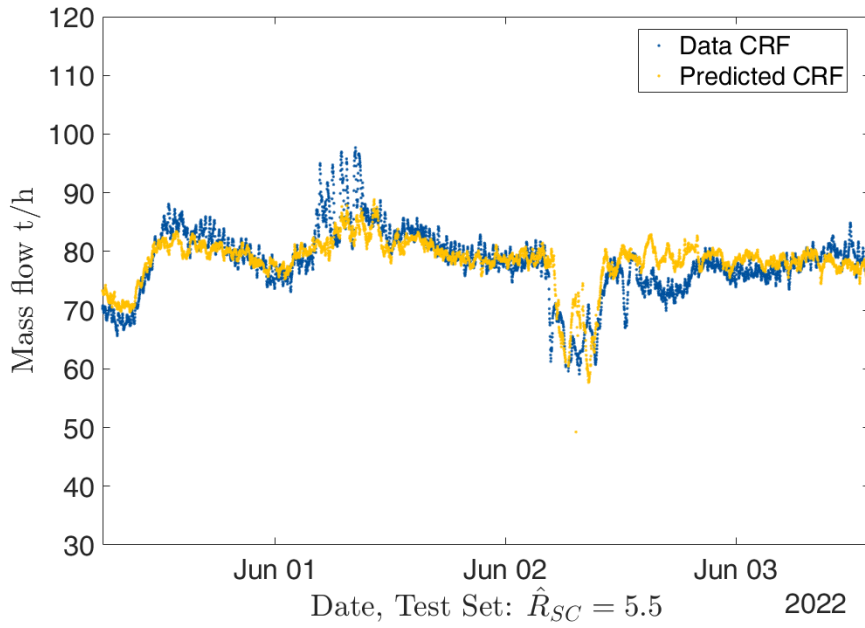


Figure 5.27: Test dataset (June 2022), $\hat{R}_{SC} = 5.5$, $n = 4,779$ observations, $MSE = 12.8$, $\rho = 0.78$, $R^2 = 0.60$

depicted in the Figure 5.28. The total values describing the accuracy of the complete test set are lower compared to the values achieved in the training dataset with an MSE of 33.19, linear correlation coefficient ρ of 0.79 and R^2 -statistic of only 0.09 (corresponding training dataset: $MSE = 10.95$, $\rho = 0.78$, $R^2 = 0.61$).

A closer analysis reveals that the test dataset is interrupted by a missing section (plant stoppage). The quality of the predictions appears superior prior to the interruption and subsequently declines in accuracy in mapping values following the interruption until the 15th of June. After the 15th of June, the quality of the predictions appears to improve again (Figure 5.28). To conduct a more detailed analysis, the test set was divided into three periods, as illustrated in Figure 5.29. The initial assumptions are validated by the quality of the forecast. Period 1 has the highest quality of predictions with a MSE of 20.5, a linear correlation coefficient ρ of 0.84 and R^2 -statistic of 0.50 associated with similar production parameters to the training set. After the production stoppage, the quality values declined significantly to an MSE of 53.7 (error increase), a linear correlation coefficient of 0.60 and R^2 -statistic of -2.87 . The negative R^2 value indicates that the MLR model performed poorly [152]. Following the values obtained in period 2, beginning after the 15th of June, the quality values regenerate to an MSE of 21.3, a linear correlation coefficient of 0.89 and an R^2 -statistic of 0.32. The values obtained in period 3 do not reach the quality levels observed before the production interruption for MSE and the R^2 -statistic. Still, they are significantly improved compared to those obtained in period 2 directly following the stoppage. The linear correlation coefficient indicates only the linear behaviour of the two variables. It thus provides information on the direction of both values, whether they are both increasing (+), decreasing, or increasing (−), or remaining constant (0). The R^2 -statistic provides a measure of the variance that can be explained by the prediction [130] and is thus lower than the value of the linear correlation coefficient.

One potential explanation is that the parameter following the interruption is not in the

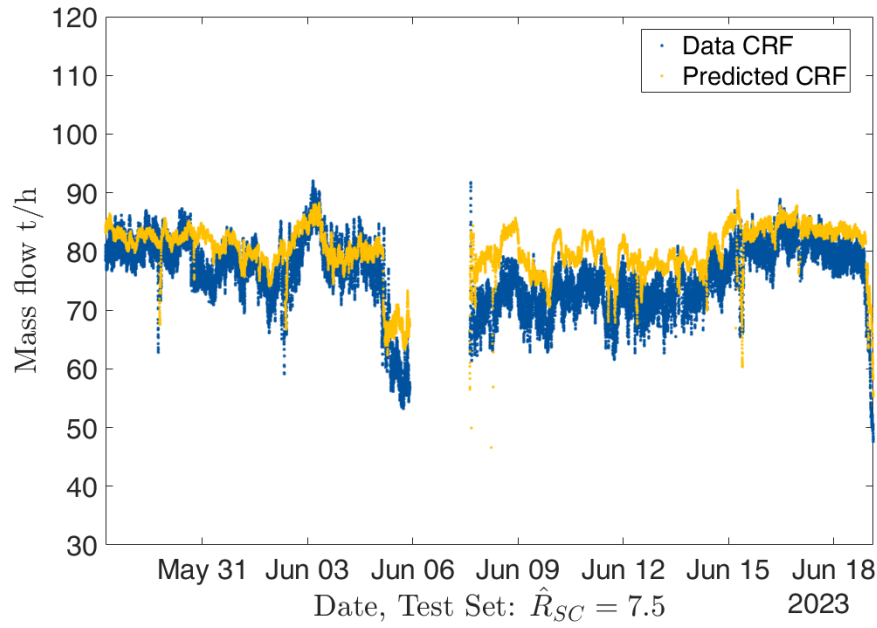


Figure 5.28: Test dataset (May 2023), $\hat{R}_{SC} = 7.5$, $n = 28,206$ observations, stoppage 41 hours, $MSE = 33.19$, $\rho = 0.79$, $R^2 = 0.09$

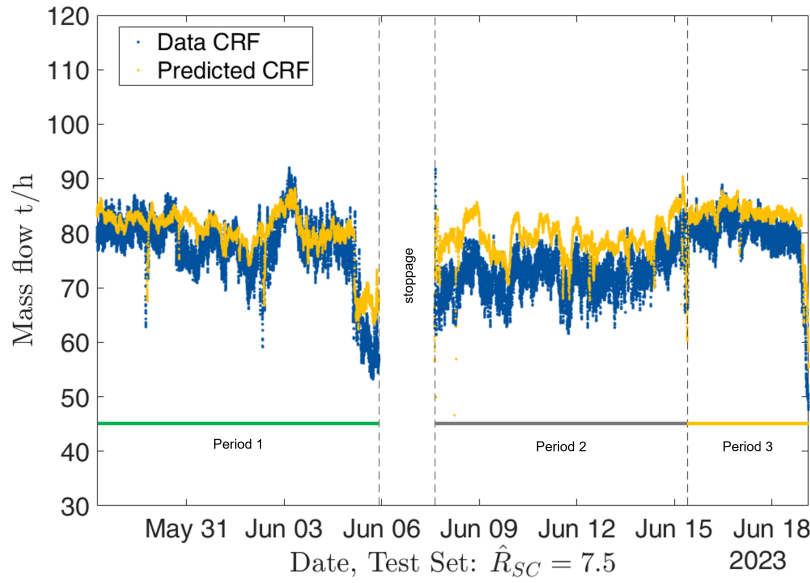


Figure 5.29: Test dataset (May 2023), $\hat{R}_{SC} = 7.5$, $n = 28,206$ total observations, stoppage 41 hours, Set divided in 3 periods:

Period 1: $MSE: 20.5$, $\rho: 0.84$, $R^2: 0.50$, $n = 12,343$ observations

Period 2: $MSE: 53.7$, $\rho: 0.60$, $R^2: -2.87$, $n = 10,663$ observations

Period 2: $MSE: 21.3$, $\rho: 0.89$, $R^2: 0.32$, $n = 5,200$ observations

typical range of "normal" sinter production, as observed in period 1 and present during the training set. Most probably, the plant operator was required to take action to counteract the circumstances that led to the disruption and restore sinter production to a normal level,

resulting in the fluctuating plant situation in period 2. As the operator had to adjust the production parameter based on manual experience, the results from period 2 confirmed the disadvantageous situation of the sinter plant with large fluctuations in product quality as stated in [18]. The examined periods are showed in Figure A.2 – A.4 in the Appendix A. A detailed investigation was not conducted in this thesis, as it is beyond the scope of this work; however, further research could provide additional knowledge.

