Method for Data-Driven Automated Parameterization of Energy Flexibility Models of Production Systems

Vom Fachbereich Maschinenbau
an der Technischen Universität Darmstadt
zur

Erlangung des Grades eines Doktor-Ingenieurs (Dr.-Ing.)
genehmigte

D i s s e r t a t i o n

vorgelegt von
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Tag der Einreichung:	01.07.2024
Tag der mündlichen Prüfung:	22.10.2024

Darmstadt 2024
D17

Lindner, Martin: Method for Data-Driven Automated Parameterization of Energy Flexibility Models of Production Systems
Darmstadt, Technical University of Darmstadt
Year of publication of the dissertation on TUprints: 2024
URN: urn:nbn:de:tuda-tuprints-288256
Day of the oral examination: 22.10.2024

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Erklärung

Hiermit erkläre ich, dass ich die vorliegende Arbeit, abgesehen von den in ihr ausdrücklich genannten Hilfen, selbständig verfasst habe. Die "Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Technischen Universität Darmstadt" und die "Leitlinien zum Umgang mit digitalen Forschungsdaten an der TU Darmstadt" wurden in den jeweils aktuellen Versionen bei der Verfassung der Dissertation beachtet.

Frankfurt am Main, 01.07.2024

Martin Lindner

Forword of the Editor

The German Federal Government has set the goal of achieving climate neutrality by 2045. The expansion of renewable energy sources is being accelerated to meet this target. With the 2022 ”Easter Package” from the Federal Ministry for Economic Affairs and Climate Action (BMWK), the aim is to triple the speed of this expansion. Integrating such a high share of renewable energy successfully requires an energy system capable of managing an increasingly fluctuating electricity supply.

The Federal Ministry of Education and Research (BMBF) launched the Kopernikus Projects in 2015 to facilitate the energy transition. One of these projects, ”SynErgie,” focuses on aligning industrial processes with a fluctuating energy supply. To use the existing energy flexibility of industrial processes, they must be technically enabled, and an appropriate market and electricity system, along with automation through information and communication technology (ICT), is also essential. ICT is a key element in connecting production and production infrastructure with the market and the electricity system. To achieve this successfully, a standardized description of energy flexibility is essential. The application of a standardized data model to describe energy flexibility enables automated communication between various parties within the energy system.

The Energy Flexibility Data Model (EFDM) represents energy flexibility in a flexibility space on the one hand and specific energy flexibility measures on the other. The EFDM thus enables the exchange of information on energy flexibility in a generic format, regardless of the actual underlying physical infrastructure and measures. This is where this dissertation by Mr. Martin Lindner comes in. The overarching aim of his dissertation is to develop a method for the automated parameterization of an energy flexibility data model using machine learning approaches and tools. Mr. Lindner refers to this developed approach as “Data-Driven Energy Flexibility Modeling” (DD-EFMod).

Darmstadt, November 2024 Prof. Dr.-Ing. Matthias Weigold

Acknowledgements

This thesis was written during my time as a research associate at the research group of Energy Technologies and Applications in Production (ETA) at the Institute of Production Management, Technology and Machine Tools (PTW) at the Technical University of Darmstadt. Working at the institute and writing this thesis has been a time full of opportunities, challenges, and growth. I am deeply indebted to the many individuals and organizations that have played a crucial role in completing this thesis.

The academic community provided by TU Darmstadt, PTW, and the ETA research group has been a key element in shaping my research by creating an atmosphere of intellectual exchange. My special thanks go to Prof. Dr.-Ing. Matthias Weigold, the institute's director, who gave me the necessary guidance, support, freedom, and trust throughout my time there. I would also like to thank Prof. Dr.-Ing. Reiner Anderl, who took on the role of the co-lecturer.

The research in this thesis was conducted as part of the German research project SynErgie, funded by the Federal Ministry of Education and Research (BMBF). I want to thank all the research and industry partners I worked with in these project for their discussions and contributions to this work.

I want to thank my colleagues at the PTW, especially Tuğrul Öztürk, for all the discussions, and a lot of thanks goes to the ETA research group members Fabian Borst, Heiko Ranzau, Lukas Theisinger, Benjamin Arzt, Tobias Koch, Dr.-Ing. Benedikt Grosch, for contributing to this work's success through technical or practical support, discussions, or other assistance. I especially thank Michael Frank, Tim Frieß, and

Dr.-Ing. Daniel Fuhrländer-Völker for their cooperation and intensive research exchange in the last years, their valuable feedback, and proof-reading, which significantly improved the quality of this thesis.
My heartfelt thanks go to my family and friends, who have supported me to the best of their ability in all situations and have always placed their deepest trust in me. Finally, I would like to thank you most of all, Alexandra, for your unlimited support. Your encouragement has been a constant source of strength, even during the most challenging times.

Frankfurt am Main, November 2024 Martin Lindner

Abstract

Implementing industrial energy flexibility is a complex challenge within complex production systems. To successfully utilize energy flexibility, it is crucial to ensure product quality, manage production schedules, and understand systemic dependencies. By adapting production processes to volatile energy prices, industrial energy flexibility makes it possible to reduce costs without compromising productivity and minimize the carbon footprint by using renewable energy efficiently. In addition, energy flexibility opens up potential revenue opportunities by trading flexibilities in future dynamic energy systems and markets.

One of the most important aspects of this adaptability is the use of a standardized data model to identify and model flexibilities. However, the complexity of industrial processes and the need for extensive domain knowledge make it difficult to model all relevant production assets. This thesis presents a methodology that simplifies the modeling process for describing energy flexibility. Therefore, the aim of the thesis is to develop an automated parameterization methodology for an energy flexibility model, hypothesizing that data-driven, automatically parameterized models and machine learning techniques can be used.

Using the Design Research Methodology, this thesis provides a comprehensive understanding of the current state of science and technology related to industrial energy systems, digital production, and energy flexibility modeling. The research identifies a research need in this area, formulates research questions and hypotheses, and develops the Data-Driven Energy Flexibility Modeling (DD-EFMod) method. This method is validated using a use case that confirms the feasibility of using data analytics and machine learning algorithms to parameter-

ize energy flexibility, with batch clustering methods showing promising results.

In addition, the work shows the energy and cost savings through energy-flexibility measures based on the detailed modeling of energy flexibility. The prototypical application use case at the ETA Research Factory shows that the energy-flexibility measure *change processing sequence* enables cost savings of 9.2 %. Additional cost savings of up to 69.4 % was achieved through a combination of the energy-flexibility measures *change processing sequence* and *shift start of job* within the validation of the use case.

Key Words List:
Demand Response, Manufacturing, Energy Flexibility, Energy Flexibility Data Model, Energy Flexibility Modeling, Data-Driven Modeling

Zusammenfassung

Die Umsetzung von industrieller Energieflexibilität stellt eine komplexe Herausforderung innerhalb komplexer Produktionssysteme dar. Um die Energieflexibilität erfolgreich zu nutzen, ist es entscheidend, die Produktqualität zu gewährleisten, Produktionszeitpläne zu verwalten und systemische Abhängigkeiten zu verstehen. Durch Anpassung von Produktionsprozessen an volatile Energiepreise ermöglicht industrielle Energieflexibilität, ohne die Produktivität zu beeinträchtigen, Kosten zu senken und den CO_2-Fußabdruck zu minimieren, indem erneuerbare Energien effizient genutzt werden. Darüber hinaus eröffnet Energieflexibilität potenzielle Einnahmequellen durch Handel mit Flexibilitäten in zukünftigen dynamischen Energiesystemen und -märkten.

Einer der wichtigsten Aspekte dieser Anpassungsfähigkeit ist die Verwendung eines standardisierten Datenmodells zur Ermittlung und Modellierung von Flexibilitäten. Die Komplexität industrieller Prozesse und der Bedarf an umfangreichem Fachwissen machen es jedoch schwierig, alle relevanten Produktionsanlagen zu modellieren. In dieser Arbeit wird eine Methodik vorgestellt, die den Modellierungsprozess zur Beschreibung der Energieflexibilität vereinfacht. Ziel der Arbeit ist es daher, eine automatisierte Parametrisierungsmethode für ein Energieflexibilitätsmodell zu entwickeln, wobei die Hypothese aufgestellt wird, dass datengesteuerte, automatisch parametrisierte Modelle und Techniken des maschinellen Lernens verwendet werden können.

Unter Verwendung der Design Research Methodology wird in dieser Arbeit ein umfassendes Verständnis des aktuellen Stands von Wissenschaft und Technologie in Bezug auf industrielle Energiesysteme, digitale Produktion und Energieflexibilitätsmodellierung vermittelt. Die

Forschung identifiziert einen Forschungsbedarf in diesem Bereich, formuliert Forschungsfragen und Hypothesen und entwickelt die Methode der datengetriebenen Energieflexibilitätsmodellierung (DD-EFMod). Diese Methode wird anhand eines Anwendungsfalls validiert, der die Machbarkeit des Einsatzes von Datenanalyse und Algorithmen des maschinellen Lernens für die Parametrierung der Energieflexibilität bestätigt, wobei Batch-Clustering-Methoden vielversprechende Ergebnisse zeigen.

Darüber hinaus zeigt die Arbeit die Energie- und Kosteneinsparungen durch Energieflexibilitätsmaßnahmen auf der Grundlage der detaillierten Modellierung der Energieflexibilität. Der prototypische Anwendungsfall in der ETA-Forschungsfabrik zeigt, dass die Energieflexibilitätsmaßnahme *Änderung der Bearbeitungsreihenfolge* Kosteneinsparungen von 9.2 % ermöglicht. Durch eine Kombination der Energieflexibilitätsmaßnahmen *Änderung der Bearbeitungsreihenfolge* und *Verschiebung des Auftragsbeginns* wurden im Rahmen der Validierung des Anwendungsfalls zusätzliche Kosteneinsparungen von bis zu 69.4 % erzielt.

Stichwörter:
Demand Response, Fertigung, Energie-Flexibilität, Energie-Flexibilitäts-Datenmodell, Energie-Flexibilitäts-Modellierung, Datengesteuerte Modellierung

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List of Abbreviations

Notation	Description
CIRP	The International Academy for Production Engineering
CRISP-DM	Cross-Industry Standard Process for Data Mining
CRISP-ML(Q)	Cross-Industry Standard Process model for the development of Machine Learning applications with Quality assurance methodology
CSV	Comma-separated values
DD-EFMod	Data-Driven Energy Flexibility Modeling
DRM	Design Research Methodology
EER	Energy Efficiency Ratio
EF	Energy Flexibility
EFDM	Energy Flexibility Data Model
EFKF	Energy Flexibility Key Figure
EFM	Energy-Flexibility Measure
EMS	Energy Management System
EPEX	European Power Exchange
ERP	Enterprise-Resource-Planning
FL	Flexible Load
FLM	Flexible Load Measure
FR-EF	Functional Requirements for Energy Flexibility Modeling
FR-M	Functional Requirements on the Method
GUI	Graphical user interface
ICT	Information and Communication Technology
IEEE	Institute of Electrical and Electronics Engineers

Notation	Description
ISO	International Organization for Standardization
JSON	JavaScript Object Notation
ML	Machine Learning
OPC UA	Open Platform Communications Unified Architecture
PDF	Portable Document Format
PLC	Programmable Logic Controller
PPC	Production Planning and Control
PR	Prerequisites
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QR	Quality Requirements
RAMI 4.0	Reference Architecture Model Industry 4.0
UML	Unified Modeling Language
VDI	Association of German Engineers e.V.

List of Symbols

Symbol	Description	Unit
Dependencies		
A_{C}	Applicability conditions	–
T_{App}	Applicability duration	s
ID_{Dep}	Dependency identification (ID)	–
Typ_{Log}	Logical type	–
ID_{Tar}	Target flexible load	–
Typ_{Temp}	Temporal type	–
ID_{Tri}	Trigger flexible load	–
Flexibility Space		
$\mathfrak{D}$	Degree of dependency of flexible loads	–
$\mathbf{A}$	Matrix of dependencies between flexible loads	–
$\mathcal{K}_i$	Individual EFKF	–
$\mathbf{K}$	Vector of relevant EFKF	–
x_n	Raw data input	–
$\mathbf{X}$	Vector of raw data input	–
$\mathcal{D}$	Flexibility space for dependency	–
$\mathcal{F}$	Flexibility space	–
$\mathcal{L}$	Flexibility space for flexible load	–
$\mathcal{S}$	Flexibility space for storage	–
Flexible Loads		
N_{Mod}	Modulation number	–
N_{Use}	Usage number	–
∇P_{Act}	Activation gradient	$\frac{\mathrm{kW}}{\mathrm{s}}$

Symbol	Description	Unit
∇P_{Dea}	Deactivation gradient	$\frac{\mathrm{kW}}{\mathrm{s}}$
∇P_{Mod}	Modulation gradient	$\frac{\mathrm{kW}}{\mathrm{s}}$
P_{S}	Power state sequence	–
$\mathbf{P}$	Vector of all power states of the ID_{Load} specific flexible load	–
T_{H}	Holding duration	s
T_{V}	Validity	s
T_{Rea}	Reaction duration	s
T_{Reg}	Regeneration duration	s
c_{Load}	The costs associated with the use of flexible load	€
ID_{Load}	Flexible load identification (ID)	–
L_{Load}	Metering point designation for the geographical and power grid topological location of a flexible load	€
p	Price of the flexible load to be achieved on the market as a minimum	€
Flexible Load Measure		
T_{Act}	Activation duration	s
T_{D}	Delivery time	s
T_{Mod}	Modulation duration	s
$\mathbf{P}_{\mathrm{FLM}}$	Load change profile	(kW,s)
ID_{FLM}	Flexible load measure ID	–
r	Reward received by a company for the implementation of a flexible load measure	€
t_0	Start time of a flexible load measure	s
t_{end}	End time of a flexible load measure	s
t_{OCD}	Order confirmation deadline	s
$t_{\mathrm{V,end}}$	End of the validity T_{V}	s
$t_{\mathrm{V,start}}$	Begin of the validity T_{V}	s
Math and Statistics		
$\mathcal{A}$	Algorithm	–

Symbol	**Description**	**Unit**
W	Width of bin	–
b	Boundary	–
$\mathbf{B}$	Model output	–
R_{ij}	Cluster similarity	–
$\mathbf{c}'$	Recalculated cluster center	–
c_i	Cluster center	–
$\mathbf{C}$	Vector of cluster centers	–
cov	Covarianz	–
$\mathbf{p}$	Vector of data samples	–
p	Single data samples	–
D	Data set	–
DB	Davies-Bouldin index	–
d	Distance function	–
η	Learning rate	–
LT	Sum of the timestamp of the last update	–
LS	Linear sum vector of the data points	–
μ	Mean value	–
$\mathbf{Y}$	Model output	–
$\mathcal{M}'$	Resulting model	–
$\mathcal{M}$	Model	–
$\mathbb{N}$	Set of natural numbers	–
ρ	Pearson's correlation coefficient	–
s	Silhouette coefficient	–
ST	Squared sum of the timestamp of the last update	–
SS	Squared sum vector of the data points	–
σ	Standard deviation	–
τ	Lag of time	s
k	Discrete time	s
$\mathbf{x}$	Time signal	–
t	Continual time	s
M	Window size	–

Symbol	Description	Unit
$\mathbf{x}_{\mathrm{MA}}$	Moving average signal	–
$x_{\mathrm{norm},i}$	Normalization of signal x at timestep i	–
$x_{\mathrm{std},i}$	Standardiszation of signal x at timestep i	–
Measured Raw Data		
I	Electric current	A
T_{Intraday}	Cycle time at intraday market	s
t_{cycle}	Cycle time	s
P	Electric power	W
f	Frequency	Hz
T_{pro}	Frequency	°C
t_{pro}	Processing time	s
t_{shift}	Shift time	s
s_{da}	Machine state - disabled	binary
s_{op}	Machine state - operational	binary
s_{st}	Machine state - standby	binary
s_{wk}	Machine state - working	binary
U	Electric voltage	V
Storages		
C_{S}	Usable capacity	kW h
c_{Stor}	Cost for operation of flexible storage	€
E_{Drain}	Energy drain from storage	(s→kW)
$E_{\mathrm{t_0}}$	Initial energy content at the start time of the validity of the associated flexible load	(kW h,s)
E_{Loss}	Energy loss	$\frac{\%}{\mathrm{s}}$
E_{Tar}	Target energy content at the end time of the validity of the associated flexible load	(kW h,s)
ID_{Stor}	Storage identification (ID)	–
S_{S}	Energy supply to storage	(–,–)

1 Introduction

”Great things are done by a series of small things brought together.”

Vincent Van Gogh

This chapter describes the motivation of this thesis and sets it into the current social and economic context in Section 1.1. Based on this, the problem is discussed in Section 1.2, from which the main contribution of this thesis is derived. The chapter concludes in Section 1.3 with an overview of the structure of this thesis based on the used research methodology.

1.1 Motivation

Climate change is one of the greatest challenges of our time and affects all levels of society and economy. This was recognized by the international community, so that in 2015 the Paris Climate Agreement was adopted to counteract this challenge [1]. The European Union has committed itself to become climate neutral by 2050 within the framework of the Green Deal [2]. As a member state of the European Union, the German government has set itself the ambitious target of achieving this goal as early as 2045 [3]. To achieve this goal, the energy transition is one of the biggest levers and goals for the future of the German economy [4, 5, 6]. The measures adopted as part of the national climate protection plan and the energy transition include the strong expansion of renewable energies. As a result, around 55 percent of electricity demand was met from non-fossil energy sources in 2022 (see Figure 1.1b) [7]. This increasing feed-in of energy from renewable energy producers into the energy grids increases the volatility of the energy supply. This, on the one hand, and the additional acceleration of the energy crisis due to the Ukraine conflict since 2022, on the other hand, have caused extremely strong fluctuations in international and national energy prices (see Figure 1.1c) [8]. These effects are particularly relevant for industry, which accounts for the majority of energy demand in Germany at around 43 percent (see Figure 1.1a) [9]. To solve these energy challenges, digitalization of industry plays a central role [10]. On the one hand, production processes can be better monitored, and equally, equally, more targeted control of production is also possible. This also applies to the energy supply and energy management of a company. On the one hand, demand response measures can better ensure the stability of the power grids, and on the other, production can be adapted to the volatile supply of electricity. Such adaptability of an industrial company, also called energy flexibility, is a central aspect of future energy supply [11]. This thesis is framed in this context.

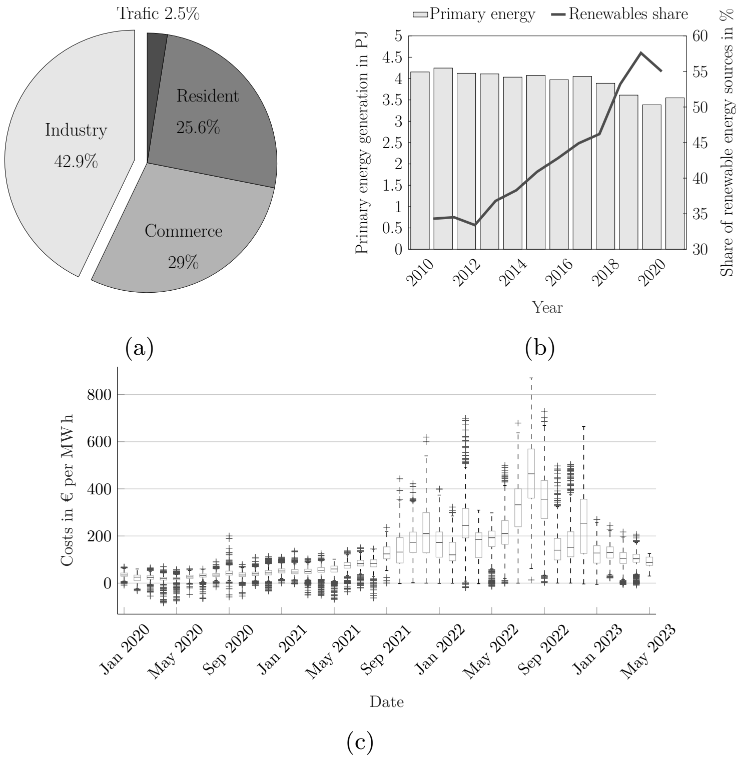


Figure 1.1: Overview of the energy market in Germany. Figure (a) shows net electricity consumption by sector in 2021 [9]. Figure (b) shows the primary energy generated and the percentage share of renewable energy in it [7]. Figure (c) shows the development of the wholesale electricity price and its increasing volatility [8]. (own figures)

1.2 General Objective and Contribution

In order to apply energy flexibility successfully in industry, it has been researched in the SynErgie research project since 2016 with a focus on its applicability in industry [12]. For this purpose, various methods were developed within the project to identify and exemplarily realize industrial energy flexibilities [5]. Due to the high complexity of industrial production, the successful application of industrial energy flexibility is associated with high obstacles. Some of the obstacles identified include the following [12, p. 234]:

- product quality must be ensured
- scheduling of the production in terms of time and quantity
- total costs should be further reduced
- production systems are complex systems with different dependencies

Taking these aspects into account, a company must also operate profitably and efficiently. This increasingly includes taking energy costs into account, especially due to the increasing volatility of energy prices. Industrial energy flexibility offers a solution to this problem. Through the targeted use of energy flexibility, it is possible to adapt a production process to fluctuating electricity prices while maintaining the same level of productivity. Thus, on the one hand energy costs can be saved and on the other hand the CO_2 footprint of a production can be reduced by increased use of renewable energies [5]. In addition, flexibilities can be traded in a future energy system, which can generate additional revenues. To enable a factory to become energy-flexible, the process shown in Figure 1.2 was developed [13]. This consists of the steps potential analysis, conceptualization and planning, application and implementation, operative flexibility marketing, controling and monitoring and optimization. Each step of the process is explained in detail in Section 2.1.

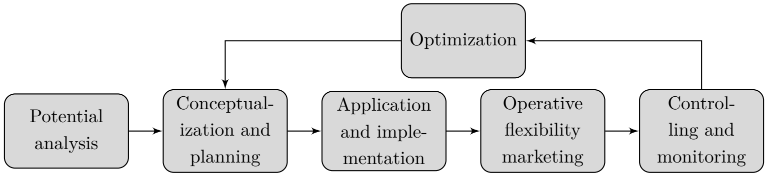


Figure 1.2: Methodology for energy flexibilization of factories (own figure based on [13]).

To implement the entire process, it is necessary to describe the flexibilities identified in the potential analysis by a standardized data model in step three. Such a model for describing energy flexibility was developed in the SynErgy project. It allows the generic description of energy flexibility [14]. This model has been designed to be applied to any technical plant or storage facility in order to realize the highest possible flexibility potential. Since industrial processes are complex and contain many different assets and dependencies, it is also difficult to create such a model for each relevant asset of a production system. In addition, a high degree of expert knowledge and system understanding is required. This is the starting point of this thesis.

The main contribution of this work is the development of the Data-Driven Energy Flexibility Modeling (DD-EFMod) method, which simplifies the parameterization of the Energy Flexibility Data Models. The following steps are applied:

1. Development of the DD-EFMod method. To achieve this, the methodology for the energetic flexibilization of factories is extended in the implementation step with a focus on the parameterization of Energy Flexibility Data Models. For this purpose, the Cross-Industry Standard Process model for the development of Machine Learning applications with Quality assurance methodology (CRISP-ML(Q)) approach is adapted and transferred accordingly to this parameterization.
2. Development of a software concept. In order to ensure the applicability of the DD-EFMod method, a software concept is devel-

oped, whereby the implementation of the method corresponds to a standardized procedure.

3. To demonstrate the practical application of the DD-EFMod method, this is validated using a use case with four different scenarios:
   a) The first scenario comprises the modeling and parameterization of the Energy Flexibility Data Model for a machine tool.
   b) In the second scenario, the Energy Flexibility Data Model for the machine tool is extended to include the data model of the associated product storage system.
   c) In the third scenario, the system boundary is changed so that the cooling water supply of the machine tool is considered and the associated Energy Flexibility Data Model is parameterized.
   d) The fourth scenario focuses on the dependencies between the systems of the previous scenarios and parameterizes the associated class of the Energy Flexibility Data Model.
4. The validation of the method concludes with an examination of the economic potential, showing that the detailed modeling of energy flexibility in the Energy Flexibility Data Model offers advantages. To this end, the energy-flexibility measures *change of processing sequence* and *shift start of job* are compared and the costs are considered with regard to the Day-Ahead and Intraday electricity market.

1.3 Research Methodology and Structure of Work

To achieve the overarching goal, this research work is based on the Design Research Methodology (DRM). [15]. This approach is suitable for achieving the objective, as it involves the following four phases as an iterative process:

According to the first phase (Research Clarification), the research field and the underlying question are identified based on literature and experience, and the overarching research objective is formulated (Chapter 1) [15].

Based on this, a fundamental understanding of the state of the art in science and technology is established in the second phase (Descriptive Study I) (Chapter 2 and 3) [15]. This work presents the fundamentals of industrial energy systems and energy flexibility in interaction with digital production. Furthermore, existing approaches to data analysis and modeling of energy flexibility are presented, and the research deficit is identified through literature research and analysis.

This work focuses on the third phase (Prescriptive Study) [15]. Based on the identified research gap, the research questions, hypotheses, and requirements for the solution method for data-driven automated modeling of energy flexibility are formulated in Chapter 4. This is followed by the development of the DD-EFMod method in Chapter 5, which provides a structured procedure for the automated modeling of energy flexibility.

In the fourth phase of the DRM (Descriptive Study II), the DD-EFMod is initially applied and validated to provide conclusions for further use in this research work [15]. To this end, the use case that forms the framework for the validation is first presented in Chapter 6. The method is then applied prototypically to various scenarios, and the results are discussed (Chapter 7). This thesis concludes with a conclusion, a summary, and an outlook in Chapter 8.

2 Fundamentals

”What I’m trying to do is to
maximise the probability of
the future being better.”

Elon Musk

After defining the overall objective of this thesis in the previous chapter, this section delves into the relevant fundamentals for the development of the methodology for the automated parameterization of energy flexibility metrics. To this Section 2.1 first provides an introduction to the complexity of industrial energy systems. The focus is on the system-theoretical connection between the production system and the different energy supply systems in the industrial environment. Furthermore, the importance of demand-side management and energy flexibility as well as the basics of modeling energy flexibility are shown. This is followed by relevant principles in the context of digital manufacturing in Section 2.2. Subsequently, Section 2.3 focuses on data analysis and machine learning in the context of the development and implementation of the method for DD-EFMod.

2.1 Industrial Energy Systems

Production systems are at the heart of modern industrial societies and are the driving force behind the production of goods and services that characterize our everyday lives. A production system is defined in the context of this work according to:

Definition 2.1: Production System [16, p. 2]

A production system is a collection of people, equipment, and procedures organized to perform the manufacturing operations of a company.

A crucial aspect that determines the performance and sustainability of production systems is their close connection with industrial energy systems. Industrial energy systems supply production systems with the required energy and thus play a key role in ensuring operational efficiency and minimizing environmental impacts [17, pp. 7–9]. Optimizing these systems is therefore crucial to overcoming the challenges of energy efficiency and environmental sustainability in production [18, pp. 15–25]. In the face of global challenges such as climate change and resource scarcity, there is an increasing focus on research in the field of industrial energy systems to develop innovative solutions for a reliable, cost-efficient, and environmentally friendly energy supply [19]. One advanced strategy that is playing an increasingly important role in this context is demand-side management and the use of industrial energy flexibility. By specifically controlling energy consumption depending on the availability and cost of energy, companies can significantly reduce their operating costs while contributing to stabilizing the power grid and integrating renewable energy [20]. Therefore, the research and application of demand-side management and energy flexibility concepts in industrial energy systems plays a key role in the design of sustainable and efficient production systems [21].

2.1.1 Demand-Side Management and Industrial Energy Flexibility

To get the possibility of adapt the power consumption of a consumer, the concept of demand-side management was defined by the American Electric Power Research Institute in 1992 [22]. Based on this the term demand response was defined in 2006 and is used in this work as:

Definition 2.2: Demand Response [23]

Demand response are the changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.

For the realization of industrial demand response the Association of German Engineers e.V. (VDI) defines energy flexibility in 2020 as a capability:

Definition 2.3: Energy Flexibility [24]

Energy Flexibility (EF) is the ability of a production system to adapt quickly and in a process-efficient way to changes in the energy market.

When considering energy flexibility, a distinction is made between different energy-flexibility potentials [24] as follows:

- Theoretical potential is the mathematical factor determined by the rated power of all forms of final energy.
- The technical potential is the possibility of varying the power requirement within the scope of technological conditions, particularly system-specific conditions that influence power consumption and single time periods.
- Economic potential is the proportion of the technical potential that can be used commercially.
- Practical potential is the subset of the technical potential which takes into account factors such as regulatory and administrative obstacles.
- Realisable potential is the intersection of economic potential and practical potential.

Figure 2.1 shows the relationships between the different potentials. To leverage energy-flexibility potential, appropriate measures are required.