The CRF amount development shown in the Figure 5.25 to Figure 5.29 gives only information about the absolute CRF mas flow amount, but without revealing the specific details on how much CRF was generated per ton of total sinter production (sum of CRF and BF-Sinter amount). To overcome the missing information, the CRF/Total-Sinter ratio was calculated for the given datasets according to:

$$CRF-Ratio = \frac{CRF}{(CRF + BF-Sinter)} \cdot 100 \quad \text{in \%} \quad (5.5)$$

where:

- CRF : is the Cold Return Fines amount in t/h
- $BF-Sinter$: is the BF-Sinter in t/h or finished sinter product
- $CRF-Ratio$: is the CRF-Ratio in %

The CRF-Ratio is displayed in combination with the correlation plot in Figure 5.30 and Figure 5.31, respectively, for the June 2022 and May 2023 datasets. Depicted are the measured values of mass flows of CRF and the calculated CRF-Ratio according to Equation (5.5) based on the measured BF-Sinter (finished sinter) mass flow. The linear correlation coefficient ρ of 0.80 in Figure 5.30 for the June 2022 dataset indicates a positive correlation of both values, which means that the amount of CRF increases when the Total-Sinter amount (sum of CRF and BF-Sinter) increases. The median CRF-Ratio lies at 24.73% with standard deviation of $\sigma = 2.15\%$ and lies in a range of 17.84–43.58% of the total produced sinter amount. The linear correlation coefficient ρ of 0.49 in Figure 5.31 for the May

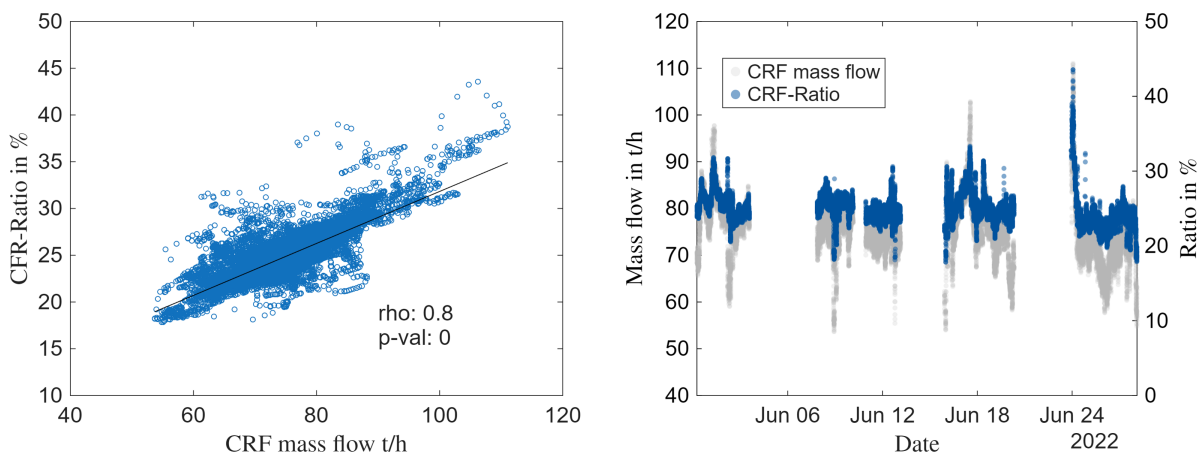


Figure 5.30: CRF/Total-Sinter ratio dataset (June 2022). Left: Correlation between CRF-Ratio and CRF mass flow Right: Development of CRF-Ratio and CRF mass flow over time.

2023 dataset indicates a lower positive correlation between the two values, which means that the CRF amount increases when the Total-Sinter amount increases or both values

decrease. The median CRF-Ratio is 25.12% and has a standard deviation of $\sigma = 1.30\%$ and lies in a range of 19.07–39.03% of the total sinter amount produced. The correlation of $\rho = 0.49$ indicates that in 49% of the values of the CRF and Total-Sinter amount increase or decrease at the same time, in the remaining values behave differently, increase, or decrease independently from each other or remain at the same level. Thus, the CRF amount can increase or decrease in 51% of the data when the level of Total-Sinter stays at the same level. However, it is beyond the scope of this thesis to investigate the correlation between CRF and Total-Sinter production. The information should provide a better understanding of the CRF value in context with the total produced sinter, which was selected as the target variable in this thesis (cf. Section 4.1.2).

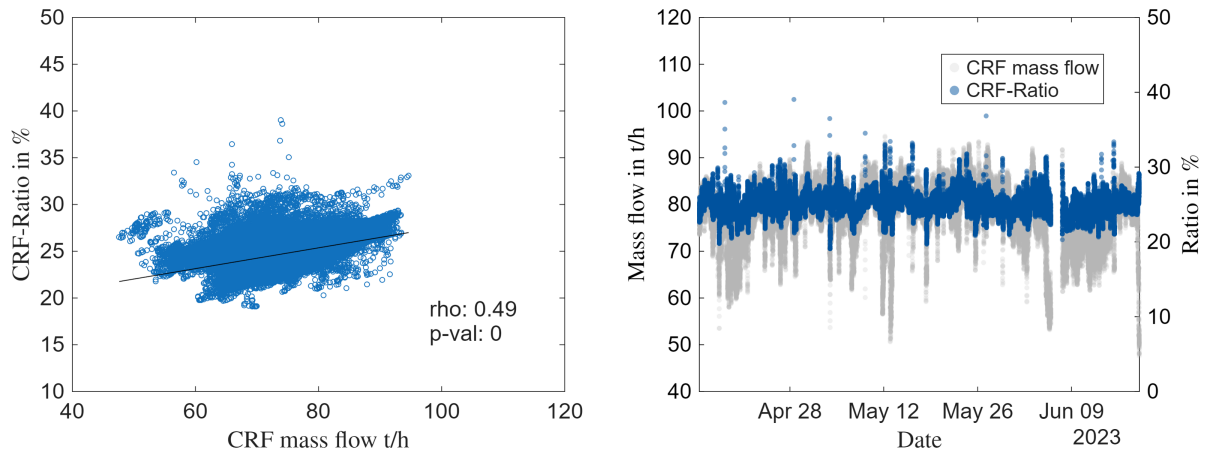


Figure 5.31: CRF/Total-Sinter ratio dataset (May 2023). Left: Correlation between CRF-Ratio and CRF mass flow Right: Development of CRF-Ratio and CRF mass flow over time

The findings demonstrate that implementing the RTE method provides the opportunity to utilise ML techniques, such as MLR, on data without (initial) known time alignment and additionally, identifies the RT for further investigation.

Nevertheless, in certain sections, the predicted CRF values deviate considerably from the raw data. In particular, the MRL model was unable to reflect the values after a sinter plant stoppage during the test dataset from the May 2023 dataset, as this supposedly deviated from the production parameters during the training period. Further development is required in these sections, and the results may be enhanced by additional filtering, the removal of implausible data or the application of more advanced ML methods. It is always a compromise: if the filtering and exclusion criteria for the data are too rigorous, the number of observations is reduced until there are insufficient observations left, leading to overfitting. On the other hand, inadequate filtering results in the inclusion of a considerable amount of extraneous data (cf. the May 2023 test dataset, Section 5.3), which subsequently reduces the accuracy of the predictions.

To quantify the improvement in prediction due to the temporal alignment of the datasets, MLR models were trained on the studied datasets from June 2022 and May 2023, including pre-processing but without temporal alignment by shifting the measured values by the estimated RTs. The accuracy characterisation is summarised in Table 5.5 for the unaligned June 2022 dataset and in Table 5.6 for the unaligned May 2023 dataset.

Table 5.5: MLR fit, based on unaligned June 2022 dataset

	Training Set ⁸	Test Set
MSE	19.07	17.77
ρ	0.71	0.70
R^2	0.50	0.48
Observations	18,510	4,780
Root Mean Squared Error	4.24	—
Adjusted R -Squared	0.50	—
F -statistic	1,180	—
p -val	0	—

Table 5.6: MLR fit, based on unaligned May 2023 dataset

	Training Set	Test Set ⁹
MSE	13.11	40.24
ρ	0.74	0.76
R^2	0.54	−0.02
Observations	61,386	28,459
Root Mean Squared Error	4.08	—
Adjusted R -Squared	0.41	—
F -statistic	2,410	—
p -val	0	—

By comparing the accuracy in terms of MSE, ρ and R^2 of the temporally aligned datasets from Table 5.3 and 5.4 with the accuracy measures of the unaligned datasets, an enhancement for the June 2022 and May 2023 datasets for the training and test case are summarised in Table 5.7 and 5.8.

⁸Include stoppage of 19:20 (hh:mm), unplausable data 66:46 (hh:mm), stoppage 86:39 (hh:mm)

⁹Include stoppage of 41:10 (hh:mm)

Table 5.7: Accuracy enhancement,
Set June 2022

	Training Set	Test Set
<i>MSE</i>	-2.81	-4.97
<i>rho</i>	+0.04	+0.08
<i>R</i> ²	+0.07	+0.12

Table 5.8: Accuracy enhancement,
Set May 2023

	Training Set	Test Set
<i>MSE</i>	-2.03	-7.05
<i>rho</i>	+0.04	+0.03
<i>R</i> ²	+0.07	+0.11

The effect of time alignment of the data by applying the RTE method has resulted in an enhancement of model accuracy compared with the direct calculation of correlations between individual variables (cf. Section 5) and unaligned datasets.

The MLR model predicts the sinter quality indices (Cold Return Fines, CRF) trend approximately 52–73 minutes in advance (based on historical data) using the measuring values upstream the HC. As conventional quality information is determined only once a day from bulk samples, the predicted values could provide a significant time advantage and insight into the current sinter quality of the produced sinter. The enhanced quality information could be used for predictive machine support.

5.3.1 Influence of Sinter Fines on Blast Furnace Performance

The indicative influence of Sinter Fines (SF) with fraction $x < 5\text{ mm}$ on the Blast Furnace (BF) was examined during MinSiDeg [1] at TKSE. A comparison was made between two periods with comparable BF operating conditions in terms of hot blast rate and reducing agent (coke rate) for two stages with high and low SF amounts. This comparison was based on one year's BF operational data and conventional daily sieve analysis. The analysis was performed to examine the influence of SF amounts on the BF performance. Comprehensive examinations were not conducted during the project to investigate the impact of sinter fines on sinter weakening due to heat or reduction. The primary focus of this project was to minimise and predict sinter degradation during conveying. The delta p, permeability, heat loss in the lower furnace shaft and η_{CO} were compared in periods with high and low SF amounts. The comparison of pressure loss over the furnace height revealed a slight increase in pressure drop for the periods with higher SF amounts (Figure 5.32, left-hand side) and a corresponding increase in permeability in the section with lower SF (Figure 5.32, right-hand side). More SF particles can fill the voids in the burden material of the BF and lead to higher pressure drop and lower permeability. The heat loss in the lower furnace shaft is presented in Figure 5.33 for both regions of low and high SF fractions amounts. The higher fines amount results in increased heat loss. The elevated heat loss in the lower furnace section indicates an inhomogeneous gas flow within that section, which can be linked to the higher SF amount. Furthermore, the efficiency of the BF is also slightly increased for the period with a lower SF amount (Figure 5.33, right-hand). It was shown that higher SF amounts measured at the outlet of TKSE sinter plants tend to decrease the BF shaft flow rate by reducing permeability. A high proportion of SF can result in unfavourable conditions within the BF, characterised by low permeability and insufficient gas flow (hot blast). This, in turn, leads to an increase in the pressure drop (delta p), which is known to cause issues in the BF operation [1, 6, 13]. The application of the data-based

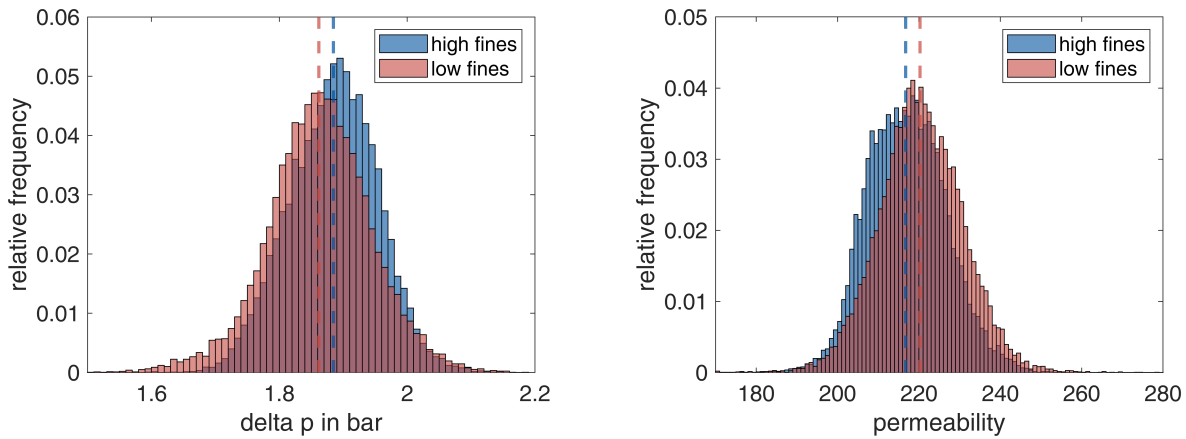


Figure 5.32: Effects of sinter fines on BF performance (TKSE BF2). Left: Pressure loss Right: Blast furnace permeability [1]

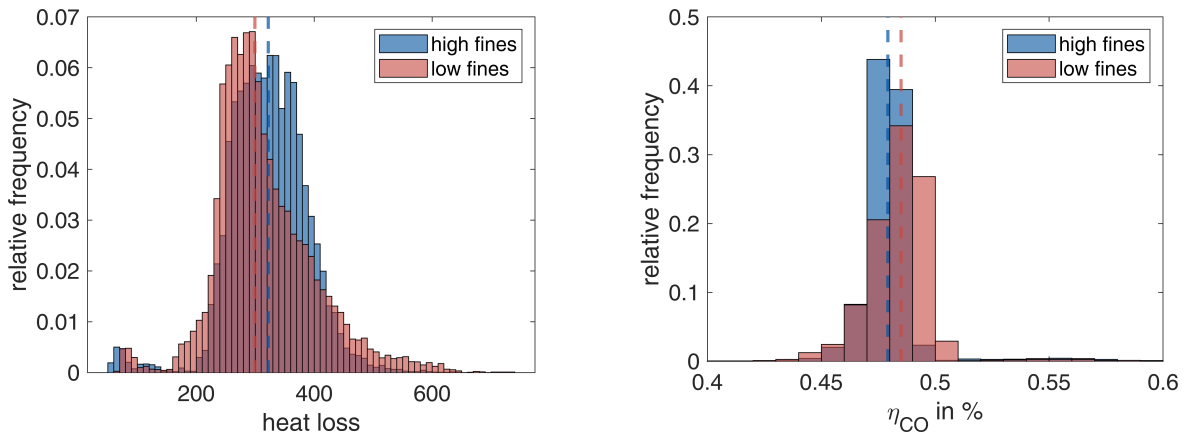


Figure 5.33: Effects of sinter fines on BF performance (TKSE BF2). Left: BF heat loss at lower furnace shaft Right: η_{CO} [1]

method, which enables the prediction of the CRF (sinter plant: Cold Return Fines, BF: Sinter Fines) of the actual sinter production, could lead to a significant time advantage and knowledge about the current sinter quality in terms of fines amount of the produced sinter, as already mentioned. Understanding the amount of fines in the sinter could help the BF operator to decide whether to burden the sinter depending on BF operating conditions. Consequently, this could result in less unfavourable BF conditions, thereby contributing to a more efficient operation of the BF.