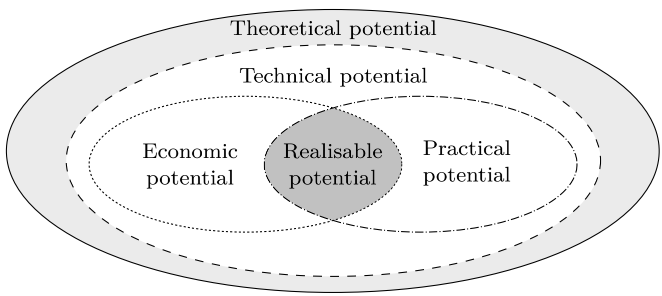


Figure 2.1: Spaces of the energy-flexibility potentials (own figure based on [12]).

These are referred to as energy-flexibility measures.

Definition 2.4: Energy-Flexibility Measure [24]

An Energy-Flexibility Measure (EFM) is a deliberate action taken to implement a defined change of state in a production system and encompasses the change in state of a production station and the interactions in the production system which this change entails.

Based on the definitions multiple measures can be used to achieve the adjustments. Table 2.1 overviews those various measures. A production system must be enabled for such an energy-flexible operation to implement a measure. A corresponding procedure is shown by the VDI in [13]. The individual steps of the enablement process are shown in Figure 1.2 and discussed below.

Table 2.1: Classification of energy-flexibility measures by duration [24] and by levels of the automation pyramid defined according to [25] (own table).

<table>
<tr><th>Automation level</th><th>Implementable energy-flexibility measure</th><th>Duration</th></tr>
<tr><td>Level 4:
Business planning and logistics
(Business level)</td><td>• Shift production start
• Shift break times
• Change production sequence
• Adjust shift times
• Adjust capacity planning</td><td>long-term</td></tr>
<tr><td rowspan="2">Level 3:
Manufacturing operations and control (Manufacturing level)</td><td>• Interrupt job
• Store energy
• Shift start of job</td><td>week</td></tr>
<tr><td>• Change job sequence
• Adjust energy procurement
• Adjust resource allocation</td><td>day</td></tr>
<tr><td rowspan="2">Level 2:
Monitoring, supervision and control (Control level)</td><td>• Interrupt process
• Store energy (inherently)
• Change processing sequence</td><td>hour</td></tr>
<tr><td>• Operate with bivalent energy
• Adjust process parameters</td><td>minute</td></tr>
<tr><td>Level 1:
Sensing and actuation (Field level)</td><td></td><td></td></tr>
</table>

1. The initial step of the six-stage methodology focuses on a non-invasive and low-effort estimation of technical and economical energy flexibility potentials. First, promising systems are assessed for energy-flexible operation prerequisites, followed by an analysis of their technical flexibility potential [26]. Subsequently, the systems are evaluated for energy-flexible operation suitability within the production ecosystem, considering factors like control type, process relevance, and temporal decoupling.
2. In the second step of design and planning, the previously prioritized energy-flexibility measures are examined in detail, data (e.g. load profiles or individual plant parameters) are collected, and measurements (e.g, following [27]) are carried out if required. On this basis, the economic efficiency of individual energy-flexibility measures are determined. Subsequently, implementation planning is done for selected EFMs.
3. The third step is the actual implementation of promising energy-flexibility measures and an energy-flexible operation of the factory. The technical enablement of individual systems must be carried out holistically, considering aspects of hardware, information and communications technology, and production planning and control. The energy-flexible operation is to be validated based on test runs, analyses, and safety checks.
4. After the successful realization of the energy-flexible operation, the operational marketing of the flexibility can be started in step four (cf. [24]).
5. During and after the implementation and marketing of flexibility, the controlling and monitoring phase analyzes the degree and quality of performance. This can be done with the help of energy management systems to identify anomalies and potential for improvement and to derive appropriate action steps.
6. With the help of the knowledge gained, further improvements in energy flexibility are possible in the step of operational optimization. Data-based analyses or simulations can further increase the

utilization of various energy-flexibility measures. The theoretical potential identified in this way can then be incorporated into a further iteration of the design and planning, thereby continuously optimizing energy-flexible operation.

Specific technical and market-related requirements are necessary to effectively and safely integrate flexibility into the future energy system based on this six-step process. A comprehensive implementation of energy flexibility requires automated marketing processes based on standardized procedures, often implemented through platform solutions at both company and market levels. In addition, intensive use of information and communication technologies is required, both within companies and across company boundaries. This makes it necessary to model the existing energy flexibility accordingly to ensure such an information exchange.

2.1.2 Modeling of Energy Flexibility

In order to describe energy flexibility, appropriate modeling is required. A method for modeling and description of energy flexibility is given by [14], which was published in 2019 and has been gradually developed since then [28, 29, 30]. This method allows a generic description of

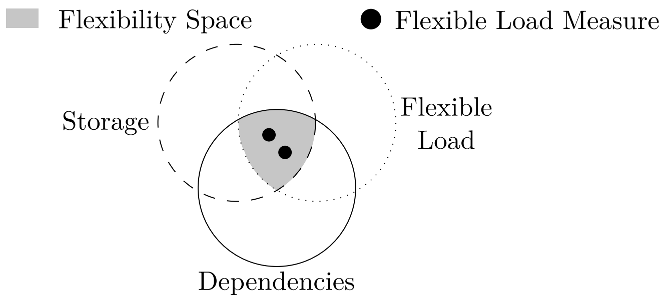


Figure 2.2: Classes of the Energy Flexibility Data Model that span the flexibility space, which can contain various flexible load measures [14] (own figure).

energy flexibility and was developed while research of the ”SynErgie” project. Thus, any technical system can theoretically be modeled accordingly. The advantage compared to other modeling approaches is the consideration of technical properties as well as market-side requirements for potential trading on the electricity market by corresponding suppliers. Since 2019, this original model has been further developed and adapted to achieve a higher degree of applicability in industry, especially using the json schema of the EFDM developed in [29]. This Energy Flexibility Data Model (EFDM) is composed of four classes that span the flexibility space, which can contain various flexible load measures (see Figure 2.2). The first class are the Flexible Load (FL).

Definition 2.5: Flexible Load [28]

A Flexible Load (FL) models a technical system or the interaction of different technical systems that have the potential to produce a change in performance.

This class flexible load is described by the key figures shown in Table 2.2. To increase the energy-flexibility potential, flexible loads can interact with one or more storages. For this purpose, storage facilities are defined as follows and the key figures are shown in Table 2.3.

Definition 2.6: Energy Storage [28]

An energy storage system is a technical system or the interaction of different technical systems that have the potential to store energy.

Table 2.2: Description of the key figures in the EFDM of class flexible loads, following [29].

Key Figure	Description
ID_{Load}	Flexible load ID
T_{V}	Validity
$\mathbf{P}$	Vector of power states
T_{H}	Holding duration
T_{Rea}	Reaction duration
P_{S}	Power state sequence
∇P_{Act}	Activation gradient
∇P_{Mod}	Modulation gradient
∇P_{Dea}	Deactivation gradient
T_{Reg}	Regeneration duration
N_{Use}	Usage number
N_{Mod}	Modulation number
c_{Load}	Costs for usage of the flexible load
p	Price for the flexible load
t_{OCD}	Order conformation deadline
L_{Load}	Metering point designation of flexible load

Table 2.3: Description of the key figures in the EFDM of class storages, following [29].

Key Figure	Description
ID_{Stor}	Storage ID
C_{S}	Usable capacity
E_{t_0}	Initial energy content at the start time of the validity
E_{Tar}	Target energy content
E_{Loss}	Energy loss
S_{S}	Suppliers
E_{Drain}	Energy drain from storage
c_{Stor}	Cost for operation of flexible storage

As shown in Figure 2.2 the third class of the Energy Flexibility Data Model (EFDM) are dependencies. These class decribes the interaction of multiple flexible loads and is defined as follows.

Definition 2.7: Dependency [28]

Dependencies model the constraints and dependencies for the interaction of multiple flexible loads.

This means, for example, the use of one flexible load can imply or exclude the use of another flexible load. Therefore those dependencies musst be taken into account while the realization of an energy-flexibility measure.

Table 2.4: Description of the key figures in the EFDM of class dependencies, following [29].

Key Figure	Description
ID_{Dep}	Dependency ID
ID_{Tri}	Trigger flexible load
ID_{Tar}	Target flexible load
Typ_{Log}	Logical type
Typ_{Temp}	Temporal type
T_{App}	Applicability duration
A_{C}	Applicability conditions

For a realization of an energy-flexibility measure on a production system based on the EFDM, a more specific description in change of power and how long this variation should be accordingly to all given contraints of the flexible loads, storages and dependencies. Therefore the class flexible load measure (FLM) is defined. The necessary key figures are given in Table 2.5.

Definition 2.8: Flexible Load Measure [28]

A flexible load measure (FLM) defines a concrete power change within the flexibility space in the form of a load change profile, takes into account the dependencies, has no degrees of freedom itself and is time scheduled.

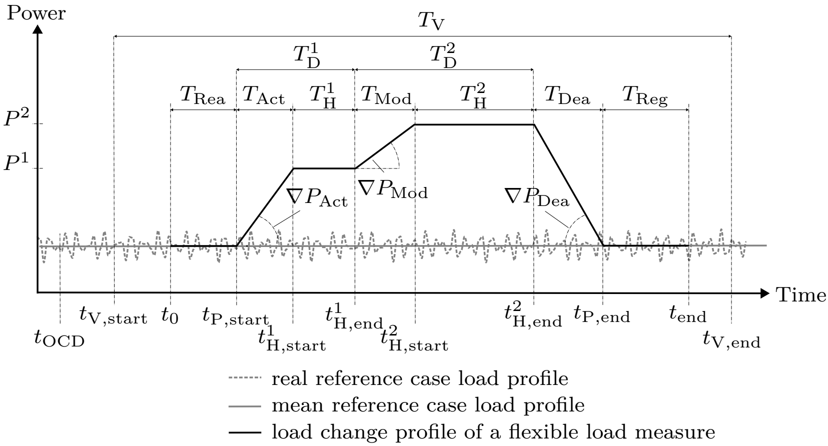
Table 2.5: Description of the key figures in the EFDM of a flexible load measure, based on [29].

Key Figure	Description
ID_{FLM}	Flexible load measure ID
ID_{Load}	ID of the flexible load to which the flexible load measure is directed.
$\mathbf{P}_{\mathrm{FLM}}$	Vector of load change profile
r	Reward

Not all energy flexibility key figures are mandatory for any system. Therefore, their necessity was defined in Lindner *et al.* [29] for each key figure. The classes storage and dependency are optional by definition, see Appendix A.3.

As seen in Figure 2.3 there are multiple periods and times which are necessary to describe and to realize a flexible load measure but not all of them are a key figure. The first relevant time is t_{OCD} which means the point in time until orders are accepted at energy markets [31]. This is following by the validity T_{V} which is given by the refering FL and starts with the timestamp $t_{\mathrm{V,start}}$ and terminates at the timestamp $t_{\mathrm{V,end}}$. Within the validity lies the flexible load measure (FLM) which spans from starting time t_0, there the system gets the initial signal to activate the FLM, to the end time t_{end}. The regeneration duration T_{Rea} describes a delay which a system could have until the first load change is detectable or realizable. For trading and usage of the FLM by a grid operator the delivery duration T_{D} is given by

$$T_{\mathrm{D}} = T_{\mathrm{Act}} + T_{\mathrm{H}} \tag{2.1}$$



T_V	Validity	∇P_{Act}	Activation gradient
T_D	Delivery duration	∇P_{Mod}	Modulation gradient
T_H	Holding duration	∇P_{Dea}	Deactivation gradient
T_{Rea}	Reaction duration	t_{OCD}	Order confirmation deadline
T_{Mod}	Modulation duration	t_0	Starting time
T_{Reg}	Regeneration duration	t_{end}	End time
T_{Act}	Activation duration	T_{Dea}	Deactivation duration

Figure 2.3: Schematic explanation of a flexible load measure and all relevant describing periods and times (own figure).

or respectivly by

$$T_D = T_{Mod} + T_H \tag{2.2}$$

and describes a active change in state of power. In Figure 2.3 the first delivery durations T_D^1 which is calculated by equation 2.1 and T_D^2 following equation 2.2. A delivery duration do not include a deactivation gradient ∇P_{Dea} or a regeneration duration T_{Reg}.

After the relevance and methodological approaches to modeling and implementing energy flexibility in industrial systems have been presented, it becomes clear that their effective implementation and optimization require deep integration into the digital processes of modern manufacturing. The topic of digital manufacturing is therefore explained in more detail below.

2.2 Digital Manufacturing

Digital manufacturing, also known as Industry 4.0, is described by [32] as the intelligent networking of machines and processes for the industry with information and communication technology. The integration of digital manufacturing processes is crucial in the context of energy flexibility as it enables the seamless implementation of energy flexibility measures, which are vital for optimizing energy demand and enhancing operational efficiency in industrial systems. This section explores how digital manufacturing technologies facilitate the realization of energy flexibility and adjust production processes to an energy-flexible operation. Some of the possibilities of Industry 4.0 are [33]:

- Flexible production: Networking facilitates coordination and planning in production by optimizing the involvement of different companies.
- Changeable factory: Production lines of the future will be modular and quickly configured for specific tasks, enabling the efficient and economical production of individual products.
- Optimized logistics: Intelligent algorithms improve the flow of materials and delivery routes and automatically report material requirements.
- Use of data: Analyzing production data enables process optimization and new data-based business models.

These aspects are characterized by the objective of achieving both optimization and flexibility in production through Industry 4.0, while at the same time supporting sustainable and economic goals. One of the central models for structuring and implementing Industrie 4.0 concepts is the Reference Architecture Model Industry 4.0 (RAMI 4.0) as shown in Figure 2.4 [34]. The model is divided into three main axes.

The hierarchy axis represents the different levels within a company, from the product level to the company level, and thus integrate all levels of the automation pyramid. This enables end-to-end networking and control of production processes. At the same time, the life cycle and value chain axis consider the entire life cycle of a product or plant, enabling a holistic view and optimization. The six structured layers on the vertical axis describe the decomposition of a machine into its properties.

Based on this, the RAMI 4.0 architecture offers a suitable structure for implementing energy flexibility. In particular, the possibilities of bidirectional data and information exchange across company levels and company boundaries to the connected world, e.g., to energy or flexibility markets, enable the description and implementation of energy flexibility [35], as in the validation use case of this work in Chapters 6 and 7. In order to automate and standardize the entire process of energy flexibility trading from the machine to marketing, integrating energy-flexibility measures into the production planning and control of the company is essential [36]. The Energy Synchronization Platform [37] addresses precisely this goal. The Energy Synchronization

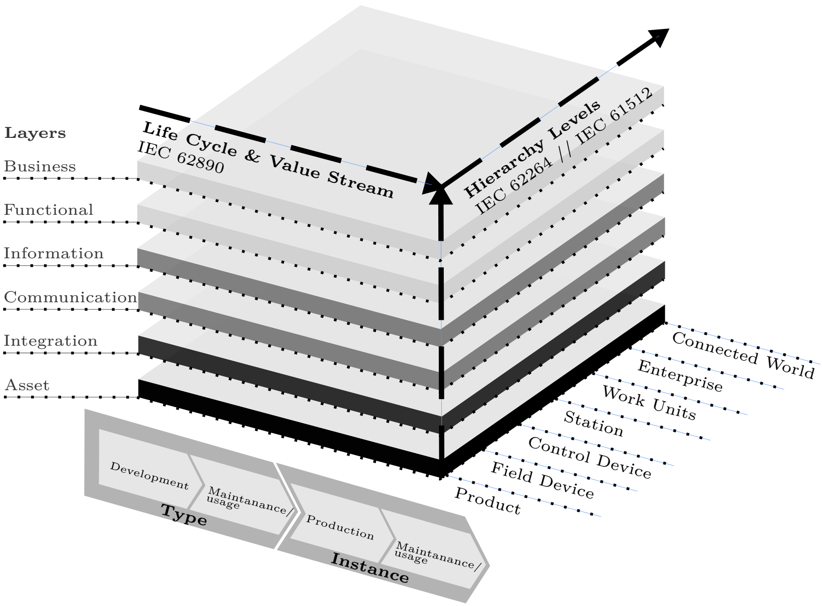


Figure 2.4: Reference Architecture Model Industry 4.0 (based on [34]).

Platform comprises framework conditions, interfaces, data models for describing energy flexibility (see Section 2.1.2), stakeholders, and security aspects and maps the entire process of automated energy flexibility trading from the machine to trading itself [38] (see Appendix A.1.2).

Modeling and simulation of machines and machine operation play a crucial role in digital manufacturing and implement energy-flexibility measures. They allow the virtual representation of production processes to test and validate optimizations in advance, for example, concerning energy efficiency or adaptability to fluctuating energy prices [39]. A simulation is defined as follows:

Definition 2.9: Simulation [40, p.3]

Simulation is the imitation of the operation of a real-world process or system over time. Simulation involves the generation of an artificial history of the system and the observation of that artificial history to draw inferences concerning the operating characteristics of the real system that is represented.

Using advanced software and algorithms, complex systems can be modeled and simulated in real-time, enabling precise prediction and planning of energy consumption and production [39]. Using those approaches different models are necessary. A model is generally defined as:

Definition 2.10: Model [41, p.13]

A model is defined as a simplification representation of a system for the purpose of studying that system.

The creation of such a model is called model specification and is defined as

Definition 2.11: Model Specification [42, p.3]

Model specification is the exercise of formally stating a model and involves formulating a statement about a set of parameters.

In the context of this work and in particular for enabling energy-flexible operation, the energy flexibility model described in Section 2.1.2 is such a representation and specification. The defined key figures to describe the energy flexibility must be filled with values to describe the energy flexibility of a system. This important step of describing one or more values for each variable quantity for each key figure of the model is called model parameterization and is defined as:

Definition 2.12: Model Parameterization [43]

Adaptation of a system, technical device, model, or software by specifying one or more values for each variable quantity.

This step for determining the key figures of the Energy Flexibility Data Model is described in Section 5.1.

Digital manufacturing refers to the comprehensive use of data in real-time to monitor and optimize the entire production process [44, pp. 181–183]. Data-based and data-driven approaches represent different degrees of integration and use of data in manufacturing. While data-based approaches use data at the beginning of a process to set parameters or workflows, data-driven approaches take a more dynamic role by continuously collecting and analyzing data to optimize processes continuously. A distinction must be made between the two approaches. Data-based is defined as:

Definition 2.13: Data-Based [45]

Data-based means the process is an open loop, and only the starting point uses data.

The term data-driven encompasses this term more broadly and is defined as:

Definition 2.14: Data-Driven [45]

Data-driven means that the process is a closed loop and its starting point and destination are both data.

In the context of digital manufacturing, these approaches enable precise monitoring and control of machines and systems, leading to more efficient and flexible processes. By implementing closed-loop systems, it is possible to react automatically to changes in the production process and operate flexible [38]. Using real-time data analysis and adaptive systems, it is also possible to parameterize models of the production system automatically. This is possible with the method developed in in this work for the Energy Flexibility Data Model. Data analytics approaches and fundamentals, which are used while implement the method for DD-EFMod, are explained in the following.

2.3 Data Analytics and Machine Learning

In order to implement data-driven approaches, methods from the fields of data analytics and machine learning play a central role. The aspects relevant to this work are examined in more detail below. First, methods of correlation analysis are discussed, as these methods are used to determine correlations between variables, which is a key aspect of the parameterization of energy flexibility. Secondly, this section shows which different clustering algorithms, such as those implemented in the DD-EFMod method, exist and how they can be validated. This is followed by an explanation of the CRISP-ML(Q) methodology, whose individual steps are adapted during the development and implementation of the DD-EFMod.

2.3.1 Data Analytics

In particular, correlation analysis is a common tool for identifying and interpreting relationships between different variables within large data sets. By calculating the correlation coefficient, insights can be gained into the strength and direction of the relationship between two variables. For this purpose, the correlation between variables can be described using the correlation coefficient ρ. The greater the amount ρ of the correlation coefficient, the more dependent two measured variables are and is in gerally defined according to [46, p. 821]:

Definition 2.15: Pearson Correlation Coefficient [46, p. 823]

Pearson's correlation coefficient

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} \tag{2.3}$$

with the covariance of the two variables $\mathrm{cov}(X,Y)$ *divided by the product of their standard deviations* σ.

A correlation coefficient of +1 means a perfect positive correlation, -1 a perfect negative correlation and 0 no correlation. This is followed by enhancing the informational value of the dataset. This involves deriving auxiliary variables and increasing the density of useful information within the data. In a more specific way for time series which are necessary for an energy-flexible operation, like power consumption or temperature data, correlation is calculated by

$$\rho = \frac{\sum\limits_{i=1}^{n} \left(x_{1,i} - \mu(x_1)\right)\left(x_{2,i} - \mu(x_2)\right)}{\sqrt{\sum\limits_{i=1}^{n} \left(x_{1,i} - \mu(x_1)\right)^2} \sqrt{\sum\limits_{i=1}^{n} \left(x_{2,i} - \mu(x_2)\right)^2}} \tag{2.4}$$

with $x_{1,i}$ and $x_{2,i}$ as values of the relvant signals $\mathbf{x_1}(t)$ and $\mathbf{x_2}(t)$ at the time i with n samples [47, p. 384] . In addition, for a deeper look, lagged correlation could be applied when there is a time delay in the relationship between two signals. The lagged correlation is calculated with a time shift τ for one of the signals by

$$\rho(\tau) = \frac{\sum\limits_{i=1}^{n-\tau} \left(x_{1,i+\tau} - \mu(x_1)\right)\left(x_{2,i} - \mu(x_2)\right)}{\sqrt{\sum\limits_{i=1}^{n-\tau} \left(x_{1,i+\tau} - \mu(x_1)\right)^2} \sqrt{\sum\limits_{i=1}^{n} \left(x_{2,i} - \mu(x_2)\right)^2}} \tag{2.5}$$

by shifting the signal $\mathbf{x_1}(t)$ by τ points in time and then correlating it with $\mathbf{x}_2(t)$. A lagged correlation can be used to investigate whether there is a time lag in the relationship between two signals. A high lagged correlation value at a certain lag τ could indicate that one signal influences the other with this time delay.
However, in order to determine meaningful correlations, it is often necessary to standardize and normalize the data. Normalization for better scaling according to

$$x_{\mathrm{norm},i}(t) = \frac{x_i(t) - \min(\mathbf{x}(t))}{\max(\mathbf{x}(t)) - \min(\mathbf{x}(t))} \tag{2.6}$$

should be done [48, p. 110]. Normalization aims to scale the data so that it lies within a specific range, typically between 0 and 1. In addition signal standardization transforms the data so that they have a mean value of 0 and a standard deviation of 1, with the calculation following

$$x_{\mathrm{std},i}(t) = \frac{x_i(t) - \mu(\mathbf{x}(t))}{\sigma(\mathbf{x}(t))} \tag{2.7}$$

with $\mu(\mathbf{x}(t))$ as mean of the input signal and $\sigma(\mathbf{x}(t))$ the standard deviation [48, p. 113]. These steps are crucial to make data sets comparable and to improve the efficiency of data processing, especially if the data comes from different sources or is available in different units.
Another important step in data analysis and the preparation of data sets for machine learning processes is quantization. This process reduces the complexity of the data by dividing continuous variables or time series into discrete intervals. Quantization not only simplifies the data structure, but can also help to reduce the risk of overfitting and increase the computational efficiency of algorithms [49, p. 115] [50, p. 290]. Let a data set D with N values and a value range from $\min(D)$ to $\max(D)$. The data set is to be divided into k bins, then according to [51, p. 332] the width W of each bin is given by

$$W = \frac{\max(D) - \min(D)}{k} \tag{2.8}$$

and its boundaries as

$$b_i = \min(D) + i \cdot W \tag{2.9}$$

for $i = 0, 1, \ldots, k$. Thus, the assignment of the data to the bins follows with

$$\operatorname{Bin}(x) = \left\lfloor \frac{x - \min(D)}{W} \right\rfloor \tag{2.10}$$

where $\lfloor \cdot \rfloor$ is the rounding function. Such a quantification method can be further used to calculate the moving average of a signal according to

$$\mathbf{x}_{\mathrm{MA}}\left(t_k\right) = \frac{1}{M} \sum_{i=k-\lfloor M/2 \rfloor}^{k+\lfloor M/2 \rfloor} \mathbf{x}\left(t_i\right) \tag{2.11}$$

with a window of size $M|M < N$ where N is the number of signal samples under consideration [52].
Another option for data and signal analysis is Boolean logic analysis, which enables the mathematical treatment of binary values (1 for ”true” and 0 for ”false”). This analysis uses fundamental logical operations [53]:

- Conjunction: $A \wedge B$ is true if both A and B are true.
- Disjunction: $A \vee B$ is true if at least one of the statements A or B is true.
- Negation: $\neg A$ reverses the truth value of A; true becomes false and vice versa.

In data analysis and processing, Boolean logic enables data sets to be filtered using defined conditions that specify specific criteria for data selection or processing.
The presented data analysis methods are often used as pre-processing steps for other data processing algorithms, like the implementation of the DD-EFMod method. Such pre-processing steps are exceptionally fundamental for machine learning algorithms.

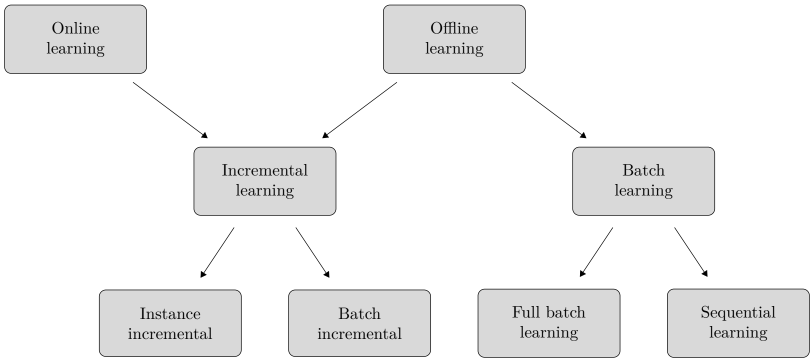


Figure 2.5: Subdivision of machine learning methods into online and offline and the subgroups incremental learning and batch learning based on [57] (own figure).

2.3.2 Machine Learning and Data Stream Mining

A machine learning algorithm is a process or method for recognizing patterns in data and learning from them [54]. It is essentially a process or set of rules applied to a data set to achieve a specific goal, such as classification or clustering. Examples of machine learning algorithms include Decision Trees, K-Nearest Neighbors, clustering algorithms such as K-means, and network algorithms such as Neural Networks [55, pp. 2–4]. In the context of production systems it is relevant to consider offline algorithms for historical or storaged data and also consider online algorithms for real-time data streams with only temporary availability to facilitate immediate operational adjustments and real-time decision making [56].
A machine learning model is the resulting product of a machine learning algorithm applied to a data set. After the algorithm has been trained, the model represents the knowledge learned, it is basically a specific representation of what has been learned from the data. The model can then be used to make predictions or decisions based on new, unknown data [51, p. 7].

Furthermore, a distinction must be made between offline and online algorithms when using machine learning. The following options must be differentiated here, as shown in Figure 2.5 while following [57]:

- **Online learning**: Refers to learning processes in which the model is continuously updated as soon as new data is available. It is ideal for applications where data must be processed in real-time.
- **Offline learning**: Also known as batch learning, it refers to the situation where the learning model is trained with a fixed data set. New data leads to a retraining of the model.
- **Batch learning**: A special form of offline learning in which large amounts of data are processed in batches to train or update the model.
- **Incremental learning**: In contrast to batch learning, this method updates the model step by step by continuously processing smaller amounts of data.
- **Instance incremental**: A form of incremental learning where each individual instance is used to incrementally update the model.
- **Batch incremental**: This uses small batches of data to incrementally update the model instead of retraining it with a full set of data.
- **Full batch learning**: A method where the entire available dataset is processed in a single batch, often used in the initial training phase.
- **Sequential learning**: Focuses on sequential processing of data, where the order of the data matters and the model is updated based on this sequence.

If the data of a data set needs to be grouped, K-means clustering, which represents an offline full batch learning algorithm, can be used for this [58, pp. 45–63]. If $\mathbf{f}[k]$ as a feature vector with historical batch data was formed through preprocessing and data engineering, initial cluster centers $\mathbf{C}$ must be defined during the initialization step. The cluster assignment is then carried out for each data point using a distance measure (e.g., using the Euclidean distance) according to

$$d(\mathbf{p}, \mathbf{C}) = \sqrt{\sum_{i=1}^{n} (p_i - c_i)^2} \tag{2.12}$$

while $\mathbf{p} = [p_1, \ldots, p_i]$ with $i \in \mathbb{N}|n > 0$ Datapoints and $\mathbf{C} = [c_1, \ldots, c_i]$ with $i \in \mathbb{N}|n > 0$ cluster centers. This is followed by the recalculation of the cluster centers $\mathbf{c}'$ according to

$$\mathbf{c}'_j = \frac{1}{|A_j|} \sum_{\mathbf{p} \in A_j} \mathbf{p} \tag{2.13}$$

as the mean value of all data points assigned to the cluster, $\mathbf{c}'_j$ is the center of the j-th cluster, and A_j is the set of all data points assigned to this cluster. The recalculation according to equations 2.12 and 2.13 is iterated until no significant changes in $\mathbf{c}'$ occur [58, pp. 45–63].