The approach described in this work can be adapted into an online model for the prediction of sinter quality as real-time machine support for the quality control at the operational level and early detection of potential issues. A brief overview of the potential applications of this approach is presented in Chapter 6.

6 Outlook

The methodology for estimating the Residence Time (RT) was developed based on historical operational data. An error analysis was not conducted in this thesis for the various RT methods. The accuracy of the dynamic RT determination could be realised with an error of 0.61% for the spatio-temporal quantification (cf. Section 4.3.1). The remaining errors in the static RT, which are difficult to quantify, as well as the inaccuracy caused by the handling of the sinter material and the segregation effects, are implicitly included in the datasets. The accuracy of the trained MLR models is given, including errors that are difficult to quantify in total. Despite the unquantified inaccuracy, the RTE method is able to determine the RT with sufficient accuracy relative to the estimated RT. The application of the RTE method and the associated quality improvement in the prediction of the CRF could substantiate this hypothesis (cf. Section 5.3).

Additional development of data pre-processing and application to larger, additional datasets could help to enhance the accuracy of the applied RTE model. Also, examination of the data during plant stoppages at the SM, especially regarding wind box temperatures and pressures, could provide more information on the effect of the stoppage on sinter quality. During the examination of new measurement techniques at sinter plants, the potential of these data could be demonstrated, as shown in [35].

To enable real-time prediction of sinter quality, further development is required, as outlined in the following section. Furthermore, the methodology offers the potential to develop further methods to determine the quality of the sinter:

1. The developed MLR model (or other ML methods) can be applied to real-time data with a static estimated RT, with the possibility of periodically validating and adjusting the estimated RT on offline data (periodic validation/adjustment).
2. The development and implementation of an automated procedure to re-estimate the RT based on data from the recent past, and to re-train as outlined in point (1)
3. Creation of lookup table based on the RTs from point (1) or (2), connection of RT with estimated sinter quality (parametrical evaluation of $RT \sim \text{sinter quality}$)
4. Evaluation of temperature distribution at the SM and estimated RT
5. Points (3) and (4) can be used for anomaly detection.

The initial approach to implementing an online system for estimating sinter quality, as an online version for continuous quality monitoring of the CRF amount, was tested at the VASD sinter plant. The online model was carried out with a constant estimated RT (based on $\hat{R}_{SC} = 5.5$ SC rotations) and an average rotation speed of the SC, with dynamic and static RT determined for the upstream SC (SC_in) position and for static RT downstream SC positions.

The online model predicted the CRF values in 10 minutes batches using the measuring values upstream of the HC (reference position). In order to determine the dynamic RT of the SC, it is necessary to obtain the actual SC rotation speed. However, this value is not available in online mode at the time of prediction when the sinter reaches the HC, as the value is generated downstream of the HC and therefore lies in the future. Consequently, the online model considers the estimation of SC rotation speed by calculating a moving average over the last 60 minutes. The implementation was conducted during the EU RFCS MinSiDeg [1] project at the VASD sinter plant to demonstrate the potential of the RTE method and online prediction of sinter quality indices (CRF quantity).

The online model framework is depicted in detail in Figure 6.1. The model is connected to the VASD database, where it gets the actual raw operational data and transmits the results of the predicted values. First results from the online model are shown for a time section

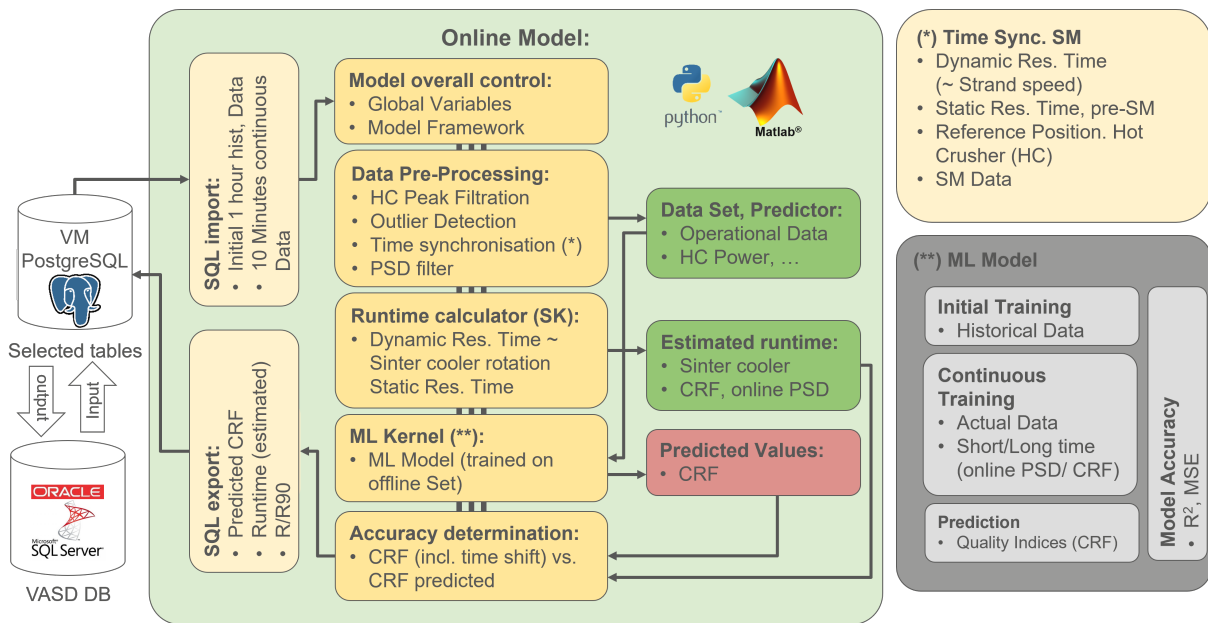


Figure 6.1: Online model framework of Sinter quality model, VASD

close to the training section from June 2022 and for values from May 2023. In Figure 6.2 and Figure 6.3, the predicted and measured CRF values are shown. The model accuracy is depicted as a total value (over all values) and as 60 minutes average over the last predicted values. The overall prediction accuracy, as indicated by the linear correlation coefficient ρ at the end of displayed period (Figure 6.2) was determined to be 0.70 for values close to the model training and 0.31 (Figure 6.3) for later values from May 2023 based on the (old) model, trained on data from June 2022. The short-term 60 minute accuracy value varies between ± 0.9 and is based on the preceding 60 minute prediction intervals. It indicates a positive or negative linear correlation between the predicted and measured values.

Timely model training is recommended to improve the model's long-term prediction accuracy, as proposed in points (1) and (2). The MLR model, trained on data from June 2022, is unable to account for temporal fluctuations in the data up to May 2023, including general drifts in values driven by multiple factors (e.g., changes in raw materials, production parameters, wear, plant conditions, etc.). Consequently, the model's performance diverges from that observed during the June 2022 training phase. Thus, the levels of predicted and

measured data can differ in the long term, as shown in Figure 6.3, while the dynamics remain well presented.