An alternative to offline full batch learning with K-means is the batch incremental learning algorithm, mini-batch K-means [59]. This algorithm divides the data into smaller batches, enabling its use in offline or online applications. Such adaptability makes it suitable for a wide range of data processing scenarios. Each batch contains a selection of n data points. These are assigned to the existing cluster centers $\mathbf{C}$, and then the cluster centers are updated according to

$$\mathbf{c}_j = (1 - \eta) \cdot \mathbf{c}_j + \eta \cdot \mu(x_{\text{batch}}) \tag{2.14}$$

which corresponds to weighted averaging, where c'_j is the center of the jth cluster, $\mu(x_{\text{batch}})$ is the mean of the data points of the batch that were assigned to the jth cluster, and η is the learning rate that determines how much the cluster center is shifted [59]. The advantage of the mini-batch K-means is its efficiency with large data sets and the ability to work in real time, as the entire data set does not have to be processed with each iteration.

In data stream mining, online clustering is central to meet the specific challenges associated with processing continuous and dynamic data streams [60, pp. 67–76] and is defined as:

Definition 2.16: Data Stream [56, p. 26]

Data stream are data generated in real-time and whose volume is potentially unlimited.

To analyze data streams, it requires approaches that are not only efficient, but also able to adapt to changes in the data streams [61, pp. 23–32] [56, pp. 87–105].
The CluStream algorithm, which represents an online learning instance incremental method, has been specifically developed for the online clustering of data streams [62]. The special feature is that the current structure of the data can be recorded in real-time, and historical data can also be taken into account [47]. The CluStream algorithm is based on the concept of micro-clusters, which summarize data streams [47, pp. 237–239]. A microcluster for a data stream is represented as $c(t) = (N, LS, SS, LT, ST)$, where [56, pp. 177–179]:

- p is the number of data points in the cluster up to time t.
- LS is the linear sum vector of the data points in the cluster.
- SS is the squared sum vector of the data points in the cluster.
- LT is the sum of the timestamp of the last update of the cluster.
- ST is the sum of the squares of the timestamp of the last update of the cluster.

When a new data point x arrives at time t, the microcluster is updated:

$$p_{new} = p_{old} + 1 \tag{2.15}$$
$$LS_{new} = LS_{old} + x \tag{2.16}$$
$$SS_{new} = SS_{old} + x^2 \tag{2.17}$$
$$LT_{new} = LT_{old} + t \tag{2.18}$$
$$ST_{new} = ST_{old} + t^2 \tag{2.19}$$

The distance d between a data point x and the center of a microcluster C is often calculated using the Euclidean distance [46, p. 252]. The center of a microcluster is determined by $\frac{LS}{N}$. The CluStream method is a robust and adaptive method that makes it possible to extract information from continuously generated data and effectively capture dynamic changes in the data that frequently occur in the production environment. Validation of clustering algorithms is required to ensure the reliability and accuracy of the clusters generated. Checking the results ensures that the algorithms create meaningful and valuable groups within the data. Validation also helps to adjust and optimize the machine learning models to improve performance in real-world application use cases, such as those in the validation Chapter 7 of this thesis.

2.3.3 Validation of Clustering Algorithms

There are various methods for evaluating the quality of clustering algorithms. Two of the most common are discussed below. The silhouette coefficient s [63], where a higher coefficient value suggests more distinctly defined clusters in the model. The silhouette coefficient, calculated for each sample, comprises two components:

a This represents the average distance between a sample and all other points in its cluster.

b This is the average distance between a sample and all other points in the nearest cluster that it is not a part of.

For an individual sample, the silhouette coefficient s is calculated by

$$s = \frac{b - a}{\max(a, b)} \quad \text{where} - 1 \leq s \leq +1 \tag{2.20}$$

with the conditions:

- $s = +1$: Indicates an ideal, high-density clustering where each group is clearly separated from others.
- $s = -1$: Represents a completely incorrect or inappropriate clustering, with no meaningful grouping of the data.

- $s \approx 0$: The clusters overlap or are not clearly distinguished from one another.

On the other hand Davies-Bouldin-Index [64] can be used to evaluate the model to indicates the average similarity between clusters, where similarity is a measure that compares the distance between the clusters with the size of the clusters themselves. The index is defined as the average similarity between each cluster c_i for $i = 1, \ldots, k$ and its most similar one c_j. In the context of this index, similarity is defined as a measure R_{ij} that trades off

- s_i, the average distance between each point of cluster i and the centroid of that cluster - also know as cluster diameter.

- d_{ij}, the distance between cluster centroids i and j.

A simple choice to construct R_{ij} so that it is nonnegative and symmetric is with

$$R_{ij} = \frac{s_i + s_j}{d_{ij}} \tag{2.21}$$

and the the Davies-Bouldin index is defined by [65] as

$$DB = \frac{1}{k} \sum_{i=1}^{k} \max_{i \neq j} R_{ij}. \tag{2.22}$$

Both the Silhouette Coefficient and the Davies-Bouldin Index are metrics for evaluating the cluster quality of an online and offline clustering algorithm. These metrics, independent of the clustering method used, assess how well data points have been assigned to clusters.
In this thesis, the DD-EFMod method is used to analyze data and derive key figures from the This is possible with the method developed in in this work for the Energy Flexibility Data Model. The machine learning algorithms and methods presented are used for this. A structured approach is required for the application and implementation of the presented algorithms. The CRISP-ML(Q) method is presented below for this purpose.

2.3.4 Implementation of Machine Learning Algorithms with CRISP-ML(Q)

The CRISP-ML(Q) model is an adaptation of the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework [66] specifically for machine learning. It represents a structured process for planning, implementing, and evaluating machine learning projects [67]. It integrates a strong focus on quality assessment in every project phase, from conceptualization to implementation and operational deployment. The CRISP-ML(Q) model aims to balance technical feasibility, practical applicability, and the creation of added value [67]. The CRISP-ML(Q) approach is essential for the development and implementation of the DD-EFMod method for determining the key figures of the EFDM. The structured procedural model of CRISP-ML(Q) ensures that all aspects of the applied machine learning algorithms, from data preparation to model evaluation, are considered systematically and under constant quality control. This quality assurance is important as the

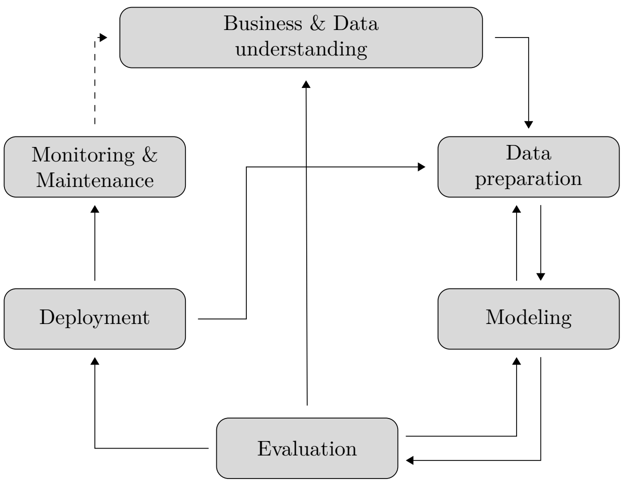


Figure 2.6: Phases of the CRISP-ML(Q) Process (own illustration adapted from [66] based on [67]).

accuracy and reliability of the identified energy flexibility key figures of the EFDM through DD-EFMod directly influence the effectiveness of the energy flexibility operation. Furthermore, the CRISP-ML(Q) supports the effective planning and implementation of machine learning-based projects through its structured approach. Adapting CRISP-ML(Q) in the development of DD-EFMod thus ensures that the identified key figures of the EFDM are robust, reliable, and directly implementable.
The CRISP-ML(Q) model is divided into several phases:

- **Business & Data Understanding**: This initial phase defines project goals and requirements from a business perspective. It lays the foundation for the entire project. The data sources are identified and examined in this phase. The aim is to deeply understand the data used during the project.
- **Data Preparation**: This phase includes all the steps required to prepare the data for analysis. This includes selecting, cleaning, and transforming the data.
- **Modeling**: In the core phase of the model, suitable machine learning algorithms are selected and applied. This phase also includes the adaptation of the algorithms to the specific requirements of the project as well as the evaluation and selection of the models based on their performance.
- **Evaluation**: The evaluation phase focuses on checking the models in terms of their effectiveness and accuracy. The technical aspects of model performance and the relevance of the results to the business objectives are considered.
- **Deployment**: In this phase of the CRISP-ML(Q) process, the selected model is transferred to the production environment. This phase also includes planning for monitoring and regular maintenance of the system to ensure its performance and reliability.
- **Monitoring & Maintenance**: This step includes the continuous monitoring of system performance and model accuracy to ensure that the models continue to function effectively and effi-

ciently under changing environmental conditions. It also includes maintenance work, where models are adjusted or retrained to maintain relevance and accuracy over time and respond to new data or requirements.

The CRISP-ML(Q) model thus supports a comprehensive and systematic approach to machine learning projects, from data preparation to model development and evaluation through to practical implementation. The inclusion of quality assessment ensures that the solutions developed are also effective and sustainable in practical application. It is, therefore, very effective for use in the context of energy flexibilization.

2.4 Interim Summary

This chapter provides a comprehensive basis for developing the method for DD-EFMod by focusing on key concepts and technologies that contribute to its effectiveness and feasibility. First, industrial energy systems in the context of production systems are discussed. This is followed by an introduction to demand-side management and the concepts of energy flexibility, as well as corresponding energy-flexibility measures. Furthermore, the core aspects of modeling energy flexibility is discussed. In particular, the Energy Flexibility Data Model (EFDM) and its classes, flexible loads, storage, their dependencies, and specific flexible load measures, are introduced. This is followed by an explanation of the importance of digital manufacturing and RAMI 4.0 in order to illustrate the implementation of energy-flexibility measures in modern production environments, such as in the validation use case of this work. The importance of modeling, simulation and data-driven approaches is emphasized, as they are essential for the development of the DD-EFMod method. Furthermore, the basics of data analytics and machine learning algorithms, especially clustering methods, are presented, which are central to the identification of key figures of the EFDM. In addition, the distinction between online and offline machine learning algorithms is discussed in order to clarify their applicability in real-time applications and more static environments. Furthermore, the validation of clustering algorithms is shown. Finally, the CRISP-ML(Q) process is described in detail, providing a structured process for quality assurance and successful implementation of machine learning algorithms, which are essential for developing and implementing the DD-EFMod method.

3 State of the Art and Research

”To raise new questions, new possibilities, to regard old problems from a new angle, requires creative imagination and marks real advance in science.”

Albert Einstein

The following chapter presents the current state of science and technology on modeling energy flexibility in production systems. This is conducted on the basis of a systematic literature review. This procedure and the methodology is explained in Section 3.1. Subsequently, Section 3.2 shows the results of the individual methodological steps and presents the relevant reports identified on the basis of the literature review. Finally, Section 3.3 discusses the identified need for research, which is addressed in this dissertation.

3.1 Procedure of Systematic Literature Review

The presented systematic literature review is based on the approach of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [68]. Following the PRISMA statement, a systematic literature review contains the overall parts of identification, screening, eligibility and including of studies and reports [69]. For clear understanding of what a report in this context is, the PRISMA statement gives these following explanations:
A report is a document (printed or electronic) supplying information about a particular study. It could be a journal article, preprint, conference abstract, study register entry, clinical study report, dissertation, unpublished manuscript, government report, or any other document providing relevant information [68]. As second, a study is an investigation, such as a clinical trial, that includes a defined group of participants and one or more interventions and outcomes. A study could contain multiple reports [68].
In addition to the PRISMA based systematic literature review, the part of concept and planning which is based on [70] and [71] is placed as the first. So my complete systematic literature review procedure is shown in Figure 3.1. The systematic literature review starts with the part concept and planning, which contains the following three steps:

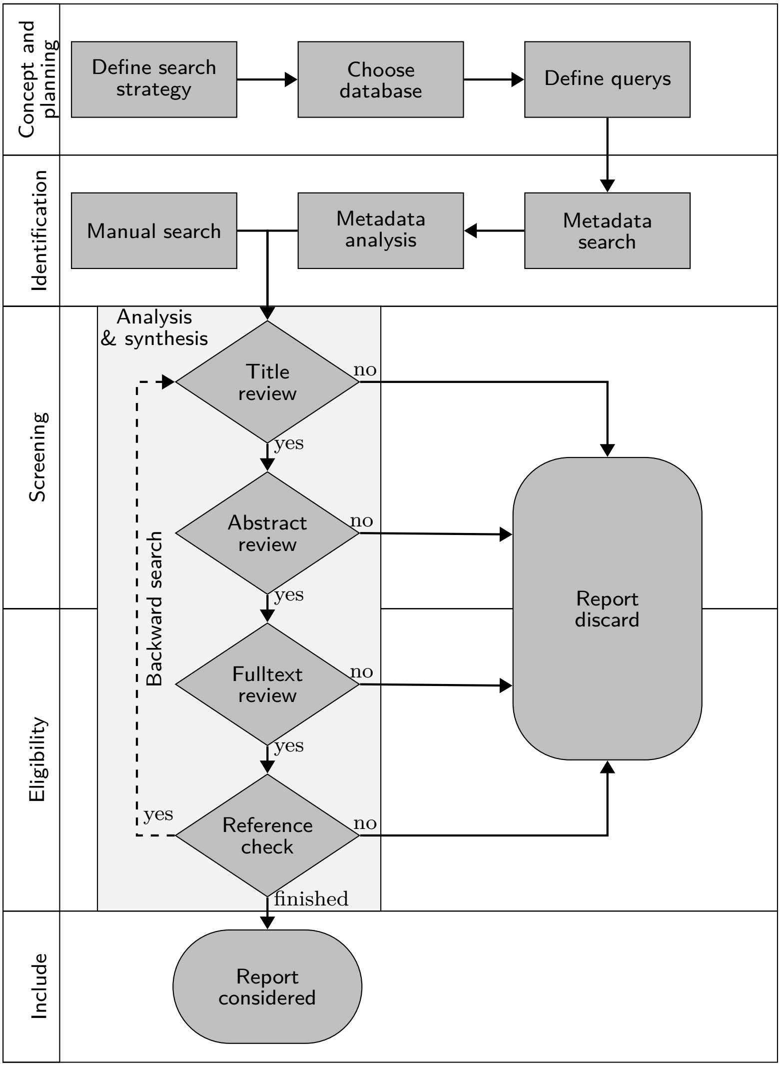


Figure 3.1: Overall steps of the systematic literature review following the PRISMA statement (own figure based on [68, 73]).

In the first step **Define search strategy** the dimensions for the systematic literature review are defined. These dimensions, following [18] and [72] are objective, system boundary, approach and method. The objective of this work is to improve the enabling process for energy-flexible factory operation. This results in the system boundary, the building of a factory with a production process. To realize and describe energy flexibility a model based approach is chosen. In addition, the modeling should be data-based to obtain a system description that is as real as possible. Therefore data from different sources like load profiles, electric or thermal energy consumption could used for data-analysis or pattern detection. To evaluate and classify the relevant reports, I developed a classification scheme. The scheme is used to evaluate and classify the identified reports for research content under the aspects of the objective, the system boundary, the approach, and the methodology to the following topics:

- energy consumption data analysis or pattern detection
- energy flexibility
- industrial energy flexibility
- identification, description, usage of energy flexibility
- modeling of energy flexibility
- use of a data-based approaches to reach one of these targets
- use of an automated approach for modeling
- use a machine learning approach

As second step **choose database** the research data bases, including open access reports, ”Web of Science” and ”ScienceDirect” are defined. These data bases include scientific journals, publishers and conferences of related engineering communities and topics such as The International Academy for Production Engineering (CIRP) and Institute of Electrical and Electronics Engineers (IEEE).

In **define query** the search queries for browsing the databases are defined. Therefore, for each dimension resulted from step one analogously and closely related terms are considered and systematically linked by

Table 3.1: Search strings for each dimension of the systematic literature review (own table).

	Demension	Search string
AND	objective	`"energy flexibility" OR "demand response" OR "demand side management"`
	system boundary	`"production" OR "factory OR "manufacturing" OR "machine tool" OR "industry"`
	approach	`"model" OR "simulation"`
	methode	`"data-based" OR "data stream mining" OR "data analysis" OR "pattern detection"`

logical operations. This results in the queries given in Table 3.1. In the next step **metadata search** these search strings are used to search the databases for each dimension starting with the dimension objective. Afterwards, the search string is successively extended by the search strings for the other dimensions with a logical AND operator. The second part of the systematic literature review is identification. This starts with the **metadata search** where the browsing is done, using the queries given in Table 3.1, and the results are collected. It follows by the **metadata analysis**. In this step, the results are interpreted and discussed. The results of my systematic literature review are discussed in Section 3.2. In addition to browsing the research databases, also the step **manual search** is done. The manual search is necessary to find relevant national standards (e.g., International Organization for Standardization (ISO) or VDI) and other previous dissertations on the topic which are not listed in the databases. In the next parts, screening and eligibility the **analysis and synthesis** of the report results from the identification part is done. Subsequently, as shown in Figure 3.1, I performed the review of the titles and abstracts of the reports one by one. For the reports, which fullfils the scheme of step one, the classification and review of the full text of the report was done. In the course of the literature synthesis, essential characteristics are recorded and summarized (see Section 3.2). Through screening of the literature references in the selected publications, additional relevant references are fed back into the literature search if suitable. Finally, I evaluate

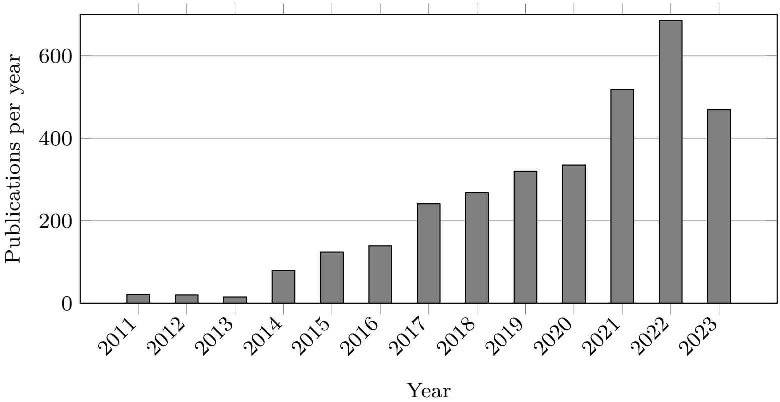


Figure 3.2: Results of the metadata analysis for the search query combination of the dimensions objective, system boundary and approach (own Figure).

the reports to the developed scheme and identified the research gap based on the analyzed literature.

3.2 Results of the Literature Review

As the first result of the systematic literature review the analysis of the metadata search shows that 166 relevant reports result from browsing the databases for all dimensions (see Table 3.2). In comparison, the objective query still yields 10677 reports. The analysis of the temporal development of the relevant publications clearly shows the increased research activities in industrial energy flexibility and demand-side management. This evolution is shown in Figure 3.2 for the third level of dimensions (objective, system boundary, and approach). Also, 20 reports related to the topic could I identify while doing the manual search. So overall I start the part of screening for 184 reports. In the title review, only 84 were left, and while reviewing the abstracts, 36 reports were identified as relevant. Finally, 26 reports result from the full text review to consider. These 26 reports are discussed shortly and classified by the scheme in the following. The results of the classification is given in Table 3.3.

Akhavan-Hejazi *et al.* present various possible applications of big data analytics in energy systems. Among other things, real-time analysis and monitoring, monitoring of decentralized energy networks, but also the improvement of demand response are listed. The necessary basis for this is big data to enable robust analyses and thus extract new information [74].

Li *et al.* show that needed data for machine learning models are difficult to collect. The most important barriers are cost, technical constraints or privacy. To address these problems they propose a data generation model to synthesize energy consumption time series. These synthetic data a used to train and validate classification models. In result the time series have satisfactory similarity with real data in terms of data distribution, pattern and performance [75].

Calikus *et al.* propose a data-driven approach for pattern detection methods for analyze power consumption data. The automatic analysis of heat load patterns of district heating networks requiring no prior knowledge. The given approach clusters the customer power load profiles into different groups and extracts their representative patterns [76].

Corsetti *et al.* give a modeling framework and an associated optimization tool to support short-term operational planning and electricity market service trading. The focus is to to deploy flexibility with specific

Table 3.2: Results of the metadata search of the systematic literature review (own Table).

Combination of demensions	Number of Reports
objective	10677
objective AND system boundary	3976
objective AND system boundary AND approach	3238
objective AND system boundary AND approach AND methode	166

application to provision of frequency control ancillary services. Therefore they discribe caracteristics of flexibility, based on energy grid time series and model it with mathematical features to use mixed-integer linear programming optimization of the flexibilities [77].

Sossenheimer gives in his work, a hybrid energy metering point concept for the implementation in industrial environments. The availability of energy demand information is the basic prerequisite for the identification, evaluation and implementation of energy efficiency and energy-flexibility measures. Accordingly, end-to-end energy monitoring at all production system levels is essential for enabling holistic energy efficient and energy-flexible factory operations. The primary objective of this work is to develop a continuous hybrid energy monitoring concept taking into account all production system levels. [27, pp. 68–76]

Tsay *et al.* provide a method, using time-series analysis, to facilitate online scheduling computations. Optimal demand-response scheduling of industrial air separation units should account for process dynamics and control to ensure that schedules are dynamically feasible. Their work presents a data-driven strategy to create machin learning models for an industrial process from routine operational data. They find that time-series models can accurately represent process dynamics over several days, but that their accuracy can suffer over time. To handle this challange they show that it is possible to online update the models, which significantly improve demand and response planning models in the future [78].

Ulbig *et al.* quantify and visualize the technically available operational flexibility of individual power system units. Necessary metrics for defining power system operational flexibility are presented. The flexibility properties of different power system unit types are qualitatively analyzed and compared to each other. The contributions of this paper are the presented modeling and analysis techniques in electric power systems. The calculation of the remaining operational flexibility in a power system after having subtracted the needed from the originally available operational flexibility was shown [79].

Zhao *et al.* discuss ensemble clustering for power data while reducing the dimensions of the data. The relationship between the data dimensions and the clustering performance were determined. Specific characteristics and practical significance for different mode were determined. Furthermore, the users' electricity consumption behavior in one week based on these modes were analyzed. This paper proves that ensemble clustering can be successfully applied for power data analysis [80].

DIN SPEC 91366 specifies a reference model that systematically shows companies which aspects must be considered and investigated when identifying, evaluating and using energy flexibility. The reference model supports the communication of energy information and knowledge as well as an evaluation of energy consumption behavior with regard to energy flexibility in order to create a basis for participation in the intelligent electricity supply system. Relevant control and planning variables in energy and load management or in production planning and control are included in the evaluation [81].

DIN SPEC 91410-2 specifies requirements for the method of identifying and evaluating the temporal flexibility of energy conversion plants in buildings and districts. The method makes it possible to identify these plants with regard to flexibility options, to characterize and evaluate them according to technical, organizational, systemic and informational criteria. Different fields of application for flexibility in the electrical energy market, grid and system are considered. Capabilities of electrical systems to dynamically respond to corresponding flexibility needs are evaluated [82].

VDI 5207 Part 1 focus on energy-flexible factories. The standard describes the process of identifying and marketing energy flexibility and defines pertinent terms. The standard is applicable to different forms of energy but focuses on electrical energy [24].

VDI 5207 Part 2 describes in detail the process of identifying and marketing options of energy flexibility for industrial companies. Also challanges and a guideline to solve them are given [26].

Lee ***et al.*** show a method to evaluate the demand respose potential of industrial loads according to a process of related load-characteristic data analysis. The proposed potential-estimation model considers frequency, consistency, and demand response event operation scores during designated ramp-up and ramp-down time intervals separately [83].

Sadeghianpourhamami ***et al.*** focus on the validation of flexibility in households. Analyses of customer load patterns show high uncertainty about customer habits in offering flexibility. Therefore, a quantitative specification of flexibility was done. To address this, they give two systematic methodologies for modeling individual customer behavior, evaluate the proposed models, and provide a fundamental analysis of factors influencing flexibility behavior based on statistical tests. [84].

Schraml shows a method which makes it possible to optimize the electrical load profile of metal-cutting machine tools, in particular by synchronizing the activities of auxiliary units over time. The results enable operators and manufacturers of machine tools to estimate and evaluate the load reduction potential of metal-cutting machine tools and, if the evaluation is positive, to realize it [85, pp. 49–54].

Schulze ***et al.*** present an approach for flexibilization of energy intensive system elements. Against this background, technical capabilities and operational strategies for energy-flexible management of industrial cooling towers are analyzed, basing upon empiric data from a plant. A synergetic approach of data-driven analysis and scenario-based simulation is applied to demonstrate benefits of energy-flexible technical building services management [86].

Schott ***et al.*** present a descriptive model for industrial flexibility with respect to power consumption. The advancing digitization in the energy sector opens up new possibilities for utilizing and automatizing the marketing of flexibility potentials and therefore facilitates a more advanced energy management. This requires a standardized description and modeling of power-related flexibility [14]. A detailed description of this Energy Flexibility Data Model is given in Section 2.1.2.

Bahmani *et al.* propose a mathematical optimization model that uses the generic data model for flexibility description based on [14]. The optimization model supports industrial companies to select when, where, and how to market their flexibility potential to optimize profit. The results of the optimization model evaluation suggest the model can fulfill its purpose under different use cases even with complex use cases such as various loads and storages [87].

In **Bank *et al.*** we present an approach to integrate Energy Flexibility (EF) into Production Planning and Control (PPC). Based on the energy-oriented PPC, the approach identifies and model EF of processes in a generic Energy Flexibility Data Model based on [14], which is subsequently integrated in the energy-oriented production plan and further optimised on the energy market side [36].

Unterberger *et al.* model energy storages, energy-flexible machines and smart controls. To realize smart control, electrical energy must be included into production planning and control as resource. Therefore an energy-flexible production control is realized by using the modeling language SysML [88].

Degefa *et al.* propose unified characterizing terms for flexibility resources. Furthermore, a taxonomy method which is applied to classify flexibility resources is presented. The taxonomy method clears the confusion on ”what-is-what” under the concept of flexibility. This paper also presents the benefits of unified characterizing terms in mapping flexibility resources to ancillary services [89].

In **Lindner *et al.*** we show an approach to modeling and aggregation of flexibility in complex manufacturing processes. To overcome this challenge, a method for the aggregation of energy flexibilities that is based on the generic Energy Flexibility Data Model given by [14]. The method proposes a two-step approach to aggregate flexibilities cost efficiently and considers manufacturing specific limitations [90].

Strobel develops a software framework to realize the demand response measures store energy inherently given in [24]. Therefore the energy storages are modeled using the key values given in [14]. For the application the energy flexibility model is used for an optimization [72, pp. 74–104].

In **Buhl *et al.*** we present an advanced model of [14] for the generic and standardized description and modeling of energy flexibility. The data model enables a (partially) automated information-technical processing of the most diverse flexibility. The aim is to develop a comprehensive data model to represent flexibility in a flexibility space and concrete flexibility measures (see Section 2.1.2). The focus is on the mapping of technically and energetically relevant information in a granularity that enables the communication and of flexibility between industrial companies and energy markets [28].

Sauer *et al.* show how an energy synchronization platform enables the entire process of automated energy flexibility trading from the machine of a production system to energy flexibility marketing services. It thus represents the overall concept of a digital ecosystem. The processes are illustrated by means of use cases. In addition, we present the further developed Energy Flexibility Data Model [28] and show the application [5, p.249-260].

In **Lindner *et al.*** we examine the practicality of a methodical approach for energy-flexible and energy-optimal operation in the field of metal-cutting production. The analysis focus on a grinding machine and its central cooling system. An Energy Flexibility Data Model is built for each subsystem, which describes energy flexibility potentials generically. This is then extended to enable combined energy cost-optimal production planning. As a basis for the links between the data model representations, the cooling between the subsystems are modeled using parameter-estimation methods. Based on the presented approach, the results successfully validate the possibility of energy-flexible cost-optimal and sensor-reduced production planning [30].

3.3 Conclusion on the State of the Art and Research Deficit

The systematic literature review conducted on the state of the art and research in the field of energy consumption data analysis and the topic of energy flexibility shows a strong increase, especially since 2016 in this field (see Figure 3.2). Based on the classification scheme (see Table 3.3), I could show that the work from the energy and consumption data analysis field uses data-based tools and methods. In addition to statistical methods, machine learning approaches, e.g., for pattern recognition or parameter estimation, are also used for this purpose.