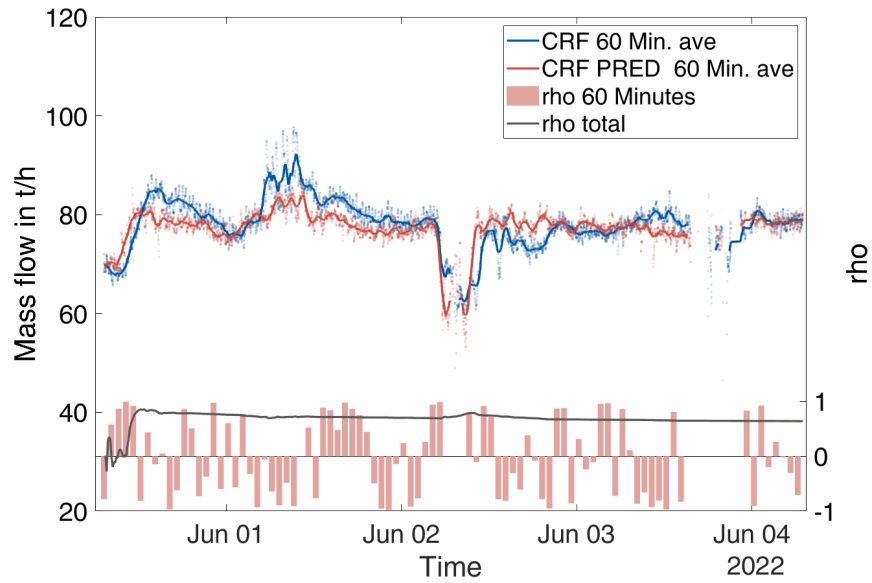


Figure 6.2: comparison of measured CRF and predicted CRF values, after model training from June 2022, total linear correlation: 0.70, 5,510 observations, semi online, based on MLR model on $\hat{R}_{SC} = 5.5$

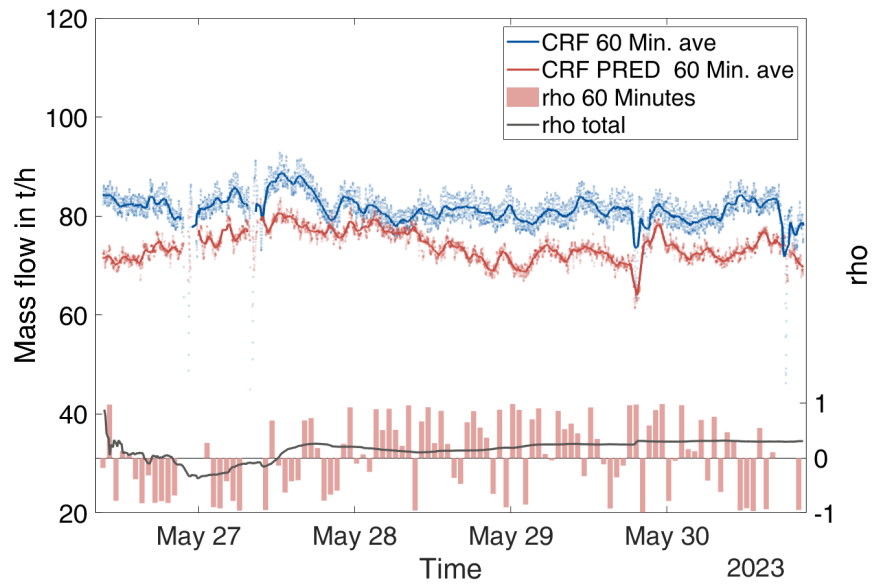


Figure 6.3: comparison of measured CRF and predicted CRF values, training from June 2022, applied on values from May 2023, total linear correlation: 0.31, 6347 observations, semi online, based on MLR model from June 2022 with $\hat{R}_{SC} = 5.5$

Additional efforts can further improve the model's behaviour, as it strongly depends on the input data and the ML model's training period. Nevertheless, the prediction periods

shown in these figures fall outside the training data period and yield promising results for further development. Thus, a variety of optimisation approaches are recommended, for example: The implementation of a data plausibility check during pre-processing, continuous or periodical re-training of the ML model kernel on contemporary historical data, optimisation of the deployed ML kernel, definition of a suitable target value e.g., $x < 5\text{ mm}$ fraction from online PSD measurement and CRF or other suitable cost functions.

Apart from its application in sinter plants, the developed RTE method can be applied to other use cases where no RT is known between multiple predictor and response variables. In such scenarios, the methodology outlined in this thesis can offer an estimated data-driven RT. While system knowledge is beneficial, it is not a prerequisite for limiting the range of RT estimates. As with the cross-correlation method, the time lag span (RT estimates) can be modified. Furthermore, the method can be utilised in scenarios where it is expensive or challenging to monitor the RT with tracers or labels. This is demonstrated in the example pertaining to bulk goods. Furthermore, the method can be applied in the absence of any geometric data related to the transport path and without knowledge of the speed of the material to be traced. In order to determine the RT in a dynamic manner, as illustrated in section 4.3, it is necessary to have information regarding the distance between the measuring points and velocity data. Validation measurements are particularly beneficial in instances where a unimodal distribution of the quality function cannot be established, thus making it challenging to identify the optimal RT. In the context of successful RT estimation, the proposed method enables the application of ML techniques to a substantial number of data series with previously unknown RT values. In cases where only the RT is of interest, the method provides an estimate of this parameter as a minimum, enabling the tracking of materials or products.

The potential for estimated RTs and Residence Time Distributions (RTD) is significant for processes with variable or even with constant material transport and flow in vessels, reactors or fluidised beds [22, 23, 25, 153, 154, 155], where chemical reactions, mixing or time-dependent influences or analyses occur. Those complex conditions arise from most industrial processes [24]. Also, for the design and optimisation of operating parameters of e.g., mixing devices, and for the diagnosis of operational ills in production, the RTD are of interest, as mentioned in the work of [28, 156]. RTD are important for the measurement of reactor performance and provides a metric to use when evaluating changes in reactor designs and operating parameters [157]. In the work of [26], the RTD plays a key role in determining the pollution rate of ground watersheds (mixing). Also, as presented in this thesis, for solid material flow, RTD are of interest for the design and performance improvement of solid unit operations, such as extruders and rotary drums [158], where measurements are taken at different locations along the production chain. The approach is generally interesting for plants with multiple aggregates, connected by varying transport velocities or times, varying reaction velocities, missing product tracking, e.g. for bulk material [63, 36, 72], hard to label products, where conventional approaches fail due to high temperatures or other extreme boundary conditions. Missing knowledge of the RT also occurs in DEM simulation, as described in [14, 102, 103, 104], and is gained by tracer experiments. In [33], the RDT was used to predict the energy consumption of sinter plants and in [1, 9, 16, 18, 34, 46, 105] to predict sinter quality indices. The developed RTE method enables and supports ML methods for time-dependent data, as presented in this thesis, for bulk material (sinter plant).

The detection of time-dependent or distributed RTs can be achieved by examining the correlation between output and input variables or between aggregates and measuring positions [86], as well as prediction quality [81], which can be an indicator of a lack of temporal alignment in the case of time-dependent data. Low prediction quality may indicate a misalignment between the predictor and response variables. The new RTE method can assist in optimising the connection by aligning the input and output variables over the estimated RT. Further hints can be gained by cross-correlation analysis, autoencoder examinations (high deviation of latent neurons), which could also detect distributed RTs of input and output data. The RTE approach can give valuable information to enhance the prediction quality by determine the average RT, if the sampling rate of the datasets with multiple predictor allow the application of ML methods.