On the other hand, some research work and standards deal with identifying and describing energy flexibility, especially in the complex environment of industrial processes. The analyses of the systematic literature review show that about one-third of the reports or studies on this topic are within the SynErgie project. The identified relevant reports or studies often focus on identifying or describing industrial energy flexibility in specific use cases. In these cases, the EFDM presented in Section 2.1.2 is used as a basis. As it turns out, no report has been identified that provides automated data-based or data-driven modeling of industrial energy flexibility through load profile analysis. This research gap is to be filled by the present work.

Table 3.3: Relevant reports as results of the systematic literature review (own table).

Report	Consumption analysis	Energy Flexibility (EF)	Industrial EF	EF Identification	EF Description	EF Use	EF Model	Data-Based	Automated	Machine Learning
Akhavan-Hejazi *et al.* [74]	●							●		
Li *et al.* [75]	●							●	●	●
Calikus *et al.* [76]	●							●		●
Corsetti *et al.* [77]	●	●			●		●	●		
Sossenheimer [27]	●	●						●	●	●
Tsay *et al.* [78]	●	●	●	●				●	●	●
Ulbig *et al.* [79]	●			●			●	●		
Zhao *et al.* [80]	●							●		●
DIN SPEC 91366 [81]		●	●	●	●					
DIN SPEC 91410-2 [82]		●		●	●					
VDI 5207 Blatt 1 [24]		●	●		●					
VDI 5207 Blatt 2 [26]		●	●	●						
Lee *et al.* [83]		●	●	●						
Sadeghianpourhamami *et al.* [84]				●				●	●	●
Lee *et al.* [83]		●	●	●						
Schraml [85]		●	●	●						
Schulze *et al.* [86]		●	●	●	●	●				
Schott *et al.* [14]		●	●		●	●	●			
Bahmani *et al.* [87]		●	●		●	●	●			
Bank *et al.* [36]		●	●		●	●	●			
Unterberger *et al.* [88]		●	●			●	●			
Degefa *et al.* [89]		●	●		●	●	●			
Lindner *et al.* [90]		●	●		●	●	●			
Strobel [72]	●	●	●	●	●	●	●			
Buhl *et al.* [28]		●	●	●	●	●	●			
Sauer *et al.* [5]		●	●	●	●	●	●			
Lindner *et al.* [30]		●	●	●	●	●	●	●		●

4 Research Gap and Concept

”A new idea must not be judged by its immediate results.”

Nikola Tesla

The previous chapters showed the necessity of modeling industrial energy flexibility. In addition, a need for research in automated parameterization of such models was identified. On this basis, the research objective, the resulting research question and the derived research hypotheses are formulated in this chapter. This chapter concludes by deriving the requirements and defining the assumptions and prerequisites for the functionalities of a method that can be applied to achieve the research objective.

4.1 Research Objective

The central research objective of this thesis is derived from the framework outlined in Chapter 1 and 2 and the research gap identified in Chapter 3. To enable a factory to become energy-flexible, it is necessary to describe the existing energy flexibility. This description is possible with the help of the data model shown in Section 2.1.2. Due to the complexity of production processes and their supply systems, the correct modeling of existing energy flexibilities is not trivial. However, this central step of the enabling process should be as simple as possible for plant operators or energy managers of a company. In summary, the research objective can be formulated as follows:

Research Objective

> The primary goal of this work is to simplify the enabling process of a factory to energy-flexible operation. For this purpose, a data-driven method should be developed, which reduces the modeling effort of energy flexibility, based on information and data from the production system.

In order to achieve this research goal in a well targeted manner, the research questions and, from these, the research hypotheses are formulated.

4.2 Research Questions and Hypotheses

From the research objective, the central research question is derived, which focuses on the modeling and parameterization of the EFDM:

Research Question

Is it possible to develop a method for automated parameterization of an energy flexibility model, based on data from a production system, to describe the energy flexibility of the production system?

This given central research question leads to further sub-research questions, which serve to answer it and reach the objective. These sub-research question focus on specific parts to reach the research objective.

Sub-Research Questions

1. What methods can enable automatic parameterization of a model to describe energy flexibility?
2. Which data and which information of a production system are necessary for modeling energy flexibility?
3. Can an automated parameterized model enable an energy-flexible production system operation?

The research hypotheses can be derived from these research questions. Accordingly, under the assumption that an automated parameterization of energy flexibility models is possible, it follows that these also fulfill the requirements to implement an energy flexibility measure. The automated parameterized models should fulfill the same requirements as a manual modeling of energy flexibility. This results in my first research hypothesis.

Research Hypothesis : 1

Data-driven automatically parameterized energy flexibility models of machines in production infrastructure can be used to enable energy-flexible operations.

Growing digitization and data availability mean that more and more data-based methods can be used to obtain information (see Chapter 2). The systematic literature review shows that machine learning and data-based or data-driven methods have the potential to be used for modeling, simulation and data analysis in the context of consumption analysis and energy flexibility. Furthermore, the developed method should also be applicable in the brownfield and systems with low amount of historical data availability, e.g. through temporary or streaming data acquisition. This leads, based on the research question, to my second research hypothesis:

Research Hypothesis : 2

Machine learning and data stream mining algorithms can be used to automate the parameterization of energy flexibility models of machines from the production infrastructure.

4.3 Requirements and Assumptions

The approach devised to achieve the research objective and address the research questions must satisfy specific functional and quality requirements. Additionally, boundary conditions and prerequisites are essential for efficiently implementing this method and its transfer to industrial applications [91]. These requirements, assumptions, and prerequisites are detailed and discussed below.

The following functional requirements on the method (FR-M) focus on the development of the method itself and are essential for the approach:

FR-M 1: Applicability: The method must be designed to be applicable for real industrial production systems and scenarios, as explained in Chapter 2.

FR-M 2: Modularity: The method is structured so that individual steps of the method can be applied separately if required.

FR-M 3: Transferability: The method is designed in such a way that different energy-flexibility measures (see Table 2.1) can be realized and should be transferable to different machine types.

FR-M 4: Reproducibility: Repeated application of the method under the same conditions leads to the same or very similar results.

In addition, with a focus on applicability, requirements are needed for the energy flexibility to be modeled. These functional requirements for energy flexibility modeling (FR-EF) are:

FR-EF 1: Feasibility: The parameterized model describing the existing energy flexibility can be used to realize it.

FR-EF 2: Accuracy: The energy flexibility models parameterized with the help of the method should be sufficiently accurate to enable an application.

FR-EF 3: Maximization: The calculated energy flexibility model should describe the maximum realizable energy-flexibility potential.

FR-EF 4: Explainability: The calculated key figures of the energy flexibility model should be as comprehensible as possible.

FR-EF 5: Safety: The parameterization of the energy flexibility key figures must take the related machines' technical boundaries into account.

The above FR-EF lead to requirements for the Machine Learning (ML) algorithms to be used for the energy flexibility modeling. The for the

DD-EFMod method relevant quality requirements (QR) for machine learning models, which were derived from the de facto standard of machine learning applications, the CRISP-ML(Q) Studer *et al.* [67] explained in Chapter 2, are as follows:

QR 1: Quality: The ML model's quality should fit the application requirements and should validated by accuracy and performance measures.

QR 2: Robustness: The ML algorithms should have the capability to maintain its performance level despite certain circumstances.

QR 3: Explainability: The ML model should directly or post-hoc explainable.

QR 4: Scalability: If necessary, the ML model should also be able to work reliably with more significant amounts of data.

QR 5: Real-time capability: The ML model should work in a application defined time.

The application and the development of the method based on prerequisites that are assumed to be fulfilled within the context of this work. These prerequisites (PR) are:

PR 1: Data Availability: All data and information (see Chapter 7, e.g., power value, operating condition) necessary to calculate and parameterize key figures of the EFDM are available and of sufficient quality.

PR 2: Information and Communication Technology (ICT)-Availability: The existing ICT infrastructure ensures sufficiently fast and secure transmission of the required data to the corresponding data processing devices.

PR 3: Energy Flexibility Identified: The relevant systems for which an energy flexibility model should be parametrized and the corresponding energy-flexibility measure are already known through methods of energy flexibility identification following [26] with tools like the E-FLEX-Scanner or the Energy-Flexibility-Audit [5, pp. 167–169].

PR 4: **Technichal Scope**: The method focuses on the determination of technical key figures for the modeling of energy flexibility.

The derived requirements and prerequisites form the framework for developing the methodology for a DD-EFMod. The development of this methodology is presented in Chapter 5.

Table 4.1: Summary of requirements and prerequisites (own table).

Type	Identifier	Requirement & Prerequisites
Functional Requirements	FR-M 1	Applicability
	FR-M 2	Modularity
	FR-M 3	Transferability
	FR-M 4	Reproducibility
	FR-EF 1	Feasibility
	FR-EF 2	Accuracy
	FR-EF 3	Maximization
	FR-EF 4	Explainability
	FR-EF 5	Safty
Quality Requirements	QR 1	Quality
	QR 2	Robustness
	QR 3	Explainability
	QR 4	Scalability
	QR 5	Real-time capability
Prerequisites	PR 1	Data Availability
	PR 2	ICT-Availability
	PR 3	EF Identified
	PR 4	Technical Scope

4.4 Interim Summary

Based on the previous systematic literature review from Chapter 3, this Chapter derives the central research objective and the research questions. Subsequently, the research hypotheses are formulated. Finally, the functional requirements and prerequisites, summarized in Table 4.1, for developing a method to automate data-driven parameterization of energy flexibility models are derived.

5 Method Development

”The true Logic for this world
is the Calculus of
Probabilities, which takes
account of the magnitude of
the probability.”

James Clerk Maxwell

To fulfill the research question and research hypotheses defined in Chapter 4, this chapter shows the development of the DD-EFMod method. First, Section 5.1 describes the approach and structure of the method, with detailed explanations of the steps and how the automated parameterization of energy flexibility models are realized within the DD-EFMod method. In Section 5.2 afterwards, the software concept for the method and its components is discussed.

5.1 Approach and Structure of the DD-EFMod Method

The research goal of simplifying the enabling process of energy flexibility in factories (cf. Figure 1.2) is the starting point. As described in Section 2.1.1, the third step of the process requires the implementation of identified possible energy-flexibility measures while taking into account the technical environment. As the systematic literature review shows, the realization requires modeling the identified energy flexibilities (e.g. Lindner *et al.* [30]). This can be done with the Energy Flexibility Data Model (EFDM) described in Section 2.1.2.
With the goal, that the parameterization of the EFDM should be as simplified and automated as possible (see Section 4.3) and as a result conducted from the systematic literature review (see Table 3.3), machine learning and data analytic algorithms can be used to achieve this.
Due to its structured approach to the planning, implementation and evaluation of machine learning projects, the application of the CRISP-ML(Q) process [67] (see Chapter 2) in this thesis provides a good basis for the realization of a method for data-driven automated parameterization of energy flexibility key figures of the EFDM in the context of this thesis. The CRISP-ML(Q) process is particularly well suited to the complexity of energy flexibility in factories, as it takes quality assurance into account at every stage of the project. This focus on quality is

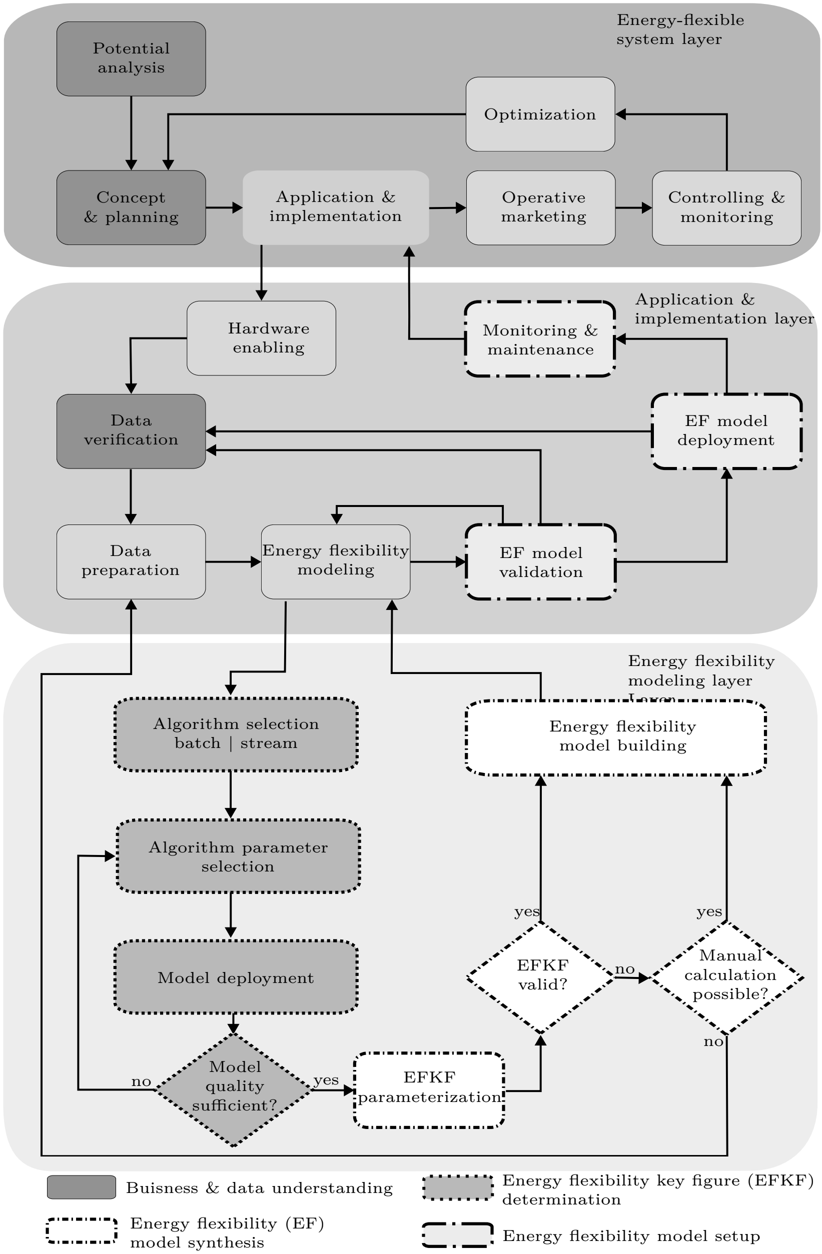


Figure 5.1: Flow chart of the DD-EFMod method for data-driven automated parameterization of energy flexibility models (own figure based on [13] and [67]).

essential for the parameterization of EFDMs, as energy flexibility needs to be modeled based on multiple data sources and variable conditions as they occur in production systems. In addition, the CRISP-ML(Q) process supports the use of advanced machine learning and data analytics algorithms, which are required to automate the parameterization of EFDMs. By adapting the CRISP-ML(Q) process steps, I can systematically address the challenges associated with accurate modeling of energy flexibility by ensuring that each step, from data verification over machine learning model deployment to energy flexibility model validation, is executed precisely. This structured methodology is essential to achieve the quality required for the modeling and parameterization of EFDMs.

The adaption of the CRISP-ML(Q) process to the automated determination of the key figures of the EFDM for the description and modeling of energy flexibility by applying machine learning or data analytic algorithms represents the DD-EFMod method. The overall consideration for developing the DD-EFMod method is divided into the three layers: **energy-flexible system layer** with focus on the complete energy-flexible system, the **application and implementation layer** with focus on the handling and implementation of the complete EFDM, and the **energy flexibility modeling layer** in which the automated parameterization of each relevant energy flexibility key figure of the EFDM is realized by the application of machine learning or data analytics algorithms. The overall methodology and the interaction between this three layers is shown in Figure 5.1 and discussed in detail in the following.

5.1.1 Layer One - Energy-Flexible System

This layer is based on the VDI process (see Figure 1.2) and defines the starting point and the process or system to be enabled in the context of the DD-EFMod method. As described in Section 2.1.1, this layer focuses on the holistic identification, enablement, implementation, deployment, and commercialization of energy flexibilities with the following steps:

1. ***Potential analysis*:** Initially, the energy-flexibility potential is evaluated both technically and economically. The input data, such as the power consumption, operating limits or system dependencies of a system, are collected with the help of an external software tool, the E-Flex Scanner. This tool supports those responsible in selecting relevant machines and systems for energy-flexible operation and helps to define company objectives for the use of energy flexibility [5, pp. 168–169].
2. ***Concept and planning*:** Detailed analysis and preparation for the implementation of selected energy-flexibility measures. In this step, the external software tool the Energy-Flexibility Audit can be used to systematically identify energy-flexibility measures and assess their potential, which is then documented for further processing [5, pp. 76–83].
3. ***Application and implementation*:** Technical realization of the energy-flexibility measures defining the corresponding EFDM and validation through test runs. This step is the primary focus of this thesis, representing the central step where theoretical energy-flexibility measures could be transformed into practical application-able load change profiles based on the EFDM to enhance energy-flexible operation.
4. ***Operative marketing*:** Start of marketing the achieved energy flexibility.
5. ***Controlling and monitoring*:** Monitoring and analysis of performance to identify potential for improvement.
6. ***Optimization*:** Enhancement of energy flexibility through continuous improvement.

The first two steps set the basis for successfully applying the DD-EFMod method. In the first step, the potential analysis, the energy-flexibility potential is determined to identify which possibilities of energy-flexible operation are technically and economically feasible. This is crucial as it determines which systems and processes are eligible. The second step builds on this by defining how and which energy-flexibility measures can be implemented. This detailed planning and preparation is essential and can be done with the help of the E-FLEX-Scanner, or the Energy-Flexibility-Audit [5, pp. 76–83]. In the context of the CRISP-ML(Q) process, these results are part of the business and data understanding. Both steps, potential analysis and concept and planning, are assumed as fulfilled as defined as the prerequisite number three in Chapter 4. The data collected in these two steps can be used in layer two of the DD-EFMod, the application and implementation layer, and further processed and analyzed to determine the key figures of the EFDM.

5.1.2 Layer Two - Application and Implementation

The focus of the DD-EFMod method is on the actual enabling, modeling, and implementation of energy flexibility measures, which are described by the EFDM. Therefore, the second layer of the DD-EF-Mod looks at the EFDM of an energy-flexible system as a whole and describes how it can be deployed. For this purpose, as it contains the modeling step of energy flexibility, the CRISP-ML(Q) process, with the steps data preparation, modeling, evaluation, deployment, and monitoring and maintenance is adapted and applied. This adaptation makes it possible to provide a methodological structure that covers the specific steps for implementing and operating an energy-flexible production. The DD-EFMod method uses this structure to effectively manage the complexity of energy consumption data and the dynamics of production systems. Data which are relevant for these steps can be taken from the previous steps of *potential analysis* and *concept and planning*, and further relevant data for the correct EFDM modeling can be determined through hardware enablement and data verification. Within the application and implementation layer, the second layer of the DD-EFMod method, various sub-steps are executed that are derived directly from the CRISP-ML(Q) process (see Chapter 2):

- ***Hardware Enabling***: Preparing and adapting the physical and technical infrastructure to collect relevant data and information to model energy-flexibility measures.
- ***Data Verification*** **and** ***Data Preparation***: Verify and prepare the collected data to ensure its quality and usability for the subsequent modeling processes.
- ***Energy Flexibility Modeling*** **and** ***Energy Flexibility Model Validation***: Modeling of the EFDM and its key figures by automated parameterization with the usage of machine learning and data analytics algorithms. The validation of the energy flexibility models applied in order to proof and quantify the automated parameterized EFDM in the energy-flexible system context.
- ***Energy Flexibility Model Deployment*** **and** ***Monitoring and Maintenance***: Implement the EFDM in the production environment and continuously monitor their performance.

Between these steps, dynamic feedback loops enable continuous feedback and adaptation of the models. These loops are for iteratively improving the energy flexibility models and adapting them to changing conditions. They enable an agile response to new findings and challenges during operation. As shown in Figure 5.1, corrective feedback between the following sub-steps are considered:

- from *energy flexibility model validation* to *energy flexibility modeling* and *data verification*
- from *energy flexibility model deployment* back to *data verification.*

These individual steps of the application and implementation layer are described below in their respective functions.

The ***Hardware Enabling*** stands at the beginning of creating a model for the description of energy flexibility. It contains the enabling of relevant hardware to ensure sufficient data availability and the associated information density. Various approaches and solution can be used for this purpose:

- data acquisition using hybrid measuring points according to [27]
- centralized or decentralized energy management systems [92]
- collecting raw data via temporary measuring technology
- readout of data points of the building automation [93]

Depending on the application, the requirements (e.g., sampling rate, consistency, and accuracy) must be defined individually, and the hardware must be selected accordingly. For more information, I refer to our previous work in Fuhrländer-Völker *et al.* [93], and Ahrens *et al.* [38]. As well as to the work of Lodwig *et al.* [92] with a focus on decentralized systems. In the context of this work, as defined in Section 4.3 as prerequisites number one and two, this step is assumed to be fulfilled.

The ***Data Verification*** step forms the basis for the subsequent steps of modeling energy flexibility. In this sub-step, data from various systems, including Enterprise-Resource-Planning (ERP), Energy Management System (EMS), machine data, data sheets, and product information, is verified. The data verification step is based on the CRISP-ML(Q) data quality verification sub-step, which sets requirements for data quality. The aim is to ensure the accuracy, consistency, and completeness of the data, which is a central condition for all subsequent steps of usage machine learning or data analytics algorithms for the automated determination of the energy flexibility key figures (EFKF) for parameterize the EFDM.
By reusing data from previous steps, duplication of work is avoided, and a consistent database is ensured. This is particularly important as *data verification* not only identifies errors, but also ensures that all relevant data and information for modeling energy flexibility is collected and interpreted correctly. Successful *data verification* makes it possible to make informed decisions about the data analytics and machine learning algorithms to be used. During data verification relevant metrics are defined. While non-technical metrics can be defined directly, technical metrics require further steps, especially those that are not trivial to

determine. In this work, the aim is to carry out automated parameterization of EFDMs to increase the depth and accuracy of energy flexibility models further. Therefore for a system under consideration, let the flexibility space be $\mathcal{F}$. This is described by

$$\mathcal{F} = \mathsf{f}(\mathcal{L}, \mathcal{S}, \mathcal{D}) \tag{5.1}$$

as a functional combination of the spaces of flexible loads $\mathcal{L}$, storages $\mathcal{S}$, and dependencies $\mathcal{D}$. Each of these spaces is spanned by the energy flexibility key figures defined in the EFDM (see Chapter 2 and Appendix A.1).
For the considered system, from the relevant defined EFKFs, it follows for the *data verification* step that $\mathbf{K} = [\mathcal{K}_1, \ldots, \mathcal{K}_i]$ with $i \in \mathbb{N}$ represents the vector of the EFKF to be determined. Data-driven modeling of the key figures is carried out based on time-variant measurement data as input variables $\mathbf{X}(t) = [x_1(t), ..., x_n(t)]$ with $n \in \mathbb{N}$. Accordingly, for

$$\mathcal{K}_i = f_i\left(x_1(t), \ldots, x_n(t)\right) \tag{5.2}$$

and thus

$$\mathbf{K} = \left[f_1\left(x_1(t), \ldots, x_n(t)\right), \ldots, f_i\left(x_1(t), \ldots, x_n(t)\right)\right] \tag{5.3}$$

apply. Taking the example of the flexibility space of the flexible load, it follows

$$\mathcal{L} = f(\mathbf{K}(\mathbf{X}(t))) \tag{5.4}$$

which means the modeling of the flexible load depends on the corresponding energy flexibility key figure, which depends on the input variables. This is equivalent for the spaces $\mathcal{S}$ and $\mathcal{D}$. By determining the relevant measurement data for the respective $\mathcal{K}_i$, relevant features required for automated key figure modeling can be derived in the next sub-step.

The ***Data Preparation*** forms a central element of the entire method.

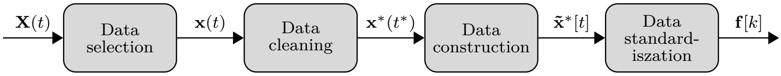


Figure 5.2: Data preparation step (own figure).

It significantly influences the quality of the machine learning or data analytics algorithm procedures used and, thus influences the accuracy of the identified EFKFs and the resulting EFDMs [67]. It is an iterative step due to feedback loops from subsequent steps (as shown in Figure 5.1). This ensures continuous improvement of both the machine learning or data analytics algorithms and the EFDM. The *data preparation* includes the sub-steps *data selection*, *data cleaning*, *data construction*, and *data standardization* as shown in Figure 5.2

The sub-step *data selection* includes the actual selection of relevant data samples and *feature selection*. In this phase, according to the CRISP-ML(Q) methodology, raw input signals or datasets $\mathbf{X}(t)$ are formed that are suitable for advanced analytical processing. This step involves several key transformations like moving average, normalization or standardization (see Chapter 2). The selection and refinement of the raw data $\mathbf{X}(t)$ leads to a more focused dataset $\mathbf{x}(t)$. This process involves identifying and extracting the most relevant data features (e.g., power values, machine states, or energy consumption) that are crucial for the *energy flexibility modeling*. Data and information that provide only little added value for achieving the target variable will be excluded. This avoids overfitting and reduces the computational effort of the resampled application [67].

This is followed by cleaning and smoothing the data values of $\mathbf{x}(t)$. During this stage, tasks such as outlier removal (e.g., IQR-Method) and denoising (e.g., Gaussian low-pass filter) are done to create more accurate and reliable data. Unwanted interfering signals, outliers, and missing data points are filtered out. Thus, an increase in data quality takes place [67]. These pre-processing steps are essential when the data has different scales, typically for modeling EFKF based on different raw data. This transformations resulting in $\mathbf{x}^*(t^*)$ as the cleaned dataset.

This step ensures the data is free of anomalies and noise, which could otherwise skew the analysis.
In the *data construction* sub-step, the feature engineering occurs. In this process, new features can be derived based on expert knowledge, data, or existing information. This can be done, for example, by generating new feature spaces or transformations (e.g., from the time domain to the frequency domain). Overall this leads to the contruction data signal $\tilde{\mathbf{x}}^*[t]$ which is processed further as shown in Figure 5.2 by using standardized data types, formats (JavaScript Object Notation (JSON), Comma-separated values (CSV)) and sampling. Finally this leads to the feature vector $\mathbf{f}[k]$ as the result of the *data preparation* step. Each of these sub-steps plays a relevant role in ensuring that the raw data is not only clean and reliable but also rich in information and structured in a way that machine learning and data analysis techniques are usable to automate the EFKF determination.

The ***Energy Flexibility Modeling*** step represents the third layer of the DD-EFMod. The automated modeling of the energy flexibility is done by the application of machine learning and data analytics algorithms for determination of the relevant EFKF for each energy-flexible system. Therefore the input of this step are the preprocessed data $f[k]$ and the output are the EFDM with the determined EFKFs. The exact procedure and the individual steps, cf. Figure 5.1, are described in the following Section 5.1.3.

The ***Energy Flexibility Model Validation*** is the step where the automated parameterized EFDM is validated. This step is a part of the energy flexibility model setup sub-process, as shown in Figure 5.3. The results of the determined energy flexibility key figure (EFKF) must be evaluated for correctness regarding the complete EFDM into account. On the one hand, this can be done manually by experts with sufficient knowledge of the domain and the system. On the other hand, it is possible to perform this automatically using validation procedures. The

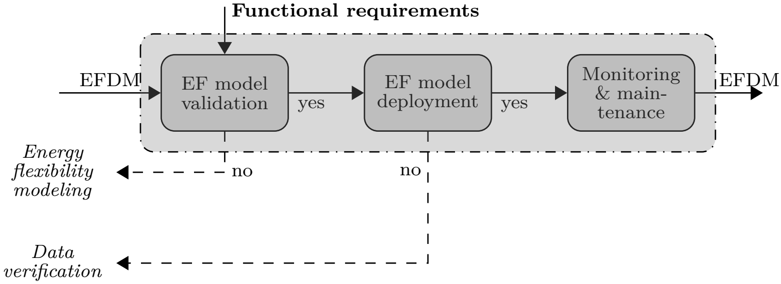


Figure 5.3: Energy flexibility model setup sub-process (own figure).

validation of the EFDM can be done by simulations as well as on real systems. Various conditions have to be evaluated [67]:

- Accuracy: Are the EFKF of the energy flexibility model correct, and do they meet the success criteria?
- Feasibility: Are the process parameters and technical limits met?
- Robustness: Which process and system tolerances are considered to react to disturbances and process deviations?
- Explainability: Are the EFDM parameterization results transparent?

Findings and possible improvements identified in this step are fed back to the previous *data verification* and *energy flexibility modeling* steps via feedback loops. This ensures the successive improvement of the EFDM quality by adjusting the EFKF. If the validation is successful, a deployment of the energy flexibility model must be tested.