7 Conclusion

Tracking bulk material, such as sinter, is challenging due to various factors. The movement of sinter particles is affected by a series of processes, including mixing, agglomeration, crushing, segregation, screening, and particle degradation caused by multiple transfer points, conveyors, bunkers, screens, and the sinter cooler. The size of the sinter and tracer particles has a significant effect on particle movement, as particle movement is related to particle size. Those effects result in Residence Time Distributions (RTD) that are distributed across the sinter particle size. However, tracer investigations are expensive or limited by specific particle sizes ($> 100\text{ mm}$). Due to the different process steps, the RFID tracer must be able to withstand hot temperatures up to 1450°C caused by the ignition of the sinter mix. Labelling of the bulk material is also challenging due to the high mass flow rates of the sinter mix, making traceability difficult and therefore only feasible for local experiments, especially for small fraction sizes $< 5\text{ mm}$. Determining the RT of the sinter is therefore almost impossible over the entire sinter plant. Data-driven ML approaches try to overcome the lack of time alignment by applying Neural Networks (NNs) with back-propagation, optimising the time allocation in the hidden layer of the model. However, these methods are difficult to interpret. Other research uses manually labelled data (low sampling rates) over long observation periods, with marginal short-term information, or is locally limited. To overcome the intransparency of distributed RT determination, this thesis has made significant efforts to track the material in question. This has involved determining the RT of sections with static, dynamic and unknown RTs as the sinter passes through the various process steps and measurements throughout the sinter plant. Particularly challenging is the passage through the cylindrical sinter shaft cooler where the sinter material is subjected to a variety of influences, including mixing, sifting, segregation, and percolation. These influences have a significant impact on particle flow (particle-size-dependent) and, consequently, on the RT. A new data-driven method has been developed in this thesis to estimate RT from time-series sinter plant data. The RT is a key parameter used to align the data collected from the plant Programmable Logic Controller (PLC) and Distributed Control Systems (DCSs). The parameters, such as temperature, pressure and mass flow, gas consumption, strand velocity, and power consumption of the hot crusher of the sinter process, are connected to the sinter mass. With the aligned datasets, the application of ML methods is enabled, resulting in optimised prediction error. Predicted sinter quality values have the potential to improve quality monitoring, as conventional practice is based on manual sampling that takes several hours and requires laboratory capacity. Once a production problem occurs, it is too late to adjust the production process. Because sinter quality cannot be calculated or tested online, it is determined by manual testing. The results of these tests take hours to reach the operator, so the operation relies on the operator's experience. As a result, the sinter process is at a disadvantage for extended periods, with high emissions, low efficiency, and significant fluctuations in product quality. The proposed RT method is based on sinter plant measurement data and does not require any additional equipment. The method allows finding the best-matching combination of

predictors, which in this case are the measured values of the plant and the response with the unknown delay. The method is similar to ordinary cross-correlation except that the quality function is represented by an ML model trained on different datasets with different RT estimates. Finally, the RT of the sinter material is determined from a combination of static, dynamic, and estimated RTs, depending on the sinter plant process section. The outcomes of the methodology applied to the VASD sinter plant data were examined in two datasets, with a period of 30 and 60 days, respectively. The first dataset from June 2022 resulted in a RT estimate based on $\hat{R}_{SC} = 5.5$ Sinter Cooler (SC) rotations (tendency to $\hat{R}_{SC} = 7.5$ SC), corresponding to a median RT of 52 minutes from the end of the Sinter Machine (SM) to the Cold Return Fines (CRF) measurement position (HC–CRF). The second dataset, from May 2023, points to $\hat{R}_{SC} = 7.5$ SC rotations, yielding a median RT of 73 minutes. The difference of two SC rotations between the two datasets can be explained by the different amounts of CRF produced in each period, which was increased by over 5 t/h (median) in the period of the May 2023 dataset. Therefore, the relationship between RT and the produced CRF was investigated on specific datasets with lower and higher CRF amounts. The analyses showed that generating more return fines increased RT, and vice versa: fewer return fines decreased RT. This behaviour is explained by the saturated voids with fines between the larger sinter particles, which act as a barrier to the passage of the smaller sinter particles (return fines), thus increasing the RT.

The actual work showed an increase (examining periods of sub datasets higher/lower CRF quantity) of $\Delta 15$ t/h (June 2022) and $\Delta 11$ t/h (May 2023) of fines, resulting in an increase of 2 SC rotations, corresponding to a 17–19 minute longer median RT. This result confirms the previous estimated RTs based on 5.5 and 7.5 SC rotations, corresponding to 52 and 73 minutes (median), respectively, based on median 74 t/h and 79 t/h of CRF during sinter production. Looking at the coke rate in both datasets (June 2022 and May 2023), it can be seen that the productivity of the sinter plant was higher during the June 2022 production period with an average coke content in the sinter mix of 4.6%, resulting in a shorter median RT (52 minutes) and less median return fines (74 t/h) compared to the May 2023 period with only 3.8% coke content, indicating lower productivity and a longer median RT (73 minutes) and higher amount of median return fines (79 t/h). These findings were underscored by examinations of subsets describing production periods with higher and lower fines generation, showing higher and lower coke rates. The investigation of the rotational speed of the SC on the RT revealed that both are directly proportional. Higher rotation speeds lead to shorter RTs, and lower rotation speeds to increased RTs. Furthermore, an increased rotational speed of the SC leads, favoured by higher vibrations, to increased percolation, even to faster RT at high CRF amounts, which would normally lead to increased RTs.

The aligned dataset was used to train and predict the CRF amount based on the determined RTD of both datasets, with the results for the training of the June 2022 training dataset with $\rho = 0.75$ and $R^2 = 0.75$, and the prediction of the CRF amount on the test dataset, yielding $\rho = 0.78$ and $R^2 = 0.60$. Similar to the 2022 dataset, the May 2023 dataset was divided into training and test sets, with results of $\rho = 0.78$ and $R^2 = 0.61$ for the training set and $\rho = 0.79$ and $R^2 = 0.09$ for all test values. The low R -squared value is explained by a 41-hour shutdown of the sinter plant during the test dataset. The prediction accuracy is significantly reduced after the stoppage. This indicates a disturbance and deviation of the production parameters and measured values during the period when the model was trained under probably normal production parameters. By omitting the affected values,

the prediction accuracy increases to $\rho = 0.84$ and $R^2 = 0.50$. The lower accuracy of the May 2023 dataset underlines the assumption of lower production productivity, which was indicated by the increased RT and lower coke content in the sinter mix during the May 2023 dataset. The application of the RTE method resulted in enhanced model accuracy when compared to the unaligned test datasets, e.g. to an enhancement of R^2 by +0.12 (June 2022 dataset) and R^2 by +0.11 (May 2023 dataset).

The development of the RTE method was based on historical data from the VASD sinter plant. Finally, the application was adapted to an online version of the sinter return fines prediction model, based on the RT of $\hat{R}_{SC} = 5.5$ sinter cooler rotations, and demonstrated on the VASD sinter plant over two time periods. The model trained in June 2022 was implemented into an online version that can predict sinter quality 60–90 minutes in advance to enable early error detection. This information can be used for real-time machine support and quality control. The findings yielded by predictions derived from training in June 2022 (estimated RT, $\hat{R}_{SC} = 5.5$ rotations) when applied to data from the same period, yielded a prediction accuracy of the linear correlation of $\rho = 0.70$. In the second period in May 2023, also based on the training from June 2022 ($\hat{R}_{SC} = 5.5$ rotations), the data show a decrease in the linear correlation to $\rho = 0.31$. The online adaptation was performed during the MinSiDeg project, where the new training on the May 2023 dataset was not completed. It was hypothesised that timely near-retraining could enhance the precision of the model, enabling it to adapt to long-term alterations in the sinter production process and resulting from changing raw material qualities, process and parameter changes, wear, etc. Since the conventional (physical) quality information in industrial sinter plants is usually determined only once a day from a bulk sample, the predicted values provide a significant time advantage and an extended sample period (60 s), leading to better knowledge of the current sinter quality. It allows early detection of potential failures and can also provide additional assistance when conventional PSD measurement results are unavailable. Sinter production and BF operation can thus be optimised. In this thesis, the RTE approach is limited to the $x < 5\text{ mm}$ fraction, as there was no continuous signal for the $x > 5\text{ mm}$ fractions at the VASD sinter plant. If continuous side measurements of the remaining particle bands ($x > 5\text{ mm}$) are available, the new method developed in this thesis could be applied and verified on these bands.

Sintering is a highly energy-intensive process, resulting in excessive costs and emissions. The energy consumption (fuel and electricity) for sinter production reaches up to 2,265 MJ/t sinter [64]. Thus, there is a savings potential of 143 MJ/t sinter in terms of conveying technology and sinter plant optimisation, at an average process cost of 20 €/t return fines. In addition to massive savings in energy and CO₂ emissions, a reduction in return fines of just 1% would result in annual savings of 18.6 million € in the EU.

Further optimisation potential was suggested for return fine prediction, and further investigation for the sinter plant could involve a look-up table to examine the dependence of return fines and RT. The generation of surrogate models from the provided data could enable the detection of various plant operational states and the identification of deviations from optimal production conditions. Another application enabled by the estimated RT could be the analysis of wind box temperatures for anomaly detection related to RT and return fines generation quantity. The approach could be adapted to other quality indices, e.g., fraction size $x < 5\text{ mm}$ or larger fractions $x > 5\text{ mm}$ from online PSD measurements, if sufficient data are available for model training or to the BF-Sinter (finished sinter) mass flow. Further improvement can be achieved by applying an improved plausibility check to

the input variables to enhance the input quality of the data.

Beyond the example of the sinter plant, the presented RTE method has high potential for time series with unknown RT. Unknown RTs often occur during industrial processes in which liquid or solid material is mixed or passes through reactors and is transported at dynamic or static velocities. Also, the lag of labelling or due to extreme boundary conditions (high temperatures) can make it impossible to determine the RT (distribution). As long as the multidimensional input variables try to predict a target variable, this method can be applied. A major advantage is that the method requires no additional equipment and is based on operational data itself. Nevertheless, the option to conduct validation experiments or utilise reference datasets can help to enhance the method and ensure its robustness. In industrial production and processes, the validation of new methods is of high importance to ensure the robustness of the method. Additional effort should therefore be invested in the validation of the method. The developed RTE method could be applied to different sinter particle sizes to validate the findings in this thesis, e.g. that the amount of CRF and particle size influence the RT. This could also be achieved with other reference datasets with known RT. The utilisation of reference datasets would also enable the examination of datasets with minimal fluctuations, which are unusual for raw data from industrial plants. Furthermore, this would provide the opportunity to study and develop the method independently of the impact of these disturbances caused by fluctuating values. Further examination of the fields is the influence of the sampling rate of the used datasets. The result of the RTE method is only valid for the applied data period. Increased sampling rates could allow shorter periods and thus provide information about the RT during those periods, enabling the resolution of RT changes. In the case of online adaptation, continuous retraining over the last several days or weeks of production could enable, or even improve, the estimation of RT and prediction of quality indices. The ML methods applied in this thesis were basic MLR approaches; it is unclear whether more advanced ML methods could improve the performance of the RTE method. The influence of self-optimising ML methods was not examined during this thesis and should be validated in future work.

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Appendix

A Figures

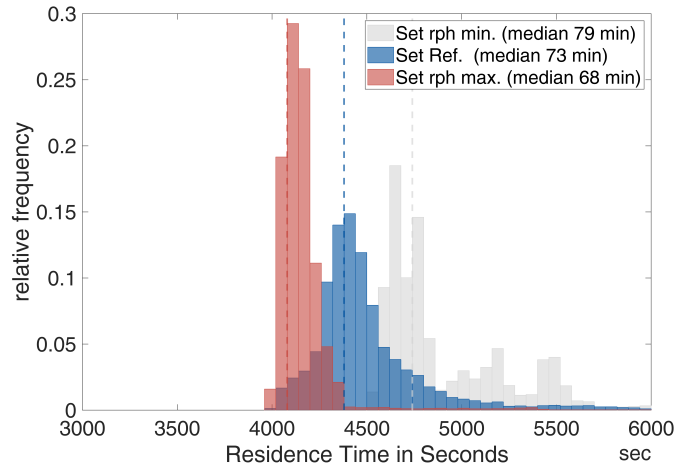


Figure A.1: corresponding RTD for: min. rph, max. rph, Ref. sets, Set May 2023, $\hat{R}_{SC} = 7.5$

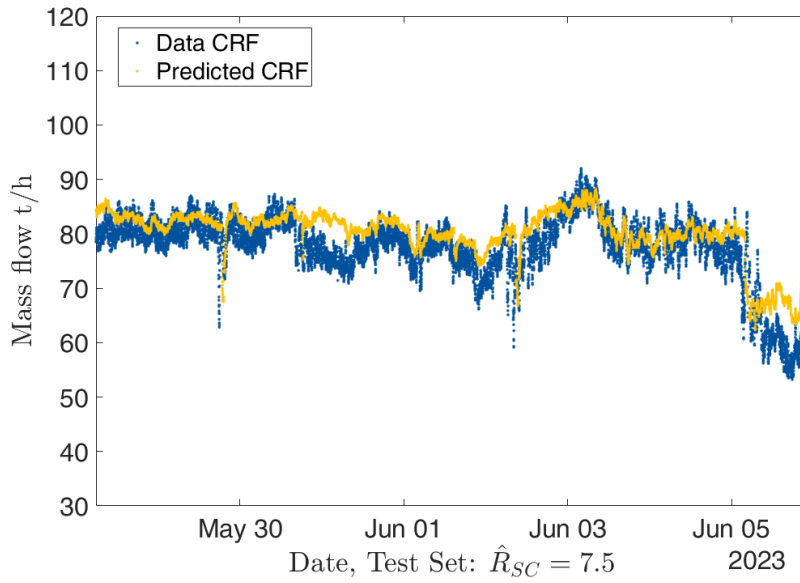


Figure A.2: Test data set (May 2023, Period 1), $\hat{R}_{SC} = 7.5$, $n = 12,343$ observations, $MSE = 20.5$, $roh = 0.84$, $R^2 = 0.50$

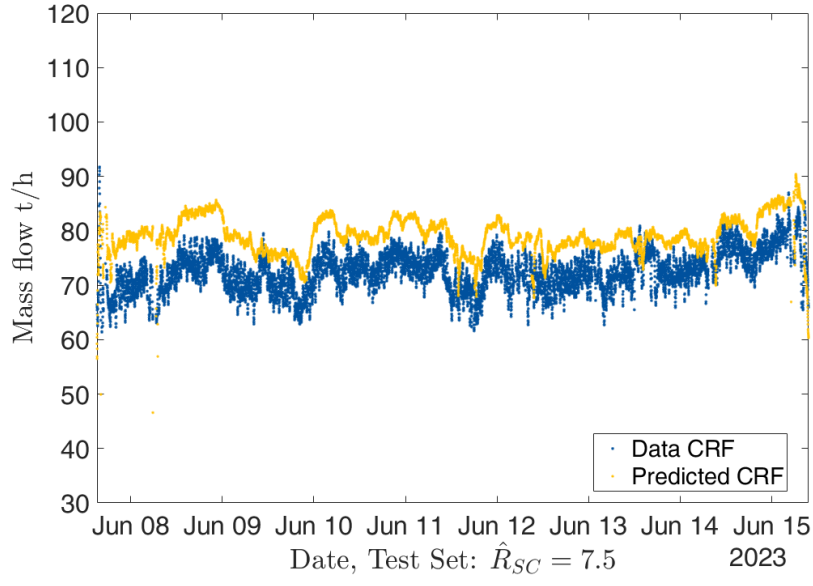


Figure A.3: Test data set (May 2023, Period 2), $\hat{R}_{SC} = 7.5$, $n = 10,663$ observations, $MSE = 53.7$, $roh = 0.60$, $R^2 = -2.87$