The ***Energy Flexibility Model Deployment*** is the application step, where the previously automated parameterized EFDM is applied. For this purpose, the EFDM is transferred to operational mode. The parameterized EFDM must be checked for actual feasibility and acceptance by the user. A deployment strategy should be applied. This means that it is defined on which instance the EFDM are stored, how the resulting flexible load measure is to be transferred to the systems for energy-flexible operation, and how the flexible load measure is implemented by the energy-flexible system. This can be done manually by the machine operator or automatically via the machine's Programmable Logic Controller (PLC). Identified obstacles, system behavior, or errors that have not yet been considered should be fed back to the previous *data verification* step to adapt the key figures of the EFDM accordingly. In addition, considering an automated fallback mechanism, as we shown in [93], should safeguard the implementation. This ensures safe system operation by automatically switching off the flexible load measure to the reference case.

The ***Monitoring and Maintenance*** step is essential for maintaining the correctness of the EFDM and the automated determined corresponding EFKFs. Monitoring and updating the EFDM is necessary due to process changes, adjustments to the operating strategy, incorrect data transfers, or wear and tear. This step is not limited to monitoring the EFKF of the EFDM but is an extension of the *controlling and monitoring* step in the layer one. The update, to take account of identified changes, must be carried out while running through the other layer one steps, including the *optimization* step. This is the only way to identify and improve higher-level systematic changes.

5.1.3 Layer Three - Energy Flexibility Modeling

The third layer, the *Energy Flexibility Modeling layer* of the DD-EFMod method describes the process of how individual energy flexibility key figures (EFKF) can be automatically determined and so the energy flexibility model is parameterized. This layer is divided in two sub-processes, the *energy flexibility key figure determination* (Figure 5.4) and the *energy flexibility model synthesis* (Figure 5.5). For this purpose based on the input from the previous *data-preparation* step in layer two, a distinction is made between the available data type, streaming data or batch data, in the *algorithm selection* sub-step. Based

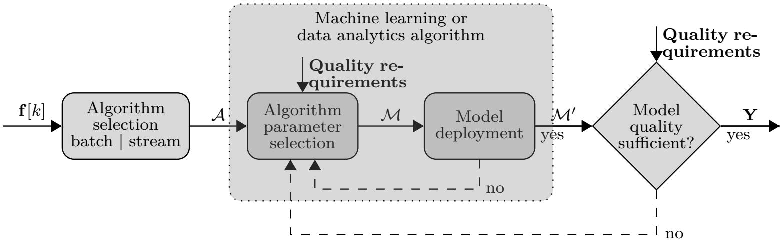


Figure 5.4: Energy flexibility key figure determination sub-process for automated determination of a single energy flexibility key figure of the EFDM (own figure).

on this, an appropriate machine learning or data analytics algorithm is applied to automatically determine the relevant key figures of the EFDM. Adapted from the CRISP-ML(Q) process, the quality requirements (defined in Section 4.3) of the machine learning algorithm must be evaluated and, if necessary, improved by adjusting the algorithm parameters. If the machine learning model is of sufficient quality, the EFKF is parameterized and evaluated. If requirements meet the actual EFKF correctly, the entire energy flexibility model can build in the step *energy flexibility model building* which is then transferred back as the output to the second layer. If the EFKF identified by the machine learning or data analytics algorithm is incorrect, a manual EFKF calculation should be performed. If this is also not possible, e.g., due to missing information or data, the process of this layer three *energy flexibility modeling* must be started again with new input data. Each sub-step of layer three is explained in detail in the following.

Algorithm Selection is based on the previous steps of *data verification* and *data preparation*, the type of machine learning or data analytics algorithm $\mathcal{A}$ to be used for the automated determination of the EFKF is selected. Conventional offline batch machine learning or data analytics algorithms can be used if sufficient historical data are available. In the other case, where only temporary measurement data were available, online data stream mining algorithms can be selected (see Chapter 2). In addition, existing framework conditions such as computing capacity and robustness must be considered when selecting an algorithm.

Algorithm Parameter Selection is the sup-step, which defines the measured data and features for the selected algorithm. In addition, quality criteria for the evaluation of the selected machine learning or data analytics algorithms must be selected (cf. Chapter 2). In this step the selected algorithm $\mathcal{A}$ results in a specific model $\mathcal{M}$.

Model Deployment includes training and applying the selected machine learning or data analytics model $\mathcal{M}$. Depending on the energy-flexible system and the EFKF to be determined, various combinations of algorithms may be possible. This step is based on the deployment according to [67]. If the internal algorithm finishes the calculation and iterations, the specific machine learning or data analytics model $\mathcal{M}'$ results. With this model $\mathcal{M}'$ the automated determination of the EFKF can derived.

Model Quality Sufficient is used as the sub-step to evaluate the deployed machine learning or data analytics $\mathcal{M}'$ and thus decide whether the results of the algorithms are usable. According to [67], the quality criteria of reproducibility, performance, robustness, accuracy, and explainability can be included in this model evaluation. If all criteria and requirements are met, the next step is to determine the corresponding EFKF from the output $\mathbf{Y}$. Otherwise, if the model quality does not meet the required conditions, a new training with adjusted *algorithm parameter selection* must be carried out.

The sub-process *energy flexibility model synthesis* (see Figure 5.5) starts with the step ***EFKF Parameterization***. This step evaluates the result $\mathbf{Y}$ of previous data-driven automated *EFKF determination* sub-process based on the selected machine learning or data anayltics algorithms for a single EFKF. For this purpose, the output variable of the *EFKF determination* sub-process $\mathbf{Y}$ is assigned to the corresponding energy flexibility key figure $\mathcal{K}_i$ and its attributes according to the energy flexibility model, in the case of this work the EFDM [29] as

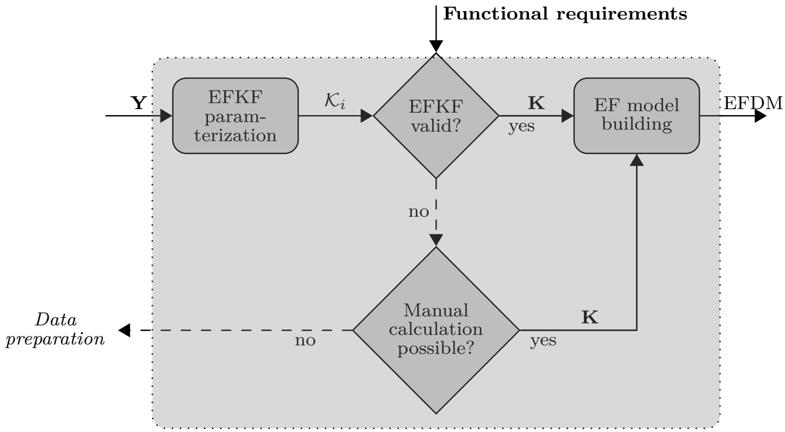


Figure 5.5: Energy flexibility model synthesis sub-process to assign the machine learning or data analytics model output $\mathbf{Y}$ to the corresponding energy flexibility key figure $\mathcal{K}_i$, validate them, and parameterize the EFDM (own figure).

shown in Appendix A.3, for further processing.

The step of the ***EFKF validation*** is to check the respective specific key figures or their attributes for correctness. The evaluation is based on the defined criteria (see Chapter 4). The validation can be found on expert knowledge, simulations, or manual calculations. The main part is to check that the operating limits b_1 as the lower limit and b_2 as the upper limit are met for a determined key figure $\mathcal{K}_i$. This can be done using

$$b_1 \leq \mathcal{K}_i \leq b_2. \tag{5.5}$$

In the case that several operating conditions $\mathbf{B} = \{b_1, b_2, \ldots, b_n\}$ are to be fulfilled, a logical operation

$$(\mathcal{K}_i > b_1) \wedge (\mathcal{K}_i < b_2) \wedge \cdots \wedge (\mathcal{K}_i > b_n) \tag{5.6}$$

can be used for validation. In the event of successful validation, $\mathbf{K}$ can

be used as a vector with the individual key figures in the next sub-step of the synthesis process, see Figure 5.5.
The ***Energy Flexibility Model Building*** step is to span the flexibility space $\mathcal{F}$. In this process, this $\mathcal{F}$ is converted into the corresponding standardized data format. In this work, the JSON schema format published in Lindner *et al.* [29] describes the energy flexibility space as EFDM. Therefore our developed external service the EFDM GUI, can be used [94] (see Appendix A.1.1).
If, on the contrary, the validation of a K_i cannot be carried out successfully, it must be checked whether a ***manual calculation*** of the corresponding key figure is possible. If not, the modeling process must be restarted as shown in Figure 5.1, starting with the *data preparation* step. If a manual determination of the key figure is possible, as shown in our previous work [30], the flexibility space $\mathcal{F}$ can be spanned on this basis.
After completion of the *energy flexibility model building* sub-step, the modeling of the energy flexibility is completed, and the automated parameterized EFDM is transferred to the *application and implementation* (see Figure 5.1). The EFDM is transferred to the second layer *energy flexibility model validation* step (see Section 5.1.3).

The developed structure of the DD-EFMod method enables a procedure to realize the automated parameterization of the Energy Flexibility Data Model by determine the relevant energy flexibility key figures of the Energy Flexibility Data Model with the application of machine learning or data analytics algorithms. A software concept is presented in the following section to demonstrate its feasibility and prototypical implementation.

5.2 Software Concept

To ensure the applicability of the DD-EFMod method, I developed a corresponding software concept. This is visualized in the Unified Modeling Language (UML) component diagram in Figure 5.6. The

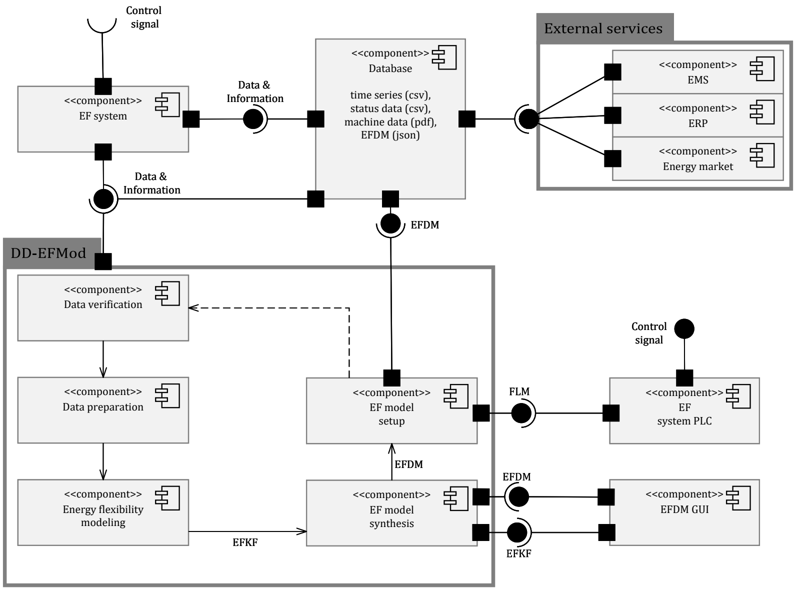


Figure 5.6: Software concept for prototype implementation as UML component diagram (own figure).

software concept corresponds to a prototypical implementation of the developed DD-EFMod method. The focus here is on demonstrating that implementing the method can be realized under consideration of the functional requirements defined in Chapter 4. The software concept is structured around several key components:

- `Energy-flexible system`, referred to as the *EF System* component, which serves as the main data source. Data and information are transmitted to a central database via corresponding interfaces (e.g., Open Platform Communications Unified Architecture (OPC UA)).

- The `Database` allows various data formats, such as time series (CSV), status data (CSV), machine data (Portable Document Format (PDF)), and the Energy Flexibility Data Model (EFDM) as JSON format to be stored and managed.

- Data and information can be transferred via interfaces from the `database` and the `energy-flexible system` to the `DD-EFMod` structure (realized in python programming language (see Section 6.2)). This is made up of the main components:
  - `data verification`
  - `data preparation`
  - `energy flexibility modeling`
  - `energy flexibility model synthesis`

  Each sub-component corresponds to the DD-EFMod method steps described above in Section 5.1. Furthermore, an interface to the central `database` is provided for the setup component to save the determined EFDMs.
- Interaction with the `external service EFDM Graphical user interface (GUI)` can transform the determined key figures of the EFDM in the standardized JSON structure. This external service is explained more in detail in Appendix A.1.1.
- A defined flexible load measure can be transmitted via an interface to the `energy flexible system PLC`. This means that the system can implement a flexible load measure derived from the EFDM.

By using appropriate interfaces (like our previuos work [95]), the `database` can also be enriched with information from `external services`, including EMS (energy management system), ERP (enterprise resource planning), or the energy market. This information can be used in the automated determination of the key figures of the EFDM.

5.3 Interim Summary

The primary objective of this work is to simplify and automate the enabling process for energy-flexible operation of production infrastructure (see Chapter 4). To achieve this, the DD-EFMod method, as shown in Figure 5.1, has been developed to facilitate the necessary modeling of energy flexibility through data-driven approaches. This method integrates and adapts the CRISP-ML(Q) process, extending the VDI process of enable factories to energy-flexible operation during the *application and implementation* step. The *application and implementation* layer of the DD-EFMod method specifically use the different steps *data verification*, *data preparation*, and the *energy flexibility model setup* to describes energy flexibility, reducing the need for manual intervention. The *energy flexibility modeling* layer further automates the process by determining the individual energy flexiblity key figures (EFKF) of the Energy Flexibility Data Model using suitable machine learning and data analytics algorithms. The DD-EFMod method provides structured steps to automate and simplify the modeling of energy flexibility. The DD-EFMod method provides structured steps to automate and simplify the modeling of energy flexibility, ensuring efficient and effective implementation of energy flexibility. Based on the developed method with the individual steps, I derived a software concept for feasibility. This software concept consists of modular subcomponents and has software and hardware interfaces to enable interactivity between external software services and the energy-flexible system under consideration. The method development and the software concept development were carried out considering the requirements and quality criteria (see Section 4.3). The following describes how these functional requirements on the method (FR-M), functional requirements for energy flexibility modeling (FR-EF), and quality requirements (QR) are addressed:

- The applicability of the methodology (FR-M 1) is addressed by the software concept, using standardized interfaces and programming languages. In addition, the applicability is also supplemented by the fulfillment of the other criteria.
- The chosen division into layers, sub-steps and into corresponding software components and steps ensures modularity (FR-M 2) so

that only sub-steps can be executed if required.

- The requirement of transferability (FR-M 3) is met, as the method can be used to calculate the key figures of a model to describe energy flexibility, which in turn can represent individual energy-flexibility measures.
- The reproducibility of the results when applying the method (FR-M 4) is ensured by iteratively running through the individual sub-steps and saving the output data and results in the database.
- The feasibility (FR-EF 1) and accuracy (FR-EF 2) of the automated determined EFKF and the parameterized energy flexibility model can be ensured by the sub-process of the *energy flexibility model setup* through validation, deployment, and monitoring of the energy flexibility model.
- The *EFKF validation* step built into the method ensures that the energy flexibility key figures consider the possible identified maximum limits (FR-EF 3 and FR-EF 5) and are also explainable and comprehensible (FR-EF 4).
- The defined criteria for the machine learning and data analytics algorithms used (QR 1-5) to determine automatically the EFKF can be considered in the *algorithm selection* step and checked for their quality as part of the *model deployment* step and machine learning and data analytics *model quality sufficency* evaluation.

The validation of the DD-EFMod method is carried out in the following chapters to check the applicability of the DD-EFMod method and the associated software concept. I will first discuss the use case in the next chapter, including the machines and components involved (Chapter 6). This is followed in Chapter 7 by the implementation and validation under consideration of the results.

6 Use Case and Application at the ETA Research Factory

”Almost everything is like a machine.”

Ray Dalio

This chapter describes the use case after showing the development of the method in the previous chapter. For this purpose, I first describe the machines used in the use case in Section 6.1 and discuss their systematic technical relationship. Then, in Section 6.2, I describe how the machines are connected to aggregate all relevant data from the different systems. This is followed by the description of four scenarios which focus on validation of the method in Section 6.3.

6.1 Process and Machines of the Use Case

To ensure the practical applicability of the developed DD-EFMod method for data-driven energy flexibility modeling, I evaluated the approach at the ETA Research Factory. The ETA Research Factory is located at the Technical University of Darmstadt and represent a real-scale research factory [96]. At the ETA Research Factory a holistic approach for an energy-efficient factory is realized. Energy efficiency is achieved by integrating the production machines, the technical building service systems, and the building shell in a thermal network. This factory setup aligns well with the RAMI 4.0 framework, which emphasizes the integration of digital and physical processes across different layers of a manufacturing system. The research factory is equipped with an exemplary production process chain for metal processing and the required technical building service systems. This production process contains the steps, lathing, cleaning, heat treatment, grinding, and final cleaning as shown in Figure 6.1.
For the validation use case of the developed DD-EFMod, I focused on

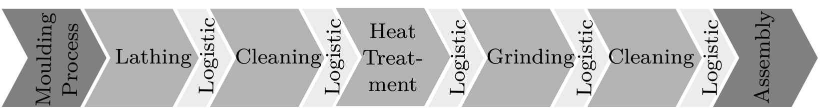
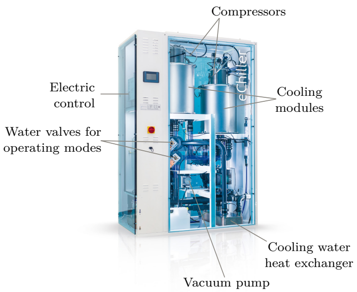
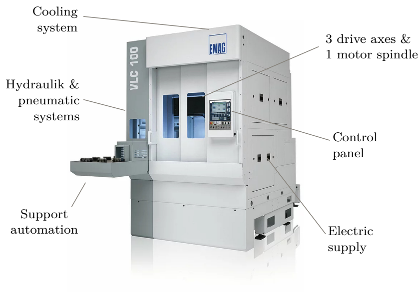


Figure 6.1: Production process chain of the ETA Research Factory (own figure adapted from [96]).



(a) Cooling machine eChiller45-II [97].



(b) Grinding machine tool EMAG VLC-100GT [98].

Figure 6.2: Flexible loads of the use case (own figure).

the grinding sub-process. I have chosen this sub-process for validation to examine a system with several flexible loads of different types, storages, and dependencies. This allows a validation of the applicability of the DD-EFMod method within a RAMI 4.0 structured environment under consideration of the defined functional requirements on the method (see Section 4.3).

The central system of the grinding process is the EMAG VLC-100GT [98] machine tool (see Figure 6.2b), which is integrated into the higher-level production process. In the context of the production process, the machine is charged with workpieces from a material storage via support automation and grinded in the machining area. The finished component is then forwarded to the product storage, where it is stored and transferred to the next production step.

To ensure process stability and take energy efficiency aspects into account, the machine is supplied with cooling via the factory's central heating and cooling system. In the application case, central cooling is provided by the eChiller45-II cooling machine from Efficient Energy GmbH [97, 99] (see Figure 6.2a). Both machines are electrical consumers must be cooled while operating, and therefore they are connected to the building's central cooling supply system, which allows the buffer storage of the central cooling supply system to be considered

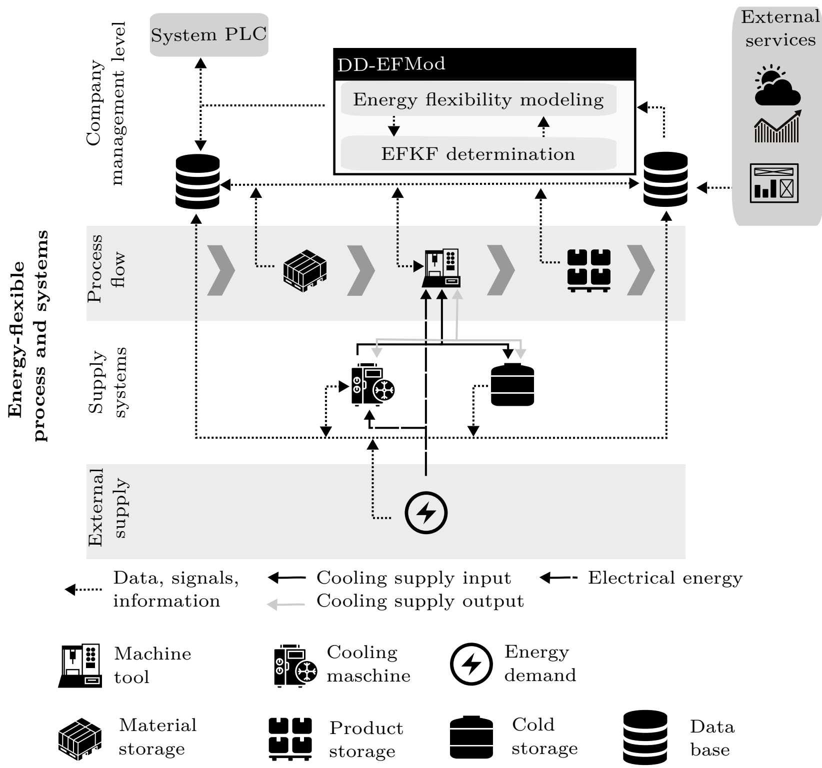


Figure 6.3: Use case process and systems their connections, information, and data flows between the sub-systems (own figure).

[100]. As mentioned in Section 4.3, a central prerequisite for the application of the DD-EFMod method is that all relevant components and systems for which an energy-flexibility measure is to be created provide the relevant data and information with the help of ICT systems (see prerequisite number two in Section 4.3). Therefore in the ETA Research Factory we implement a framework which we developed over the last years [95] to enable different machine types, various databases and monitoring systems implemented in the ETA Research Factory. This framework facilitates the data integration and management required for effective energy flexibility modeling, reflecting the hierarchical and

functional structuring proposed by RAMI 4.0 (see Chapter 2). All relevant components and their energy supplies and data connections of my validation use case are shown in Figure 6.3.

6.2 Hardware and Software Enabling

As mentioned in Section 4.3, this work focuses on the parameterization of energy flexibility models and the automated determination of technical energy flexibility key figures. This is possible by integrating the software concept presented in Section 5.2. Therefore, the hardware capability of all relevant systems is assumed to be fulfilled (see prerequisites 1-4 in Chapter 4). We allready presented the hardware enablement in Fuhrländer-Völker *et al.* [93]. Also refer to Bauer *et al.* [101] as well as to the results of Sossenheimer [27] and Fuhrländer-Völker [102]. To address the functional requirement on the method number one for the applicability of the DD-EFMod method as part of the implementation of my software concept, I used the open-source standard libraries listed in Table 6.1. The method was implemented in

Table 6.1: Software and hardware used for implementation of the software concept (own table).

Software	**Version**	**Reference**
Python	3.10.11	[103]
scikit-learn	1.3.2	[104]
scipy	1.11.3	[105]
numpy	1.26.2	[106]
pandas	2.0.3	[107][108]
river	0.21.0	[109]
Hardware		
System	Lenovo 20WE	
Operating system	10.0 Pro 64 Bit	
Processor	Intel(R) Core(TM) i7 2.80GHz	
Memory	16 GB	

the specified open-source Python libraries to enable the broadest possible applicability without the vendor lock effect of software licenses. The implementation was carried out using the hardware also set in Table 6.1. This is a standard workstation, which also ensures simple implementation and transferability. There is no need for special high-performance computers or cloud applications, as at least the prototype implementation in the context of this work does not require intensive computing power. This work focuses on determining and calculating the technical key figures describing energy flexibility. Four different scenarios are discussed below.

6.3 Scenario Definition

All relevant components, energy supplies, and data connections of my validation use case are shown in Figure 6.3. As shown, the processes and systems that should operate energy-flexible are the grinding machine tool and the cooling machine, which extend their flexible potential by considering product storage and cold storage. These systems and their connections result in the following scenarios, which are used to validate developed DD-EFMod method:

Scenario 1: The focus is on the EMAG VLC-100GT machine tool to show that the method works for a machine modeled as the EFDM class flexible load. I will also validate the deployment of batch and data stream machine learning algorithms for automated determination of the EFKF.

Scenario 2: This extends scenario one by considering the machine tool EMAG VLC-100GT combined with the product storage to show the DD-EFMod methods application for the EFDM class storages.

Scenario 3: Validation of the transferability of the method is demonstrated with this third scenario. For this purpose, the DD-EFMod method is transferred to another machine type, the cooling machine eChiller45-II, and the cold storage.

Scenario 4: The focus here is on two flexible loads, the machine tool EMAG VLC-100GT together with product storage and considering the cooling machine eChiller45-II with the cold storage to validate the DD-EFMod capability for automated determination of the EFKF of the EFDM class dependency.

In addition to the four scenarios mentioned above, an evaluation of the potential energy and cost savings that are possible through the use of energy-flexibility measures defined as flexible load measures, based on the automated parameterized EFDM, on different energy markets is carried out. The implementation and application, as well as the discussion of the results, are discussed in the next Chapter 7.

6.4 Interim Summary

This chapter first describes the use case for the validation of the DD-EFMod method I developed as part of this thesis. For this purpose, the process chain of the ETA Research Factory was described, and the individual machines, the machine tool EMAG VLC-100GT, and the cooling machine eChiller45 are relevant. I also listed the appropriate software that I used while implementing the software concept of the DD-EFMod method. This was followed by defining the four scenarios used to validate the method.

7 Implementation and Validation

”An experiment disproving a prediction is discovery.”

Enrico Fermi

This chapter shows the validation of the developed DD-EFMod method, which was applied to the use case and four different scenarios (see section 6.3). A separate system boundary is considered for each scenario in order to test different applications of the method. For this purpose, each scenario is divided into three sub-steps. First, the framework conditions of the scenario and the energy flexibility key figures to be determined are discussed. This is followed by an explanation of the implementation based on the sub-steps using the DD-EFMod method. Finally, the results of the individual sub-steps for each scenario are presented and discussed. Following the four scenarios, the implementation of the energy flexibility measures *change processing sequence* and *shift start of job* defined as flexible load measures based on the automated parameterized Energy Flexibility Data Models of the four scenarios is validated. This additionally evaluates the implementation of the DD-EFMod method in practice. The chapter concludes with a summarizing interim conclusion. To ensure sufficient traceability of the validation of this work, all measurement data, implemented algorithms, and results used in this work are documented and made available as a publicly accessible TUdatalib repository [110].

7.1 Scenario 1 - EMAG GT

The focus of this scenario is on the EMAG VLC-100GT machine tool (see Chapter 6) to show that the method works for the EFDM class flexible load. In this scenario, I will also investigate the use of offline and online streaming machine learning algorithms to calculate the corresponding EFKF.
Based on the method (see Figure 5.1), the first step is to determine which energy-flexible system is to be examined (layer 1). The system boundary of this scenario in the use case presented in the previous chapter is shown in Figure 7.1 and is defined around the machine tool EMAG VLC-100GT itself. This means that only the energy supply, particularly the electrical power consumption, is considered as a sim-

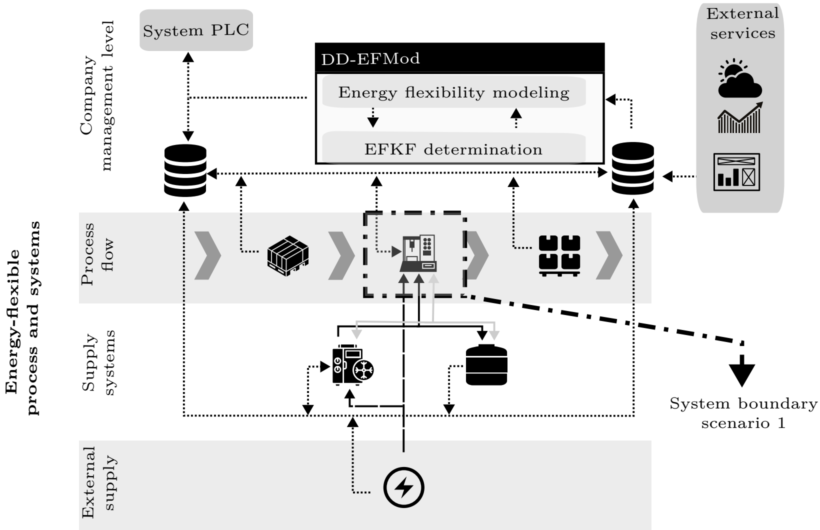


Figure 7.1: System of scenario 1 (own figure).

plification in this scenario to analyze and determine energy flexibility. The next step is to analyze and select the data required to determine the relevant technical EFKF for describing the energy flexibility of the machine. For this purpose, an exemplary electrical power consumption of the machine, shown in Figure 7.2 recorded on 31.08.2023, is examined as a starting point and reference case operation load profile.

7.1.1 Key Figure Definition

The *data verification* begins with the definition of the relevant EFKF. Assuming that the EFDM is used to describe energy flexibility, as described in Chapter 2.1.2. In the following, it is assumed that the EFDM according to [29] is used to describe the existing energy flexibility. In the case of the EFDM class flexible load, the following selected submodel of technical key figures is shown in Table 7.1.
As discussed in the fundamentals chapter, not all key figures are always

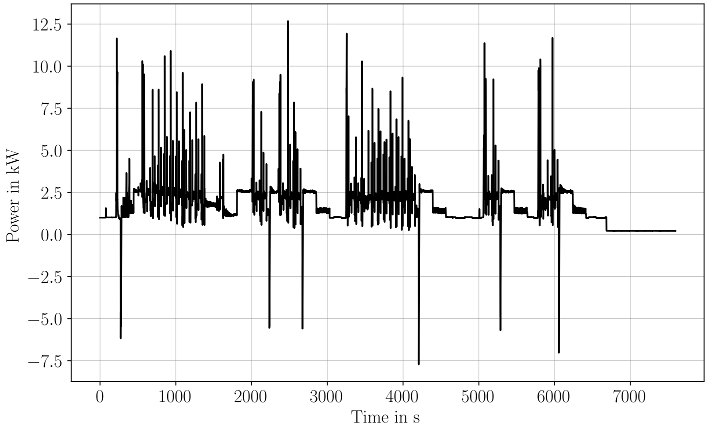


Figure 7.2: Electrical power consumption of EMAG GT (own figure).

necessary. For this scenario, determining the power states is defined as the minimum criterion, and the other technical key figures are considered optional. This results in the vector of relevant EFKF

$$\mathbf{K} = [\mathbf{P}, T_{\text{Rea}}, T_{\text{V}}, T_{\text{H}}, \nabla P_{\text{Act}}, \nabla P_{\text{Mod}}, \nabla P_{\text{Dea}}, T_{\text{Reg}}] \,. \tag{7.1}$$

I examined in the *data verification* step the measured variables and input data listed in Table 7.2 as the data basis for the next steps. In the first step, I examined the measurement variables mentioned based on system knowledge. The aforementioned prioritization could be carried out based on these. Based on this prioritization, the definition of the input variables follows

$$\mathbf{X}(t) = [P(t), s_{\text{st}}, s_{\text{wk}}, s_{\text{op}}, s_{\text{da}}, t_{\text{pro}}] \tag{7.2}$$

to determine the flexibility space $\mathcal{L}$.

Algorithm 1 Data Verification and Preparation

Input: Dataset of measured data $\mathbf{X}$
Output: Feature vector $\mathbf{f}[k]$
1: Load dataset $\mathbf{X}$;
2: Analyze power values $P(t)$:
3: Calculate min, max, and mean of $P(t)$;
4: Apply IQR method to detect and filter outliers in $P(t)$;
5: Compute Moving Average $\mathbf{x}_{\mathrm{MA}}$ of $P(t)$ with window size M (Eq.: 2.11);

7.1.2 Implementation

The next step in layer 2 is *data preparation*. Here I have processed the input data from $\mathbf{X}(t)$ using standard methods (e.g., normalization, moving average, see Chapter 2), from which the respective feature vector $\mathbf{f}[k]$ is derived.
The example code of the implementation for this step is shown in Algorithm 1 as an example for $\mathbf{X}(t) = [P(t)]$. The results are shown and discussed in the next section. This is followed by the step of *energy flexibility modeling*, starting with the *algorithm selection* sub-step in

Table 7.1: Technical key figures in the EFDM for describing the flexibility space and their feasibility levels of scenario 1 following Lindner *et al.* [29] (own table).

Class	**Key Figure**	**Description**	**Feasibility Level**
Flexible Load	$\mathbf{P}$	Power states	1
	T_{Rea}	Reaction duration	2
	T_{V}	Validity	2
	T_{H}	Holding duration	2
	∇P_{Act}	Activation gradient	2
	∇P_{Mod}	Modulation gradient	2
	∇P_{Dea}	Deactivation gradient	2
	T_{Reg}	Regeneration duration	2

Table 7.2: Priority of measured values of the EMAG GT for scenario 1 (own table).

Measured Value	**Symbol**	**Unit**	**Priority**
Electric Power	P	W	●
Machine state - standby	s_{st}	binary	●
Machine state - working	s_{wk}	binary	●
Machine state - operational	s_{op}	binary	●
Machine state - disabled	s_{da}	binary	●
Processing time	t_{pro}	s	●
Electric voltage	U	V	◑
Electric current	I	A	◑
Frequency	f	Hz	◔
Machine temperatur	T_{pro}	°C	◔

layer three of the DD-EFMod. In this scenario, the focus is initially on automatically determining the power states of the EMAG GT, as this is the minimum requirement (see Table 7.1). For this purpose, a offline batch clustering algorithm is first selected to quantify the possible machine states and their associated power states based on historical data. As a clustering algorithm, I first select a batch K-means cluster algorithm (see Chapter 2). This was implemented on the basis of [58] in Algorithm 2 using [111]. The deployment of the algorithm is followed by the *model quality sufficient* validation step of the machine learning algorithm (see Figure 5.4). I have used the Algorithm 3 for this purpose. If the quality measures are sufficient, the *energy flexibility model synthesis* sub-process follows (see Figure 5.5). Thus, based on the clustering results, the *EFKF parameterization* of the power states $\mathbf{P}$ follows. One cluster c_i represents one power state. Each of these cluster centers is associated with a power state P_i, where $P_{i,\min}$ and $P_{i,\max}$ represent the corresponding minimum and maximum power values of the power state. This applies

$$P_i = [P_{i,\min}, P_{i,\max}] \tag{7.3}$$

Algorithm 2 Deployment: K-Means Clustering

Input: $\mathbf{x}_{MA}$ with $\mathbf{C}$ clusters
Output: Custercenters $\mathbf{C}$, Clusterboundries $\mathbf{C}_{\mathrm{B}}$
Apply K-means clustering with c_i clusters;
repeat
    Assignment of the data from $\mathbf{x}_{MA}$ to the respective cluster with the next cluster center (Eq.: 2.12);
    Recalculation of the c_i cluster centers as centers of the objects of the individual clusters (Eq.: 2.13);
until Cluster partition remains unchanged;
Initialize indentify cluster boundaries;
for each data and center in $\mathbf{C}$ **do**
    Calculate lower boundary as 10% below the center as $c_{i,\min}$;
    Calculate upper boundary as 10% above the center as $c_{i,\max}$;
end for

where

$$P_{i,\min} = c_{i,\min} \tag{7.4}$$

$$P_{i,\max} = c_{i,\max} \tag{7.5}$$

for all clusters and power states. These must then be checked according to the *energy flexibility model synthesis* and saved in the corresponding EFDM data format. Once the power states have been calculated, the minimum requirement for determining the power states is fulfilled (see Table 7.1).
To determine the other EFKFs, the power states already identified were the basis. For this purpose, the sub-processes of *EFKF determination*

Algorithm 3 Model Quality: Clustering Quality

Input: $\mathbf{C}'$ clusters
Output: Cluster Performance Values
Calculate the Silhouette Score for the data and clusters (Eq.: 2.20);
Calculate the Davies-Bouldin Score for the data and clusters (Eq.: 2.22);

Algorithm 4 Deployment: Power State Duaration Analysis

Input: Power Data $P(t)$, Operation states $\mathbf{S}$
Output: Intervals of Power States $\mathbf{I}$, Power State Durations $\mathbf{D}$,

```
Allocation machine state temporal intervals I;
Define power states S;
for each mode s_i in S do
    Identify continuous intervals I_s where
     machine state s is constant;
    Record start and end indices of each interval I_s;
    I[s_i] ← I_s;
end for
Analyze Durations of I:
     Calculate duration for each interval in I;
     Identify unique power states in D.
     Determine minimum and maximum duration T_H
     for each unique power state.
```

(see Figure 5.4) and *energy flexibility model synthesis* (see Figure 5.5) are rerun for each EFKF to be determined (see Equation 7.1).
To identify the key figure power state duration T_{H} of the grinding machine, the different machine operation states are defined as
$\mathbf{S}$ with $s_i \in \{Working, Operation, Standby, Disabled\}$.

The automated determination of the key figures holding duration is done by deployment of Algorithm 4. Here, $\mathbf{D}$ describes an unspecific data vector with all holding durations T_{H}.
To determine the key figures power gradients (∇P_{Act}, ∇P_{Dea}, ∇P_{Mod}) for each power state change, the gradients are calculated with

$$\nabla \mathbf{P} = \frac{(P_{end} - P_{start})}{t_{end} - t_{start}}. \tag{7.6}$$

The identification of the power gradients is done by Algorithm 5. Thereby $\mathbf{T}$ is an unspecifc data vector for all transitions.
To automatically determine the key figure reaction duration T_{Rea}, it is necessary to analyze the processing time of a workpiece. This is based on the assumption that the shortest time horizon of a energy-flexible

Algorithm 5 Deployment: Gradient Analysis

Input: Power Data $P(t)$, Power States Transitions $\mathbf{T}$
Output: Average Gradients for Transitions

```
Determine current power state gradient for value:
for each transition pair (fromState, toState) in T do
    for each Data Value in P(t) do
        Check if power state transition occurs;
        if transition starts then
            Record start power and time;
        else if transition ends then
            Record end power and time;
            Calculate gradient (Eq.: 7.6);
        end if
    end for
    Calculate average gradient ∇P for the transitions;
end for
```

operation is based on the electricity market. For the Intraday energy market, this is divided into $T_{\text{Intraday}} = 15\,\text{min}$ sections [112]. This means that the cycle time corresponds to $t_{\text{cycle}} = 15\,\text{min}$. From the analysis of the load profiles of the machine tool (see Figure 7.2) and the process times t_{pro}, the following relationship emerges

$$t_{\text{pro}} = \frac{t_{\text{cycle}}}{n} \quad \text{with} \quad t_{\text{cycle}} = T_{\text{Intraday}} \tag{7.7}$$

with n number of processed parts, which directly results in the maximum reaction duration

$$T_{\text{Rea}} = t_{\text{pro}}. \tag{7.8}$$

The EFKF for regeneration duration T_{Reg} is also use case or scenario specific. For the machine tool of the use case, assuming that the machine goes into regular operation after an energy-flexible operation or is in standby mode, then

$$T_{\text{Reg}} = \max(t_{\text{pro}}) \tag{7.9}$$

if a machining process has to be terminated.
The EFKF validity T_{V} is defined manual. I choose this approach because it is a very benefit-specific key figure. This primarily influences the period the energy-flexible system under consideration can be switched to energy-flexible operation (see Appendix A.3). This can be, for example, the next hour, the duration of a shift, a specific day, or even several days.
As described in the previous chapter (see Chapter 5) and shown in the software concept, the building and transfer of the key figures, which are automated determined with the mentioned machine learning or data analytics algorithms, into the standardized EFDM format takes place in the step *energy flexibility model building*. For this work, with a focus on the DD-EFMod, I use the external software service EFDM GUI [94] for building the standardized EFDM in JSON schema (see Appendix A.1.1). Flexible load measures can then be derived and further processed from the defined flexibility space.

Alternative Implementation with Data Streaming Algorithms

To address the second research hypothesis (see Chapter 4), I also investigate the applicability and feasibility of online machine learning

Algorithm 6 Deployment: Mini-Batch K-Means Clustering

Input: Data Stream $\mathbf{X}_{\text{scaled}}$, number of clusters k, batch size n
Output: Cluster centers $\mathbf{C}$, Predicted clusters $\mathbf{P}$

Initialize mini-batch K-means with k clusters and batch size n
for $i = 0$ to len($\mathbf{X}_{\text{scaled}}$) step n **do**
    batch $\leftarrow \mathbf{X}_{\text{scaled}}[i : i + n]$
    Perform partial fit of mini-batch K-means on batch (Eq.: 2.14)
end for
Predict clusters for all data in $\mathbf{X}_{\text{scaled}}$ to get $\mathbf{P}$
Retrieve cluster centers $\mathbf{C}$ from mini-batch K-means
Inverse transform cluster centers if necessary

Algorithm 7 Deployment: CluStream Clustering

Input: Data stream **X**, window size w
Output: Cluster centers **C**, Predicted clusters **P**

Load dataset **X**
Compute moving average of **X** with window size w
Initialize CluStream
for each value x in the moving average **do**
    Update CluStream with x (Eq.: 2.15 - 2.19)
end for
Simulate data stream
for each data point x in **X do**
    Assign x to the nearest cluster center (Eq.: 2.12)
end for
Compute cluster centers **C** and predicted clusters **P**

methods as part of the first scenario. Since the automated determination of the EFKF of the power states is the minimum requirement, the focus of testing data stream mining algorithms is on this key figure. The batch incremental learning clustering method mini-batch K-means (see Algorithm 6) [59] and the instance incremental method CluStream (see Algorithm 7) are selected as standard clustering algorithms for data stream mining problems [56]. The selection of these two methods was based on the fact that they are proven standard methods from data stream analysis and on the open-source availability of the algorithms as well. Furthermore, the basic principles of the two methods are similar to the batch K-means clustering algorithms wich performed well for the automated parameterization of the key figure power states in the context of the DD-EFMod method in scenario 1. For this very reason, the three methods are comparable. The respective implementation of the selected data stream algorithms is part of the DD-EFMod within the *EFKF determination* sub-process (see Figure 5.4). Due to technical limitations (network failures, excessive latencies), the three algorithms were compared using two data sets: a measurement data set and a simulated data set with significantly increased measurement points. The results are listed and evaluated in the next section.

7.1.3 Evaluation and Results

The results and their evaluation of the implementation of the DD-EFMod method based on the software concept (see Figure 5.6) of the first scenario using the algorithms discussed in the previous section are presented in this section.
Based on the known reference case operation load profile of the EMAG GT (see Figure 7.2), the *data verification* and *data preparation* step (Algorithm 1) was applied. The data profile of the dataset from the load profile consists of 7595 samples with a sampling rate of 1 second, result-

Table 7.3: Results of data verification and preparation of scenario 1 (own table).

Value	**Result**	**Unit**
Minimum	-7718.63	W
Maximum	12681.04	W
Mean	1634.01	W

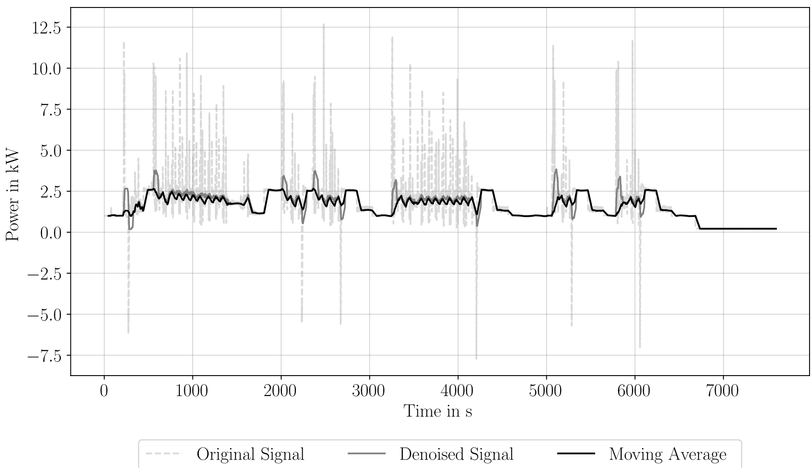


Figure 7.3: Preprocessed electrical power consumption of EMAG GT (own figure).

ing in a dataset size of 0.370 MB. The data was sourced from recordings in the machine's PLC system and contained no missing values. The power consumption data exhibits strong transient behavior, which is typical for this machine's operation, as illustrated in Figure 7.2. This transient nature highlights the dynamic changes in power usage during the machining process, necessitating careful denoising and smoothing to obtain accurate characteristic values for subsequent analysis. The calculated characteristic values resulted from the *data verification* and *data preparation* step shown in Table 7.3 and the signal curves for the denoised power consumption and the power consumption signal with moving average (with window size $M = 50$) shown in Figure 7.3.
Figure 7.3 clearly shows the necessity of the *data verification* and *data preparation* step. The original measured load profile repeatedly shows power transients that are part of the normal operating behavior (e.g. spindle movements). However, these must be suppressed to enable the automated determination of the key figures like the power states with machine learning algorithms in a targeted manner. The resulting moving average $\mathbf{x_{MA}}$ power signal achieves this because it is free of extreme outliers. Based on this, I could apply the Algorithm 2 as the *EFKF determination* sub-process. For this purpose, the batch K-means algorithm was executed with the signal $\mathbf{x_{MA}}$ and the specification $\mathbf{C} = 3$. Here, $\mathbf{C} = 3$ is derived from the machine states relevant for the analysis (see Table 7.2). For this purpose, I have combined the states s_{st} and s_{op} as one common state. Thus

$$c_1 = s_{\text{st}} \cup s_{\text{op}} \tag{7.10}$$

$$c_2 = s_{\text{da}} \tag{7.11}$$

$$c_3 = s_{\text{wk}} \tag{7.12}$$

follows as individual clusters to be determined, representing the power states. The combination of c_1 is based on the operating behavior of the machine. It was shown that the EMAG GT automatically switches from mode s_{op} to s_{st} after 3min if there is no further manual state

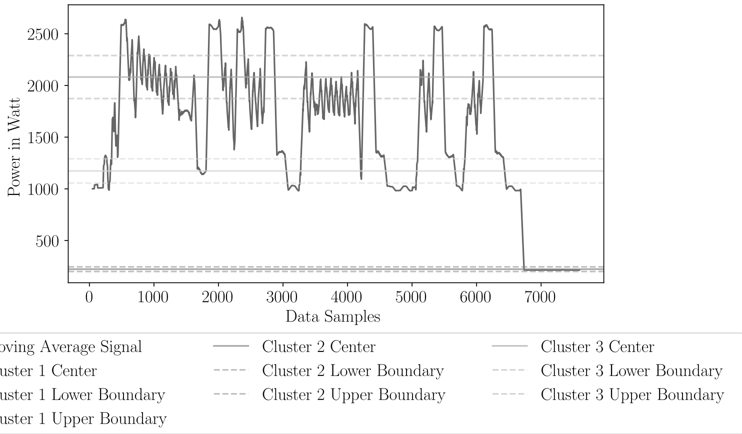


Figure 7.4: K-means clustering results EMAG GT (own figure).

change. Thus, the outcome of this *model deployment* step is shown in Figure 7.4 results from implementing Algorithm 2 for the automated *EFKF determination* step for the key figure power states. Within the *model quality sufficient* step, the results of the batch K-means clustering algorithm are used to validate and analyze the statistical consistency and homogeneity of the clusters. This is shown by the values given in Table 7.4 and illustrated in the corresponding boxplot in Figure 7.5. As the figure and table show, the cluster centers determined for each

Table 7.4: EMAG GT K-means clustering statistical results (own table).

Cluster	Standby	Disabled	Working
Center	1172.91	222.93	2081.26
Min	704.66	214.03	1627.49
Q1	1010.07	214.24	1819.01
Median	1119.5	214.4	2016.22
Q3	1327.58	214.64	2328.25
Max	1626.45	689.32	2658.07

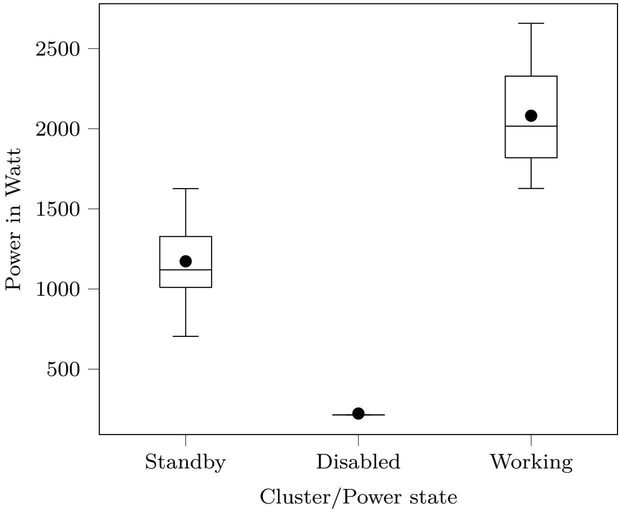


Figure 7.5: Boxplot of the clusters formed for the EMAG GT (own figure).

cluster are close to the median of the associated data point.
To further test the cluster quality, I determined the quality measures of the Silhouette Score and Davis-Bouldin Score (see Chapter 2). The implementation of the Algorithm 3 leads to the results in Table 7.5, which confirm the good quality of the clustering algorithm in this case. Thus, the automatically determined cluster centers from Table 7.6 can be used as the EFKF power states.

Table 7.5: Quality measures of batch K-means clustering (own table).

Quality measure	**Value**
Silhouette Score	0.68
Davis-Bouldin Score	0.37

As part of the step *EFKF parameterization* it follows

$$P_{\text{standby}} = [1055, 1290]\text{W} \tag{7.13}$$

$$P_{\text{disabled}} = [200, 245]\text{W} \tag{7.14}$$

$$P_{\text{working}} = [1873, 2289]\text{W} \tag{7.15}$$

as the elementary key figure power states because these EFKFs are valid.

To further refine the Energy Flexibility Data Model and enhance its applicability, it is essential to extend the parameterization by incorporating optional key figures. This leads to revisit the steps of *EFKF determination* and *energy flexibility model synthesis*. Algorithm 4 is implemented in order to assign a possible holding duration to each power state, which results in the values given in Table 7.7.

Thereby $\max(T_H^{\text{standby}})$ is determined from the operating behavior of the machine tool, which automatically switches from the standby state to the P_{disabled} state at 30 min of inactivity. For $\min(T_H^{\text{working}})$, the 90 s corresponds to the processing time of a process step (see equation 7.7) of the machine tool EMAG GT.

The next rerun of the *EFKF determination* sub-process with implementing the Algorithm 5 for automated determining the EFKF of the power gradients results in the mean gradients as shown in Table 7.8.

Analyzing this results as part of the *energy flexibility model synthesis* sub-process, no transition from P_{disabled} to P_{standby} could be measured

Table 7.6: Results of batch K-means clustering (own table).

Value	**Cluster Standby**	**Cluster Disabled**	**Cluster Working**
Cluster Center	1172.91 W	222.93 W	2081.26 W
Upper bound Cluster	1290.20 W	245.23 W	2289.39 W
Lower bound Cluster	1055.62 W	200.64 W	1873.14 W

Table 7.7: Identified holding durations of EMAG GT (own table).

Value	T_H^{standby}	T_H^{disabled}	T_H^{working}
Minimum	$66\,\text{s}$	$0\,\text{s}$	$90\,\text{s}$
Maximum	$1800\,\text{s}$	inf	$1365\,\text{s}$

Table 7.8: Identified power gradients of EMAG GT (own table).

Transition	**Value**
P_{disabled} to P_{standby}	$0.0\,\frac{\text{W}}{\text{s}}$
P_{standby} to P_{working}	$320.0\,\frac{\text{W}}{\text{s}}$
P_{working} to P_{standby}	$-13.8\,\frac{\text{W}}{\text{s}}$
P_{standby} to P_{disabled}	$-804.5\,\frac{\text{W}}{\text{s}}$

in this data set. This was due to the technical network problems that had already occurred. However, it can be deduced from all the tests carried out, and the other state changes that the state changes are instantaneous and, therefore, immediate. This is typical behavior for an electrical consumer. This can be seen, for example, in the activation P_{standby} to P_{working} with $320.0\,\frac{\text{W}}{\text{s}}$ or the deactivation of P_{standby} to P_{disabled} with $-804.5\,\frac{\text{W}}{\text{s}}$.
Finally for this scenario, the EFDM is further extended by determine the key figures T_{Rea} and T_{Reg} which can be determined with the equation 7.8 and 7.9. This results in $T_{\text{Rea}} = 90\,\text{s}$ and $T_{\text{Reg}} = 90\,\text{s}$.
Overall, this creates the flexibility space as EFDM of the EMAG GT with the automatically determined key figures as shown in Table 7.9. I manually defined the key figure validity as an example for a day from 06:00 to 22:00.

This resulting flexibility space is shown in Figure 7.6. The space of possibilities for the implementation of a possible flexible load measure, which can be realized by the EMAG GT, is limited as a set with the smallest ($P_{\text{disabled}} = 0.200\,\text{kW}$) and largest power value ($P_{\text{working}} = 2.289\,\text{kW}$), the smallest ($T_H^{\text{disabled}} = 0\,\text{s}$) and largest holding duration

Table 7.9: Automated determined key figures of the EFDM parameterized via the DD-EFMod method for the EMAG GT (own table).

Key Figure	Min	Max
P		
P_{disabled}	0.200 kW	0.245 kW
P_{standby}	1.055 kW	1.290 kW
P_{working}	1.873 kW	2.289 kW
T_{Rea}	-	90 s
T_{V}	2023-08-31 06:00:00	2023-08-31 22:00:00
T_{H}		
T_H^{disabled}	0 s	inf
T_H^{standby}	66 s	1800 s
T_H^{working}	90 s	1365 s
∇P_{Act}	-	$0.320\ \frac{\text{kW}}{\text{s}}$
∇P_{Mod}	-	$-0.013\ \frac{\text{kW}}{\text{s}}$
∇P_{Dea}	-	$-0.804\ \frac{\text{kW}}{\text{s}}$
T_{Reg}	-	90 s

($T_H^{\text{standby}} = 1800\,\text{s}$) as well as the maximum rate of change ($\nabla P_{\text{Act}} = 0.320\ \frac{\text{kW}}{\text{s}}$).
The results indicate that accurately determining power states is crucial for evaluating other energy flexibility key figure (EFKF). Consequently, assessing the prototypical implementation of online streaming data algorithms, specifically Algorithm 6 and 7, is deliberately focused on this key figure. This focused approach thoroughly examines the effectiveness of data streaming algorithms in real-time processing environments. By concentrating on the key figure power states, we can effectively demonstrate the algorithm's utility in capturing incremental changes and their potential applicability to other key figures in the context of energy flexibility.

The results of the implementation of the Algorithms 6 for mini-batch K-means and Algorithm 7 for CluStream, as part of the sub-process *en-*

ergy flexibility key figure determination are given in Table 7.10. This automated determined clusters, which representing the key figure power states are based on a measured data set. In Appendix A.2 the graphical representation for each test run is given.
Comparing the performance of the clustering algorithms with the measured data set provides essential insights into their applicability. The batch K-means and mini-batch K-means algorithms are close to each other in their cluster centers for the power states Disabled, Standby,

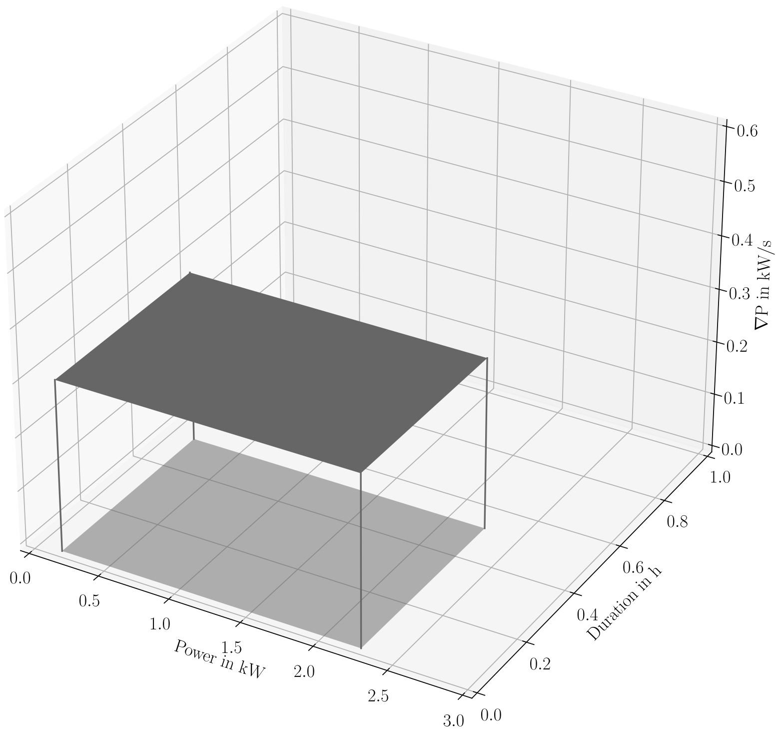


Figure 7.6: Resulting flexibility space of EMAG GT represented quantity as a function of the flexibilizable power, duration and rate of change (own figure).

and Working, with mini-batch K-means showing a slightly higher value for the Working state. CluStream shows a significantly different cluster center for the disabled state and higher values for the standby and working states, indicating a different clustering sensitivity than the K-means variants. In this respect, the CluStream algorithm must be rated as critical. Regarding silhouette values, mini-batch K-means slightly outperforms the others, indicating better cluster cohesion and separation. The Davies-Bouldin index, which is lower for CluStream, suggests that CluStream may produce clusters with better separation.
From these results, it's evident that both K-means algorithms offers a good balance between computational efficiency and clustering quality for offline (batch) or online (data streams) clustering, as shown by its silhouette score and Davies-Bouldin Index. This is confirmed by the evaluation of the simulated significantly longer data set in Table 7.11 and Appendix A.2. Therefore, I select the batch K-means algorithm for the automated determination of the key figure power state in the

Table 7.10: Comparison of clustering algorithms performance relating to measured data set (own table).