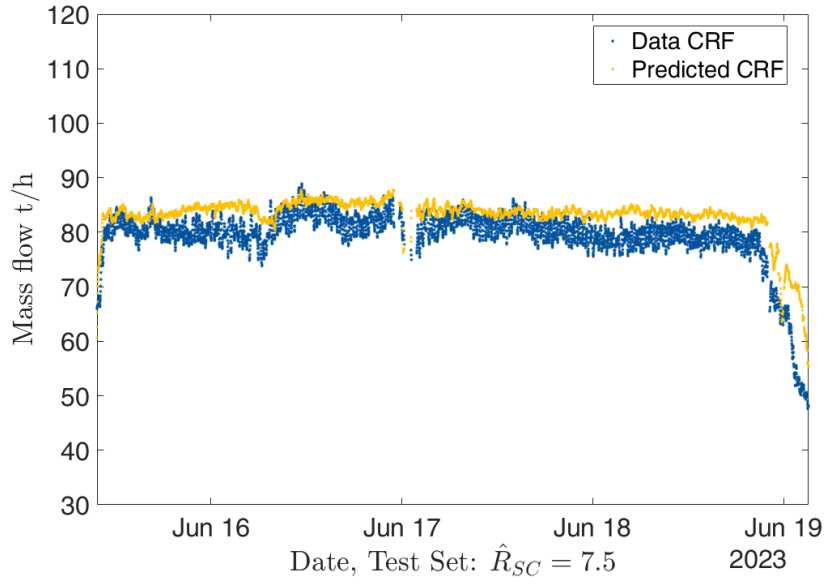


Figure A.4: Test data set (May 2023, Period 2), $\hat{R}_{SC} = 7.5$, $n = 5,200$ observations, $MSE = 21.3$, $roh = 0.89$, $R^2 = 0.32$

B Tables

Table B.1: Overview of the main attributes used from the VASD sinter plant

No.	Attribute	Unit	Description	Sample rate Hz
1	Conveyor type weigher 1	t/h	mass flow of Rawmix without internal RF without coke breeze	0.1
2	Conveyor type weigher 2	t/h	mass flow of Rawmix + coke breeze	0.1
3	Conveyor type weigher 3	t/h	mass flow of Rawmix + coke breeze + internal RF	0.1
4	BF return fines	t/h	mass flow of BF return fines, external RF	0.1
5	Sinter raw mixture	t/h	mass flow of final raw sinter mixture	0.1
6	Water quantity	m^3/h	Water volume flow, Drum mixer	0.1
7	Strand speed	m/min	Actual strand speed	0.1
8	Ignition hood air temperature	°C	Combustion air temperature	0.1
9	Ignition hood air volume flow in	m^3/h	Combustion air volume flow	0.1
10	Ignition hood fuel gas volume flow	m^3/h	Fuel gas volume flow	0.1
11	Ignition hood lambda	–	actual air-fuel ratio	0.1
12	Ignition hood temperature 1	°C	Temperature Zone 1	0.1
13	Ignition hood temperature 2	°C	Temperature Zone 2	0.1
14	Ignition hood power	kWh/m^2	actual specific power rate	0.1
15	Wind box pressure 1–11	mbar	Actual pressure at each wind box	0.1
16	Wind box temperature 1–11	°C	Actual temperature at each wind box	0.1
17	Flue gas total pressure	mbar	Collecting main pipe pressure (wind box 1–11)	0.1
18	Burn through point (BTP)	m	Sinter strand position	0.1

Continued on the next page

Table B.1: Overview of the main attributes used from the VASD sinter plant (cont.)

No.	Attribute	Unit	Description	Sample rate Hz
19	Burn through point Temperature	°C	Temperature @ BTP	0.1
20	Hot return fines	t/h	mass flow of Hot RF after SM calculated	0.1
21	Hot crusher active power	kW	Hot crusher actual active power	1
22	Sinter cooler rotational speed	rpm	Sinter cooler, actual rotational speed	0.1
23	Sinter temperature conveyor belt AS39	°C	After hearth layer screening	0.1
24	Conveyor type weigher AS39	t/h	mass flow of sinter after hearth layer screening	0.1
25	Cold return fines (CRF)	t/h	mass flow of Cold RF (after online PSD), ($x \leq 5\text{ mm}$)	0.1
26	Finished sinter 1	t/h	mass flow of Sinter for BF	0.1
27	Online PSD	%	Online particle size distribution	1/60
27.1	$\leq 5\text{ mm}$	%	$x \leq 5\text{ mm}$	
27.2	$5 \geq 6.3\text{ mm}$	%	$5 < x \leq 6.3\text{ mm}$	
27.3	$6.3 \geq 10\text{ mm}$	%	$6.3 < x \leq 10\text{ mm}$	
27.4	$10 \geq 16\text{ mm}$	%	$10 < x \leq 16\text{ mm}$	
27.5	$16 \geq 25\text{ mm}$	%	$16 < x \leq 25\text{ mm}$	
27.6	$25 \geq 40\text{ mm}$	%	$25 < x \leq 40\text{ mm}$	
27.7	$40 \geq 50\text{ mm}$	%	$40 < x \leq 50\text{ mm}$	
27.8	$50 \geq 80\text{ mm}$	%	$50 < x \leq 80\text{ mm}$	
27.9	$80 \geq 100\text{ mm}$	%	$80 < x \leq 100\text{ mm}$	

Table B.2: Predictor Pre-Selection after RRelief

Rank	Attribute	Unit	Description
1	IRF (RF_in)	t/h	Internal-RF
2	kWm ³	kW/m ³	Specific power consumption HC
3	Coke	t/h	Coke breeze
4	PeakmaxPower	kW	Maximum Power Peak HC
5	H ₂₀	m ³ /h	Water amount
6	Peakareaadj.	kWs	HC energy consumption adjusted
7	m ³ Sinter	m ³	Sinter volume per drop
8	TWB001	°C	Wind box 1 temp.
9	peakarea	kWs	HC energy consumption
10	TWB027	°C	Wind box 27 temp.
11	peakduration	seconds	Power peak duration (per drop)
12	kWsm ³	kWs/m ³	Specific energy consumption HC
13	TWB011	°C	Wind box 11 temp.
14	TWB040	°C	Wind box 40 temp.
15	TWB008	°C	Wind box 8 temp.
16	BF_RF	t/h	BF-RF
17	TWB020	°C	Wind box 20 temp.
18	BTP_Pos	m	Burn through point in m
19	TWB010	°C	Wind box 10 temp.
20	BTP_Temp	°C	Burn through point temp.
21	m ³ hSinter	m ³ /h	Sinter volume flow
22	TWB048	°C	Wind box 48 temp.
23	TWB047	°C	Wind box 47 temp.
24	IG_Gas	m ³ /h	Gas volume flow
25	TWB009	°C	Wind box 9 temp.
26	TWB003	°C	Wind box 3 temp.
27	IG_kWh	kWh/m ²	Specific energy consumption IG

Table B.3: Excluded Predictors: High collinearity or weak measurements (suggestions from the network operator)

Attribute	Unit	Description
Peakareaadj.	kWs	HC energy consumption adjusted
m ³ Sinter	m ³	Sinter volume per drop
peakduration	seconds	Power peak duration (per drop)
m ³ hSinter	m ³ /h	Sinter volume flow
TWB048	°C	Wind box 48 temp.
TWB047	°C	Wind box 47 temp.
IG_Gas	m ³ /h	Gas volume flow
TWB003	°C	Wind box 3 temp.