Value	**Batch K-means**	**Mini-batch K-means**	**CluStream**
Disabled			
Cluster Center	222.93 W	291.11 W	0.07 W
Standby			
Cluster Center	1172.93 W	1151.05 W	1344.66 W
Working			
Cluster Center	2081.26 W	2224.02 W	2236.13 W
Silhouttte-Score	0.68	0.69	0.67
Davies-Bouldin-Index	0.37	0.36	0.34
Samplenumber of data set	7595	7595	7595
Computation time	0.057 s	0.245 s	8.42 s

next scenarios in the following sections.

Table 7.11: Comparison of clustering algorithms performance relating to simulated data set (own table).

Value	**Batch K-means**	**Mini-batch K-means**	**CluStream**
Disabled			
Cluster Center	258.13 W	270.67 W	410.15 W
Standby			
Cluster Center	1050.70 W	1107.04 W	0.00 W
Working			
Cluster Center	2080.77 W	2199.71 W	2088.21 W
Silhouttte-Score	0.78	0.75	0.73
Davies-Bouldin-Index	0.24	0.32	0.36
Samplenumber of data set	167400	167400	167400
Computation time	0.474 s	4.686 s	19.65 s

In conclusion, the validation and implementation conducted in Scenario 1 confirms the feasibility of automating the determination of energy flexibility key figures for the Energy Flexibility Data Model for machine tools as flexible loads using the DD-EFMod method. The findings demonstrate that determination of key figures possible with historical data, but also with data streams. Furthermore the importance of selecting and evaluating the appropriate algorithms to ensure accuracy and reliability of algorithms for the energy flexibility modeling is shown. This initial success underscores the potential of the DD-EFMod method in enhancing the operational flexibility of industrial environments.

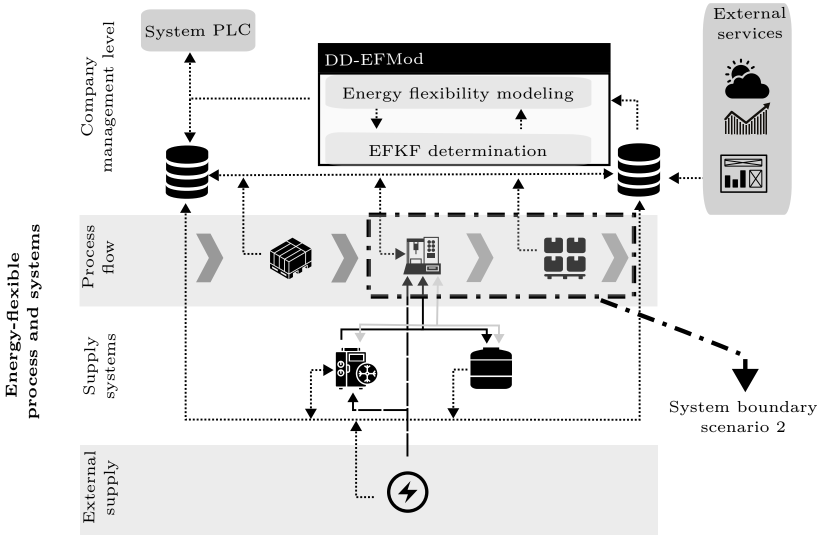


Figure 7.7: System of scenario 2 (own figure).

7.2 Scenario 2 - EMAG GT and Product Storage

This scenario extends the system boundary of the EMAG VLC-100GT machine tool (see Section 7.1) to the product storage in which the processed, manufactured parts are stored. This is intended to demonstrate the applicability of DD-EFMod to the class storage of the EFDM (see Section 2.1.2) and product storage in particular and to show what additional energy-flexibility potential can be realized by taking material storage into account. The results and key figures for the machine tool are taken from the first scenario for these system considerations. This means that the focus of this scenario can be placed on validate the automated determination of the energy flexibility key figures of the EFDM for the storage system by apply the DD-EFMod method.

Table 7.12: Technical key figures in the EFDM for describing the flexibility space and their feasibility levels of scenario 2 following Lindner *et al.* [29] (own table).

Class	Key Figure	Description	Feasibility Level
Storage	C_S	Usable capacity	1
	E_{t_0}	Initial energy content	1
	S_S	Suppliers	1
	E_Tar	Target energy content	2
	E_Loss	Energy loss	2
	E_Drain	Energy drain from storage	2

7.2.1 Key Figure Definition

Following the steps of DD-EFMod method the *data verification* step starts with the definition of the relevant key figures of the EFDM to determine. As described in the fundamentals chapter, according to the definition of EFDM [29], a storage system can only be considered in conjunction with a flexible load. Therefore, the known key figures from Table 7.9, which are extended by the energy flexibility key figures (EFKF) shown in Table 7.12 to describe the class storage, result for the system consisting of EMAG GT and product storage. The minimum requirements to be determined are the technical key figures of the usable capacity, the initial energy content, and the associated supply system. Together with the EFKF of feasibility level 2, it follows

$$\mathbf{K} = [C_\mathrm{S}, E_{\mathrm{t}_0}, S_\mathrm{S}, E_\mathrm{Tar}, E_\mathrm{Loss}, E_\mathrm{Drain}] \tag{7.16}$$

as the vector of relevant EFKF for this scenario. Knowledge of the amount of energy in the product storage is relevant to determining the key figure storage capacity and its current state. The measured variables in Table 7.13 are pertinent to decide on this. In addition, the conditions defined in Table 7.14 are selected for this scenario. The values shown are derived from the fact that 10 raw materials pieces

Table 7.13: Priority of measured values of the EMAG GT for scenario 2 (own table).

Measured Value	**Symbol**	**Unit**	**Priority**
Electric Power	$P(t)$	W	●
Processing time	t_{pro}	s	●

can be processed by the EMAG GT within 15 min (see Section 7.1). As a further boundary condition, I asumed that the storage capacity consumed 40 produced parts to start the next processing step (see Figure 6.1).

Table 7.14: General conditions for the product storage (own table).

Term	**Symbol**	**Value**
Working shift time	t_{shift}	8 h
Cycle time	t_{cycle}	15 min
Storage capacity min	$C_S^{\min}$	20 pcs
Storage capacity soll	C_S^{soll}	40 pcs
Storage capacity max	$C_S^{\max}$	320 pcs

Based on this prioritization, the definition of the input variables follows

$$\mathbf{X}(t) = \left[P(t), t_{\text{pro}}, t_{\text{shift}}, t_{\text{cycle}}, C_S^{\min}, C_S^{soll}, C_S^{\max}\right] \tag{7.17}$$

to determine the flexibility space of the storage $\mathcal{S}$.

7.2.2 Implementation

The *data preparation* step for the following step of *energy flexibility modeling* for the product storage begins with the definition of framework parameters. Therefore the total energy requirement of the sup-

Algorithm 8 Deployment: Storage Capacity

Input: Raw Data $\mathbf{X(t)}$
Output: Storage EFKF,
1: Load data from $\mathbf{X(t)}$;
2: Define production cycle;
3: Calculate energy consumption per part (Eq.: 7.19);
4: Calculate storage capacity (Eq.: 7.20);
5: Calculate energy content (Eq.: 7.21);

plier of the storage during a production cycle is relevant with

$$E_{\text{total}} = \frac{\sum \left(\frac{P(t)}{1000} \cdot t_{\text{cycle}} \right)}{3600} \tag{7.18}$$

resulting in the energy per part with n number of parts per cycle

$$E_{\text{part}} = \frac{E_{\text{total}}}{n} \tag{7.19}$$

can be determined. The maximum and minimum storage capacity then follows with

$$C_{\text{S}} = \left(C_S^{\min} \cdot E_{\text{part}}, C_S^{\max} \cdot E_{\text{part}} \right) \tag{7.20}$$

and equivalently the initial energy content by

$$E_{\text{t}_0} = \left(C_S^{\min} \cdot E_{\text{part}}, C_S^{soll} \cdot E_{\text{part}} \right) . \tag{7.21}$$

For the scenario, the initial energy content is defined as the target energy content. The energy requirement E_{Drain} of the product storage depends on the production plan

$$E_{\text{Drain}} = f(E_{out}, t) \tag{7.22}$$

and should, therefore, not be relevant for the product storage. This assumption is permissible, as the subsequent processing step is not part of the system boundary of this scenario. The implementation of the steps defined by the DD-EFMod method of *EFKF determination* an *energy flexibility model synthesis* for the automated determination of the key figures of the EFDM for this scenario is summarized in Algorithm 8.

7.2.3 Evaluation and Results

The dataset used for this second scenario extends the dataset of the first scenario described in Section 7.1.3 with the scenario-specific information given in Table 7.14. This results in a data profile of 7595 samples with a sampling rate of 1 second recorded from the machine tool PLC. The data quality was assessed and confirmed to be consistent with the requirements of the analysis, exhibiting similar transient behaviors as noted in the first scenario. The scenario-specific storage information includes product storage characteristics, allowing a more comprehensive analysis of energy flexibility under varying storage loads. The application of Algorithm 8 for the *energy flexibility modeling* of the product storage resulted in the key figures listed in Table 7.15. This results in a maximum possible energy content of 18.97 kW h. Within step *energy flexibility model validation*, the positive validation of these key figures with the combination of the key figures from the first scenario is relevant. In conjunction with the machine tool, this results in a significant increase in flexibility potential. This flexibility potential is shown in Figure 7.8. Compared to the isolated consideration of the EMAG GT

Table 7.15: Automated determined key figures of the EFDM parameterized via the DD-EFMod method for the product storage (own table).

Key Figure	**Min**	**Max**
C_S	1.16 kW h	18.97 kW h
E_{t_0}	1.19 kW h	2.37 kW h
S_S	EMAG GT	
E_Tar	1.19 kW h	2.37 kW h
E_Loss	$0\,\frac{\%}{\mathrm{h}}$	

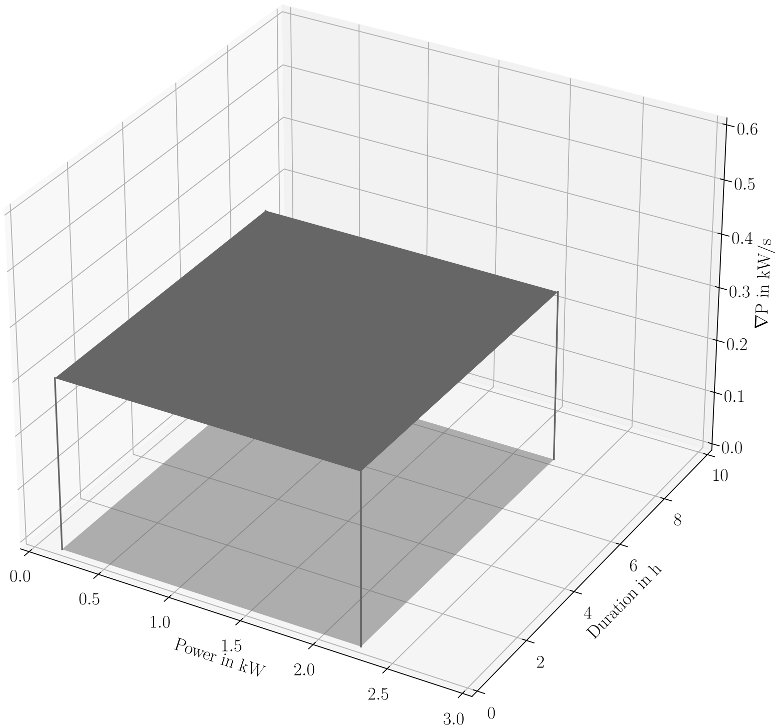


Figure 7.8: Resulting flexibility space of EMAG GT and product storage represented quantity as a function of the flexibilizable power, duration and rate of change (own figure).

from scenario 1, the combination with the product storage results in an increase in the possible holding duration of flexibilization from 0.5 h to 8.0 h, which corresponds to an increase of 1500 %.

The results of the implementation and validation of this second scenario and the resulting EFDM, which was created using the software concept, are available as a repository in the TUdata Lib directory [110]. The EFDM was systematically parameterized through the steps in the DD-EFMod method, demonstrating automated key figure determination of the EFDM. This process not only validates the applicability of the DD-EFMod method for the EDFM class storage but also highlights how the inclusion of material or product storage can increase the flexibility potential.

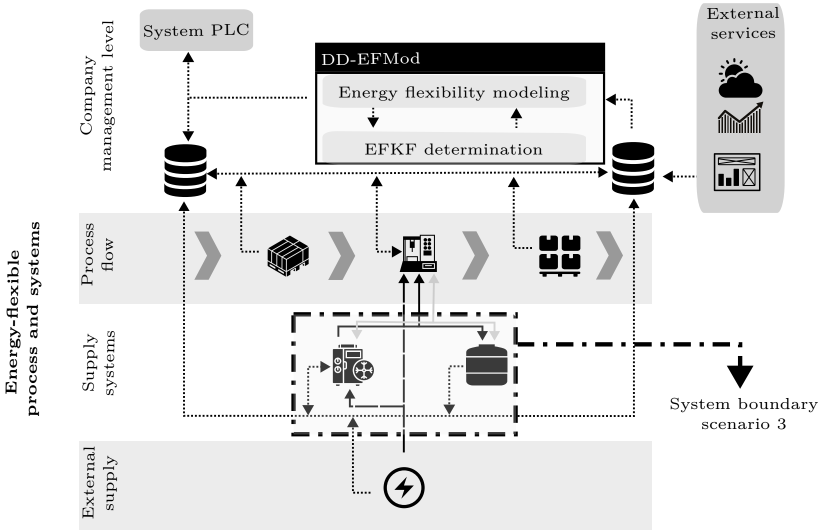


Figure 7.9: System of scenario 3 (own figure).

7.3 Scenario 3 - Cooling Machine and Cold Storage

The third scenario focuses on the supply systems of the use case. For this, I define the system boundary, as shown in Figure 7.9, around the chiller eCHiller45 [99] and the cold storage [100]. As in the previous scenarios, I have recorded the corresponding measured values. These measured data are used to validate the steps of the DD-EFMod method to realize the EFDM parameterization. Applying the method to this scenario checks whether the developed DD-EFMod method can be applied to different machine types to consider the functional requirement on the method number three (see Chapter 4). In comparison to the previous scenarios, a flexible load and a storage system are considered in combination.

Table 7.16: Technical key figures in the EFDM for describing the flexibility space and their feasibility levels of scenario 3 following Lindner *et al.* [29] (own table).

Class	**Key Figure**	**Description**	**Feasibility Level**
Flexible Load	$\mathbf{P}$	Power states	1
	T_{Rea}	Reaction duration	2
	T_{V}	Validity	2
	T_{H}	Holding duration	2
	∇P_{Act}	Activation gradient	2
	∇P_{Mod}	Modulation gradient	2
	∇P_{Dea}	Deactivation gradient	2
	T_{Reg}	Regeneration duration	2
Storage*	C_{S}	Usable capacity	1
	$E_{\mathrm{t_0}}$	Initial energy content	1
	S_{S}	Suppliers	1
	E_{Tar}	Target energy content	2
	E_{Loss}	Energy loss	2

7.3.1 Key Figure Definition

First, in the *application and implementation layer* of the DD-EFMod method, the step of *data verification* is done by selecting the relevant energy flexibility key figures of the EFDM of this scenario. These are listed in Table 7.16. As with scenarios 1 and 2, the necessary and sufficient feasibility levels are based on the EFDM [29], so

$$\mathbf{K}_{\mathrm{Chiller}} = [\mathbf{P}, T_{\mathrm{Rea}}, T_{\mathrm{V}}, T_{\mathrm{H}}, \nabla P_{\mathrm{Act}}, \nabla P_{\mathrm{Mod}}, \nabla P_{\mathrm{Dea}}, T_{\mathrm{Reg}}] \tag{7.23}$$

$$\mathbf{K}_{\mathrm{Storage}} = [C_{\mathrm{S}}, E_{\mathrm{t_0}}, S_{\mathrm{S}}, E_{\mathrm{Tar}}, E_{\mathrm{Loss}}, E_{\mathrm{Drain}}] \tag{7.24}$$

as vectors of all relevant EFKF follows.

To determine these EFKFs, I analyzed the input variables listed in Table 7.17 as part of the *data verification* step. In addition, the boundary conditions and technical limits defined in Table 7.18, as well as the manufacturer specifications, must be taken into account [100]. From

Table 7.17: Priority of measured values of the eChiller45 for scenario 3 (own table).

Measured Value	**Symbol**	**Unit**	**Priority**
Electric power	P_{el}	W	●
Thermal power	P_{th}	W	◑
Operating point	p_{op}	°C	●
Time	t	s	●
EER	EER	-	◑
Operating state	s_{op}	binary	◑
Storage temperatur	ϑ_{stor}	°C	●

Table 7.18: General boundary conditions for the cold storage (own table).

Term	**Symbol**	**Value**
Cooling network set temperature	ϑ_{set}	15 °C
Technical maximum temperatur	$\vartheta_{\text{stor}}^{cmax}$	25 °C
Technical minimum temperatur	$\vartheta_{\text{stor}}^{cmin}$	12 °C
Maximum flexibility temperature	$\vartheta_{\text{stor}}^{fmax}$	20 °C
Minimum flexibility temperature	$\vartheta_{\text{stor}}^{fmin}$	15 °C
Volumen of storage	V_{stor}	1000 L
Mass of storage	m_{stor}	1000 kg
Specific heat capacity	c_{p}	$4.184\,\frac{\text{kJ}}{\text{kg K}}$
Heat loss of the storage	q_{BS}	$\frac{1.37\,\text{kW h}}{24\,\text{h}}$

this data, the vector of input variables

$$\mathbf{X}(t) = [P_{el}, P_{th}, p_{\text{op}}, t, EER, s_{op}, \vartheta_{\text{stor}}] \tag{7.25}$$

for further processing derives. Using these measured variables and the boundary conditions in Table 7.18, the *data preparation* step and the *energy flexibility modeling* step is used to determine the flexibility space $\mathcal{F} = f(\mathcal{L}, \mathcal{S})$.

7.3.2 Implementation

Based on the available input data $\mathbf{X}(t)$, it is not possible to identify typical production power states for the cooling machine by using clustering algorithms like batch K-means clustering directly (see Figure 7.10). The reason is, that this machine type is a continuous flexible load. So a procedure different from the application of clustering algorithms used for the EMAG GT in scenario one (see Section 7.1) is necessary. As part of the *data preparation* step the electric power consumption of the eChiller45 cooling machine is first quantified into different power ranges, starting from the power range specified by the manufacturer from $P_{el,min} = 0.3\,\text{kW}$ to $P_{el,max} = 14.5\,\text{kW}$. Assuming that the building automation and control allows the chiller to be controlled (I refer to the work of my research colleagues Borst *et al.* [113] and our previous work Fuhrländer-Völker *et al.* [93]), it is possible to determine $\mathbf{P}$ using Equal-Width Binning (see Section 2.3 in Equation 2.8 to 2.10). Based on this, the key figures of the flexible load eChiller45 can be determined through the implementation of data analytics algorithms, as realized in Algorithm 9. This is part of the *energy flexibility modeling* step with the sub-processes *EFKF determination* and *energy flexibility model synthesis* and is described in the following.
Taking the cold storage for implementation into account of the EFDM of this scenario this leads to a holding duration determined by

$$T_\text{H} = \frac{C_\text{S}}{\mathbf{P}}. \tag{7.26}$$

Algorithm 9 Deployment: EFKF of eChiller45

Input: Raw Data $\mathbf{X(t)}$
Output: EFKF eChiller45

1: Data Preparation;
2: Calculate $\mathbf{P}$ (Eq.: 2.8);
3: Calculate T_H (Eq.: 7.26);
4: Identification of gradients (Eq.: 7.6);
5: Calculate T_Rea (Eq. 7.27);

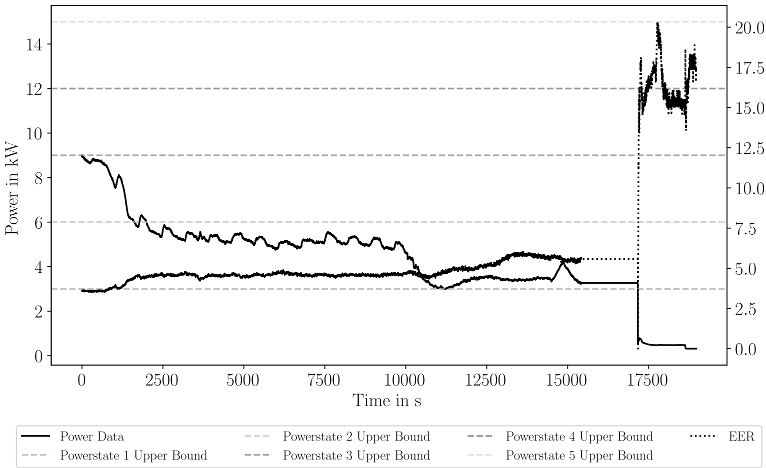


Figure 7.10: Measured data of power consumption from cooling machine with defined power states (own figure).

The key figure of the power gradients could be determined based on Equation 7.6. Subsequently, the key figure reaction duration of the cooling machine could be determined according to

$$T_{\text{Rea}} = \frac{P_5^{\text{max}} - P_1^{\text{min}}}{\text{mean}(\nabla P)}. \tag{7.27}$$

It is possible with the mean value of the power gradients as the maximum reaction time. The implementation of the calculations in the context of the software concept are implemented according to Algorithm 9.

The determination of the EFKF for the cold storage [100] is shown in my previous work Lindner *et al.* [30] and briefly summarized below, taking into account the boundary conditions from Table 7.18. The following equations are implemented in Algorithm 10 in the context of

Algorithm 10 Deployment: EFKF of Cold Storage

Input: Raw Data $\mathbf{X(t)}$
Output: EFKF cold storage
1: Data Preparation;
2: Calculate C_{S} (Eq.: 7.28)
3: Identification of $E_{\mathrm{t_0}}$ and E_{Tar} (Eq.:7.29-7.30)
4: Calculate E_{Loss} (Eq.: 7.32)

the software concept:

$$C_{\mathrm{S}} = m_{\mathrm{stor}} \cdot c_{\mathrm{p}} \cdot \frac{\vartheta_{\mathrm{stor}}^{cmax} - \vartheta_{\mathrm{stor}}^{cmin}}{r_{\mathrm{u}}} \tag{7.28}$$

$$E_{\mathrm{t_0}} = m_{\mathrm{stor}} \cdot c_{\mathrm{p}} \cdot \frac{\vartheta_{\mathrm{stor}}^{fmax} - \vartheta_{\mathrm{stor}}^{fmin}}{r_{\mathrm{u}}} \tag{7.29}$$

$$E_{\mathrm{Tar}} = E_{\mathrm{t_0}} \tag{7.30}$$

$$\Delta T = \vartheta_{\mathrm{stor}}^{fmax} - \vartheta_{\mathrm{stor}}^{fmin} \tag{7.31}$$

$$E_{\mathrm{Loss}} = \frac{q_{\mathrm{BS}}}{V \cdot c_p \cdot \rho \cdot \Delta T} \cdot 100 = 0.98\,\frac{\%}{\mathrm{h}} \tag{7.32}$$

Here, $r_{\mathrm{u}} = \frac{1}{3600}$ is the conversion coefficient between J and W h. These equations and their implementation in Algorithm 10 represents the DD-EFMod sub-process of EFKF determination. The results and the steps of *energy flexibility synthesis* is discussed below.

7.3.3 Evaluation and Results

The application of the DD-EFMod method in this scenario was successfully implemented. The data profile for this scenario consists of 18,974 samples with a sampling rate of 1 second, resulting in a dataset size of 3.167 MB. It includes data points recorded from the energy monitoring system of the ETA Research Factory given in Table 7.17, capturing information on both the cooling machine and the cold storage. No outliers were detected, but there were missing data points due to network errors that caused incomplete data transmission. These gaps were

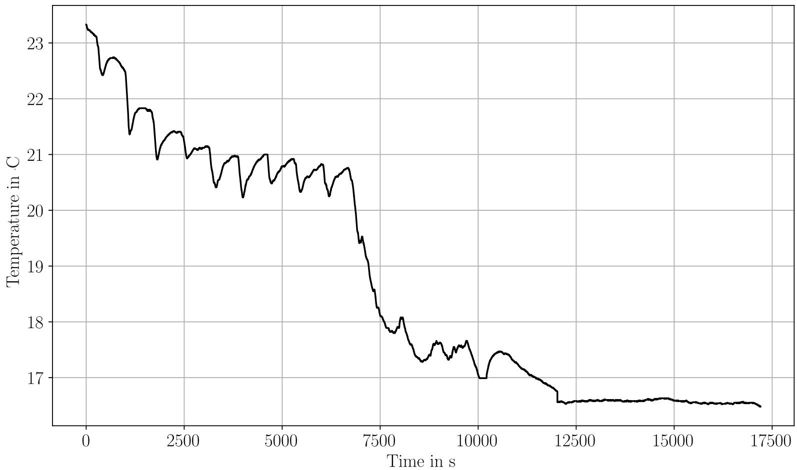


Figure 7.11: Measured data of temperature from cold storage (own figure).

addressed through data imputation [104] during the *data preparation* step. The main challenge of this scenario was that no distinguishable power states of the cooling machine eChiller45 could be identified in the period under investigation. Therefore I used the Equal-Width Binning method in the *data preparation* step. This allowed the operating range to be divided into power states. This is applicable due to the continuous controllability of the machine and leads to the operating ranges shown in Figure 7.10. In addition to the power load profile, the figure also shows the Energy Efficiency Ratio (EER) of the machine, as this can be used to derive the dependency of the cooling capacity of the machine.

I have also considered the cold storage in this scenario and use data analytics algorithms for the *energy flexibility modeling* step. By this implementation of the Algorithms 9 and 10 as part of the *energy flexibility key figure determination* step it was possible to realize the automated determination of the key figures. Thereby technical boundary conditions and manufacturer information are required for the cold storage

Table 7.19: Automated determined key figures of the EFDM parameterized via the DD-EFMod method for the cooling machine eChiller45 (own table).

Key Figure	Min	Max
P		
P_1	0.3 kW	2.9 kW
P_2	3 kW	5.9 kW
P_3	6 kW	8.9 kW
P_4	9 kW	11.9 kW
P_5	12 kW	14.5 kW
T_{Rea}	-	2892 s
T_{V}	2023-08-31 06:00:00	2023-08-31 22:00:00
T_{H}		
T_H^1	18 620 s	180 000 s
T_H^2	9152 s	18 000 s
T_H^3	6067 s	9000 s
T_H^4	4537 s	6000 s
T_H^5	3600 s	4500 s
∇P_{Act}	-	$0.005\ \frac{\text{kW}}{\text{s}}$
∇P_{Mod}	-	$0.005\ \frac{\text{kW}}{\text{s}}$
∇P_{Dea}	-	$0.005\ \frac{\text{kW}}{\text{s}}$
T_{Reg}	-	-

Table 7.20: Automated determined key figures of the EFDM parameterized via the DD-EFMod method for the cold storage (own table).

Key Figure	Min	Max
C_{S}	0 kW h	15.10 kW h
E_{t_0}	0 kW h	5.81 kW h
S_{S}	eChiller45	
E_{Tar}	0 kW h	5.81 kW h
E_{Loss}	$0.98\ \frac{\%}{\text{h}}$	

system to determine the EFKF, in particular, to maximize the flexibility potential. If only the measurement data shown in the observation

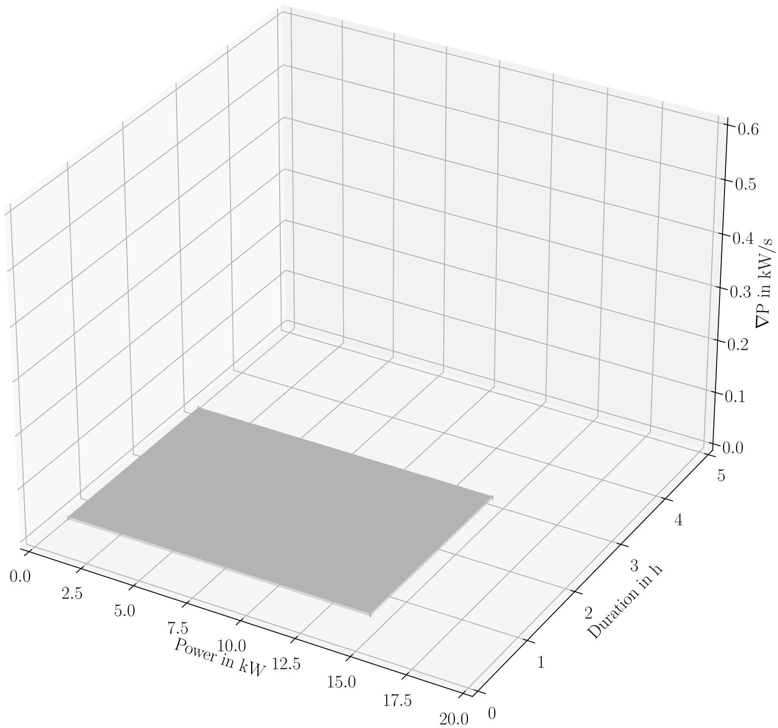


Figure 7.12: Resulting flexibility space of eChiller45 and the cold storage (own figure).

period (see Figure 7.11) is used to determine the EFKF, a lower storage capacity would be identified as the entire storage potential was not utilized during the measurement recording.

The flexibility spaces resulting from the *energy flexibility model synthesis* the EFDM which was built are listed in the Tables 7.19 and 7.20. This leads to the *energy flexibility model validation* step to check this EFDM. The resulting flexibility space with the flexibilizable power between 0.3 kW to 14.5 kW can be flexibilized by taking into account the cold storage over a period of 5.2 h to 1.25 h with a change in power of

$0.005\,\frac{\mathrm{kW}}{\mathrm{s}}$. These results are valid since the operating boundary conditions are met. The resulting flexibility space is shown in Figure 7.12 as an example for an average power of 5 kW. Compared to the flexibility space from scenario 2 (Figure 7.8), the low power gradients indicate that this system is very inertial.

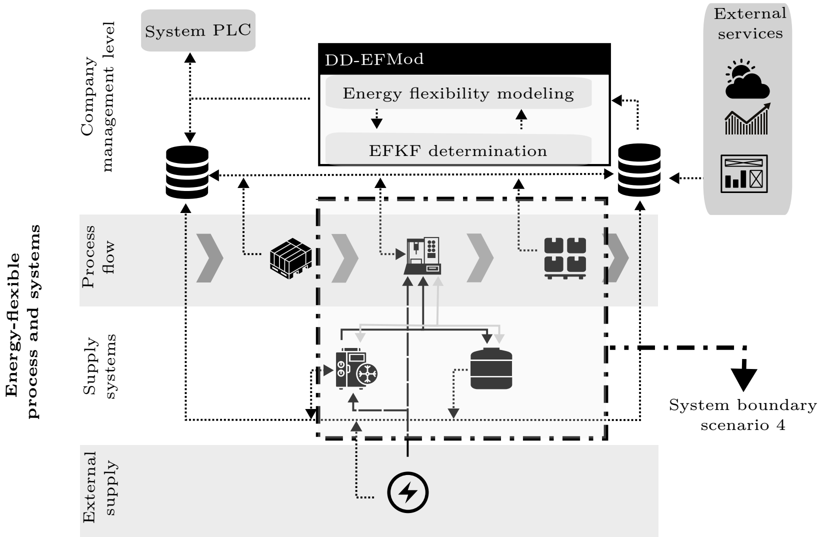


Figure 7.13: System of scenario 4 (own figure).

7.4 Scenario 4 - Identification of Dependencies

The fourth scenario focuses on the Energy Flexibility Data Model (EFDM) class dependency, which models the dependencies among flexible loads in the use case. For this purpose, all previous subsystems, including the machine tool EMAG GT, the product storage, the cooling machine eChiller45, and the cold storage, are considered (see Figure 7.13). This scenario explores the potential for automated determination of the energy flexibility key figures (EFKF) for the class dependency, following the steps outlined in the DD-EFMod method. In the *data verification* step, the necessary EFKF, as defined in Table 2.4, are established, and various analyses of the input measurement data are executed. This includes a correlation analysis to assess direct relationships and a lagged correlation analysis to identify possible dependencies with temporal shifts among the subsystems. Following this, the *energy flex-*

ibility modeling step involves implementing a data analytics algorithm for Boolean analysis (see Chapter 2), which facilitates the recognition of logical links between the data from the flexible loads. The implementation according to the software concept (see Section 5.2) is explained in the following.

7.4.1 Key Figure Definition

The relevant energy flexibility key figures to be determined are based on the conditions of the EFDM according to [29]. Based on this, the key figures for dependencies between the flexible loads are defined in Table 7.21. For this purpose, the corresponding power values and machine states of the flexible loads (see Table 7.2 and Table 7.17) are analyzed as a combined set of data. Consequently, the vector of EFKF is defined

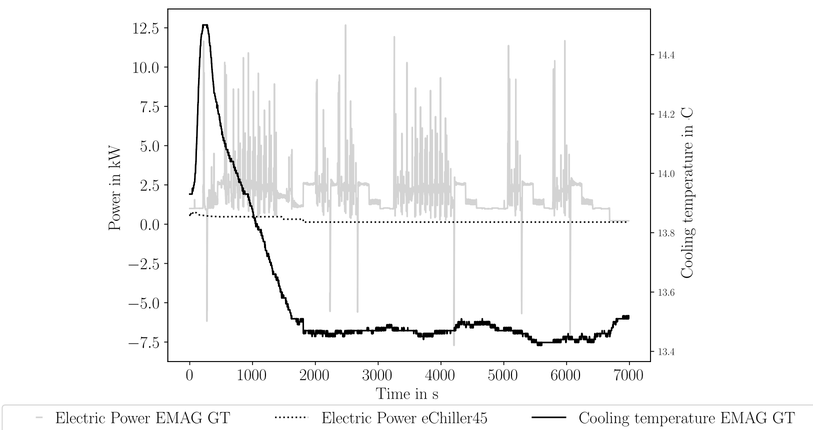


Figure 7.14: Power consumption of the flexible loads EMAG GT and eChiller45 and the cooling temperature for EMAG GT (own figure).

Table 7.21: Technical key figures in the EFDM for describing the flexibility space and their feasibility levels of scenario 4 following Lindner *et al.* [29] (own table).

Class	Key Figure	Description	Feasibility Level
Dependency*	ID_{Tar}	Target flexible load	1
	ID_{Tri}	Trigger flexible load	1
	Typ_{Temp}	Temporal type	1
	Typ_{Log}	Logical type	1

as

$$\mathbf{K} = [ID_{\text{Tar}}, Typ_{\text{Temp}}, ID_{\text{Tri}}, Typ_{\text{Log}}] \tag{7.33}$$

$$\tag{7.34}$$

as the vector of input data for the following *energy flexibility modeling* steps as

$$\mathbf{X}(t) = \left[P_{el}^{EMAG}, P_{el}^{Chiller}, s_{\text{st}}, s_{\text{wk}}, s_{\text{op}}, s_{\text{da}}, T_{\text{pro}} P_{th}, p_{\text{op}}, t, \vartheta_{\text{stor}}\right]. \tag{7.35}$$

For illustrative purposes Figure 7.14 displays the measured power values for the flexible load eChiller45 and EMAG GT, together with the cooling temperature of the machine tool. This figure shows the variable power states of the machine tool with only low electrical power consumption of the chiller.

7.4.2 Implementation

To identify dependencies between the machines and their corresponding measured variables in the *data verifaction* step. Therfore I first carried out a correlation analysis (see Chapter 2). Thereby I focused on the electrical power consumption of the two machines. I then extended the correlation analysis to include a lagged correlation to identify possible

time-delayed operational process dependencies.
In addition, I performed a Boolean analysis using the binary machine states to identify possible logical dependencies between the power states of the individual machines as part of the *EFKF determination* subprocess. In order to better evaluate the dependency between several flexible loads, I further introduce the parameter $\mathfrak{D} \in [0, 1]$ as the degree of dependency. This describes the degree of dependency of a flexible load in relation to all flexible loads in the system under consideration and is calculated according to

$$\mathfrak{D}_i = \frac{\sum_{j=1}^{n} a_{ij}}{n-1}. \tag{7.36}$$

Let $\mathbf{A}$ be an $n \times n$ matrix with a_{ij} elements and with $n \in \mathbb{N}$ as the total number of machines in the system, which represents the dependencies between the machines. Here, $a_{ij} = 1$ means that machine i is dependent on machine j and $a_{ij} = 0$ means that there is no logical dependency. The degree of dependency $\mathfrak{D}_i$ is, therefore, a measure of how strongly machine i is dependent on other machines in the system relative to the maximum possible number of dependencies. This parameter can therefore support the selection of potential energy-flexibility measures and correponding flexible load measures, as the lower the degree of dependency, the easier it is to implement. The determination of $\mathfrak{D}$ is according to DD-EFMod in the step *energy flexibility key figure determination* consider the developed software concept in Section 5.6.

7.4.3 Evaluation and Results

The application of the DD-EFMod method to determine the EFKF of the EFDM class dependency was successfully applied for the flexible loads EMAG GT and eChiller45 considered in the system of scenario four. The data profile for this scenario consists of 6.989 samples with a sampling rate of 1 second, resulting in a dataset size of 4.0 MB. The data was sourced from the machine tool PLC system for the EMAG GT

Table 7.22: Correlation matrix of flexible loads of scenario 4 (own table).

Flexible Load	EMAG GT	eChiller45
EMAG GT	1	0.053
eChiller45	0.053	1

and the energy management system of the ETA Research Factory and represent the input data $\mathbf{X}(t)$. No outliers or missing data points were detected during the observed period. The correlation analysis of the input data applied in the step *data verification* shows no dependency due to the low correlation coefficients (see Table 7.22). The extended analysis using the lagged correlation over the time horizon of 1800 s also indicates only very low to no dependency (see Figure 7.15). However, the evaluation of this result in the *EFKF synthesis* sub-process must be assessed critically, as it is known from expert knowledge that the production operation must be cooled during operation and therefore requires the operation of the cooling machine eChiller45. However, it is possible that other machines that were not explicitly considered in the use case, but which are present in the overall infrastructure of the ETA Research Factory, complicate the correlation analysis accordingly.

To determine the dependency key figures in the *EFKF determination* sub-process, I performed the Boolean analysis (see Chapter 2) based

Algorithm 11 Deployment: Dependency Identification

Input: $\mathbf{X}(t)$
Output: Dependencies between machines
1: Load data from $\mathbf{X}(t)$;
2: Compute correlation:
3: Compute correlation (Eq.: 2.3)
4: Compute lagged correlation (Eq.: 2.5);
5: Analyze operating states;
6: Compute Boolean analysis;
7: Derivate logical dependendcies;

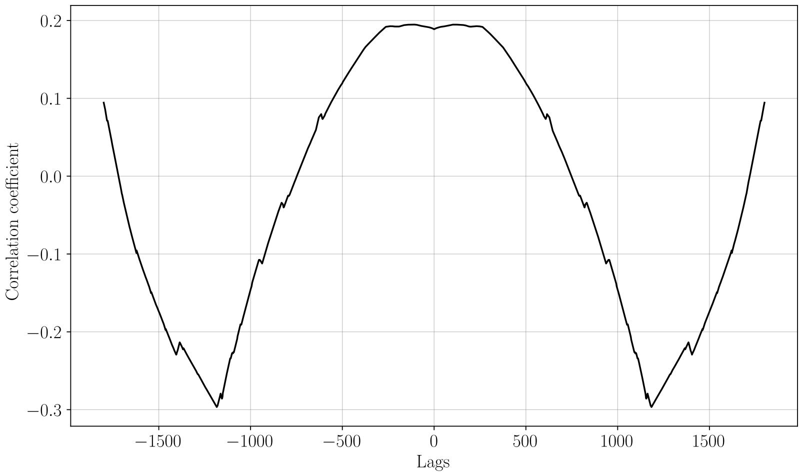


Figure 7.15: Lagged correlation of eChiller45 and EMAG GT (own figure).

on the machines and operating states ($s_{\mathrm{st}}, s_{\mathrm{wk}}, s_{\mathrm{op}}, s_{\mathrm{da}}$). This analysis, implemented by Algorithm 11 leads to the following results:

- Mutual Exclusion: False
- Concurrent Operation: True
- EMAG GT operation implies eChiller operation: True
- eChiller operation implies EMAG GT operation: False

As a result, when the machine tool is in operation, the chiller is also in operation. However, the chiller can work without the machine tool being in operation.
From this, the dependency matrix

$$\mathbf{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \tag{7.37}$$

follows. As part of the *energy flexiblity model synthesis* stpes, this results in $\mathfrak{D}_{\mathrm{EMAG}} = 1.0$ and $\mathfrak{D}_{\mathrm{Chiller}} = 0.0$ for the flexible loads. This means that the EFKF for the dependencies of the machines can be

Table 7.23: Automated determined key figures of the EFDM parameterized via the DD-EFMod method for the dependency between two flexible loads (own table).

Key Figure	**Value**
ID_{Tri}	EMAG GT
Typ_{Temp}	total
ID_{Tar}	eChiller
Typ_{Temp}	total
Typ_{Log}	implies

build as listed in Table 7.23 and transferred to the EFDM.

In summary, the combined flexibility space $\mathcal{F} = f(\mathcal{L}, \mathcal{S})$ of scenario 4 can be created taking into account the previous automated parameterized EFDMs of the previous scenarios. The resulting flexibility space is shown in Figure 7.16. In the DD-EFMod sup-process *EFKF synthesis*, I added the degree of dependency $\mathfrak{D}$ as an additional evaluation variable to quantify how strong one flexible loads influences another flexible load. This can support the realization of a flexible load measure, especially in automated information processing. For the final building of the Energy Flexibility Data Model in a standardized form, I used the external software tool EFDM GUI [94] (see Appendix A.1.1) as described in the Software Concept. The automated parameterized Energy Flexibility Data Model is available in the standardized JSON format in the supplementary material collected in TUDataLib [110].

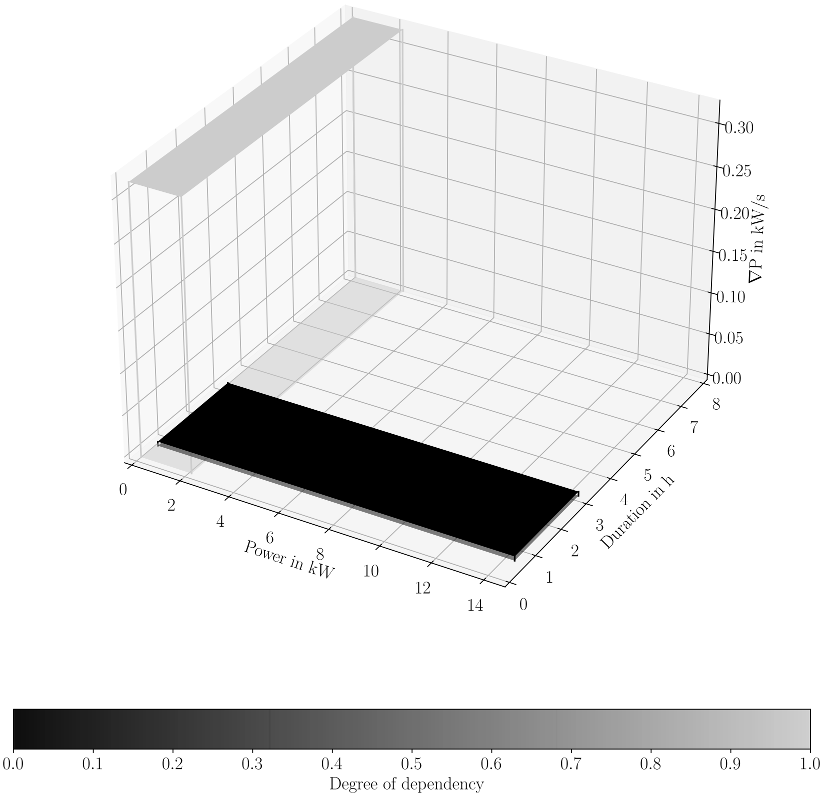


Figure 7.16: Combined flexibility space of eChiller45 and EMAG GT and all storage units of the use case. The combination of the two flexible loads in one flexibility space increases the possible applications as flexible load measures. The degree of dependency between the two flexible loads, which indicates mutual dependency during operation, must be considered when implementing flexible load measures (own figure).

7.5 Evaluation of Flexible Load Measures

This section shows how the automated parameterized Energy Flexibility Data Model as the result of the DD-EFMod method can be used. For this purpose, I use simulated machine operation of the EMAG GT machine tool to show the revenue that an energy-flexible operation can achieve as defined by a flexible load measure. The reference case operation of the EMAG GT is used as a basis for comparison with a production of 30 parts over a period of 2 h. The data profile for the reference load curve is identical to that described in scenario one in Section 7.1.3, consisting of 7,595 samples with a resolution of 1 second, a dataset size of 0.37 MB, and no missing values or outliers. For the simulated load profile, the dataset contains 8,475 samples with the same 1-second resolution and a size of 0.25 MB. The data was synthetically generated to represent the expected power consumption of the EMAG GT under energy-flexible operation. No outliers or missing values were present in the simulated dataset, ensuring high-quality input for the evaluation process. To determine the energy costs, I use the energy prices with different resolutions of auction Day-Ahead 60 min, auction Intraday 15min, Intraday Continuous 60 min, and Intraday Continuous 15 min from 31.08.2023 of the European Power Exchange (EPEX) energy market [114] (see Figure 7.17). The EPEX electricity market features two primary trading mechanisms: auction trading and continuous trading. Auction trading, including Day-Ahead and Intraday Auctions, operates at specific times with prices set by the market clearing principle, facilitating better planning and demand coverage for the next day [112]. In contrast, continuous trading runs from the previous day up to shortly before delivery, with prices determined on a pay-as-bid basis, offering real-time flexibility for adjusting positions and managing short-term imbalances [115]. Both methods are essential for market stability, catering to different aspects of efficiency and planning.

The reference case operation with a total electrical energy consumption of 14.35 kW h results in total costs of 1.73 € in relation to the Day-Ahead

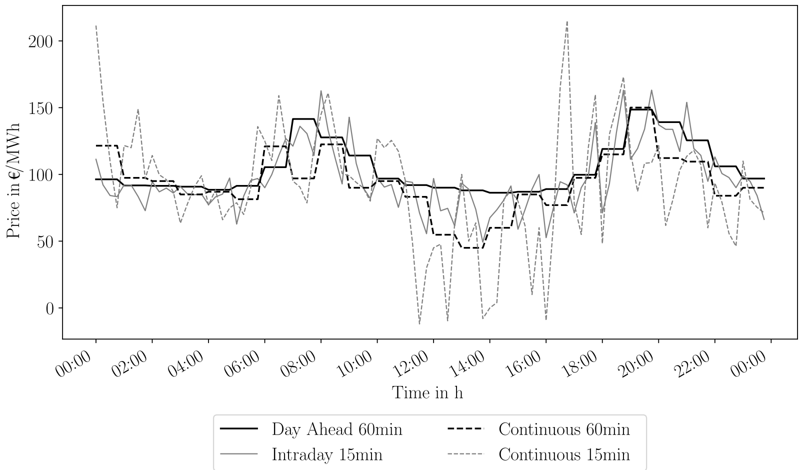


Figure 7.17: Energy prices of different energy markets on 31.08.2023 (own figure).

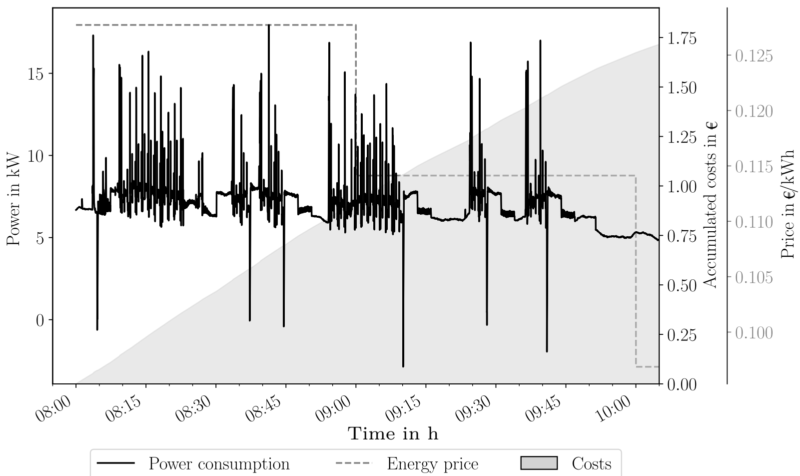


Figure 7.18: Electrical energy consumption and costs on Day-Ahead market for reference case operation (own figure).

market. The total consumption is made up of the aggregated operation of the EMAG GT machine tool and the eChiller45. The electric power consumption load profile for the period on 31.08.2023 from 08:00-10:00 o'clock is shown in Figure 7.18.

The energy-flexibility measure *change processing sequence* should be applied (see Table 2.1) and is chosen because it's applicability for the machine tool EMAG GT was shown in [85], [116] and in my previous work with a similar use case [30]. The energy flexibility measure

Table 7.24: Flexible load measure for *change processing sequence* (own table).

Key Figure	**Value**
ID_{FLM}	*Change processing sequence*
ID_{Load}	EMAG GT
$\mathbf{P}_{\mathrm{FLM}}$	[(8 kW, 08:00), (8 kW, 09:00),(5 kW, 09:00),(5 kW, 10:00)]

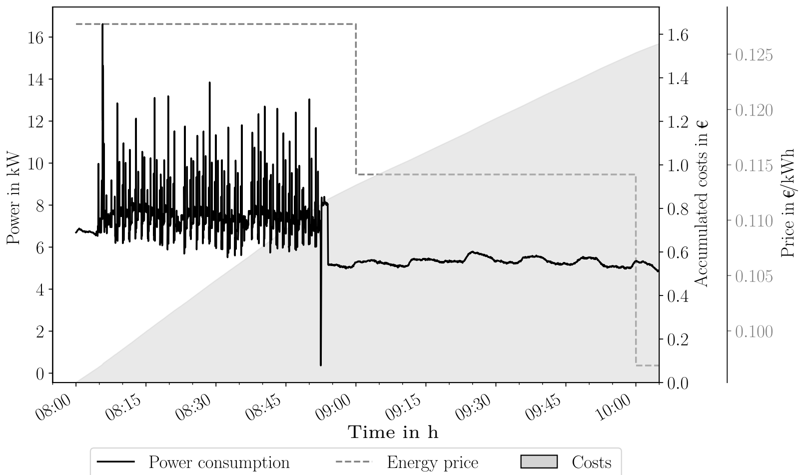


Figure 7.19: Electrical energy consumption and costs on Day-Ahead market for energy-flexibility measure *change processing sequence* (own figure).

change processing sequence was applied following the definition in VDI 5207 (see Table 2.1). This measure is usually defined as rearranging individual processing steps with different energy requirements to smooth out energy consumption peaks and optimize costs. In my specific case, however, there is no classic reorganization of the processing steps. Instead, the adjustment is made through production in a compact production batch without breaks, which reduces the production time for the entire production batch. The batch size, defined as the number of units processed in a production run, remains unchanged at 30 parts in 2 hours, as in the reference case. The selected batch size in combination with continuous processing without interruptions creates a compact load profile. This enables the entire production batch to be completed in one continuous period. This compact production method makes the prerequisite for a subsequent energy-flexibility measure *shift start of job* to periods with lower electricity prices. This following second energy-flexibility measure *shift start of job* decreases energy costs while production targets are still met. By choosing a fixed batch size and carrying out production without breaks, the *change processing sequence* measure is implemented following VDI 5207, but adapted to the specific requirements by carrying out continuous processing in a compact production batch. The flexible load measure can be defined according to Table 7.24 as the load change profile $\mathbf{P}_{\mathrm{FLM}}$ as data tuples of electrical power consumption and timestamp. This would lead to a total consumption of 12.98 kW h, resulting in total costs of 1.57 € in relation to the Day-Ahead market. This would correspond to a cost saving of 0.16 € or 9.2 % compared to the reference case operation. The energy demand over time and the resulting costs are shown in Figure 7.19.

In a further step, the energy-flexibility measure *change processing sequence* is now combined with the energy-flexibility measure *shift start of job* (see Table 7.25) [30]. The selected energy flexibility measures *change processing sequence* and *shift start of job* provide a balanced approach to achieving energy flexibility without disrupting the grind-

Table 7.25: Flexible load measure for *shift start of job* (own table).

Key Figure	Value
ID_{FLM}	*Shift start of job*
ID_{Load}	EMAG GT
$\mathbf{P}_{\text{FLM}}$	[(8 kW, 12:00), (8 kW, 13:00),(5 kW, 13:00),(5 kW, 14:00)]

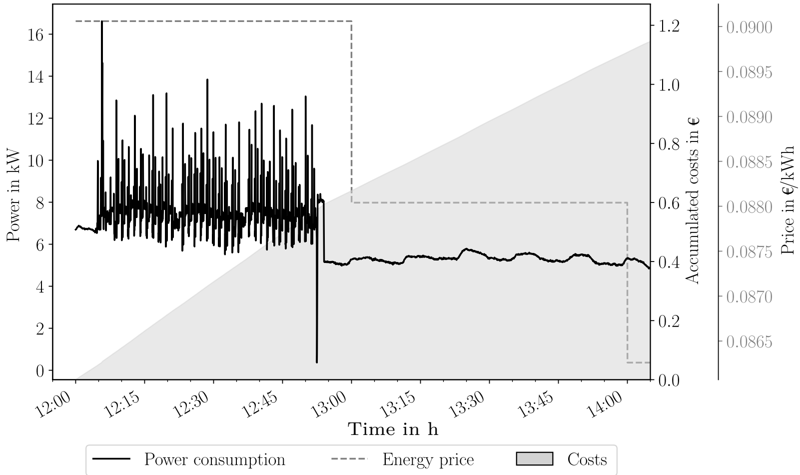


Figure 7.20: Electrical energy consumption and costs for energy-flexibility measure *shift start of job* on Day-Ahead market (own figure).

ing process or compromising product quality. These measures can be applied to the systems with minimal modifications, making them cost-effective and quick to deploy [26]. For this purpose, the operation of the machine tool is simulatively shifted to the period from 12:00 to 14:00 o'clock. This results in a total energy consumption of 12.98 kW h. The total costs are reduced to 1.16 € in relation to the Day-Ahead market due to the adjusted lower electricity prices for this period. This corresponds to a cost saving of 0.57 € or 33.0 % compared to the reference case operation. The time horizon of the energy demand and the re-

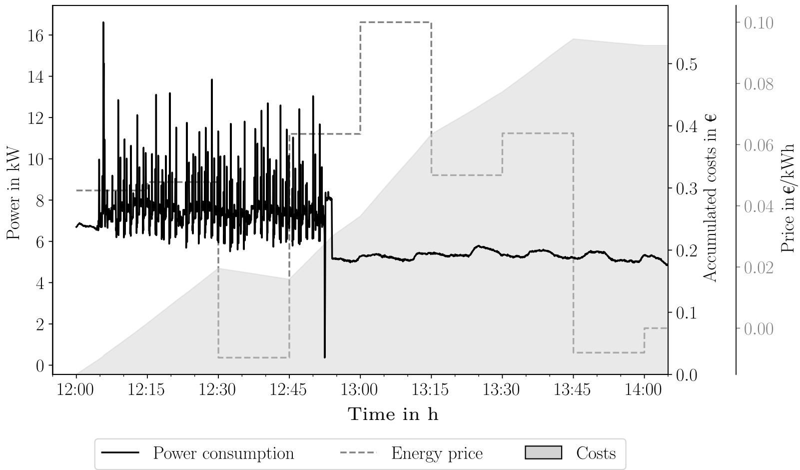


Figure 7.21: Electrical energy consumption and costs on Intraday market for energy-flexibility measure *shift start of job* (own figure).

sulting costs are shown in Figure 7.20. Since fine-grained power states and corresponding holding periods can be identified with the help of the EFDM and the developed DD-EFMod method, I finally look at the possibility of revenue when procuring electricity on the Intraday market. For this purpose, I transfer the existing combined flexible load measure from Table 7.25 and calculate the resulting costs with regard to the Intraday Continuous market with a resolution of 15 min. As a result, the total energy consumption remains the same at 12.98 kW h compared to the previous flexible load measure. The total costs are further reduced to 0.53 € due to the higher volatility of electricity prices for this period. This corresponds to a cost saving of 1.20 € or 69.4 % compared to the reference case operation. The energy demand over time and the resulting costs are shown in Figure 7.21. This clearly shows that detailed knowledge of energy flexibilities and their application in the form of a standardized data model leads to considerable cost savings during implementation.

7.6 Interim conclusion

This chapter is dedicated to validate the DD-EFMod method and the associated software concept developed in Chapter 5) applied on the use case presented in Chapter 6.

The first scenario successfully validated the basic functionality of automatically determining the EFKF for the EFDM based on historical machine data. In the first step *data verification*, the input data was verified for relevance, and the determining EFKFs were defined. In the second step of *data preparation*, the necessary data for further processing was prepared accordingly (e.g. by eliminating outliers). This was followed by the *energy flexibility modeling* step. This involved the deployment of offline clustering algorithm (K-means) and online data stream clustering algorithms (mini-batch K-means, CluStream) in the *energy flexibility key figure determination* sub-process to identify power states. Based on this successful application, further automated determination of the EFKF for the EFDM class flexible load for the machine tool EMAG GT was possible by the implementation of data analytics algorithms. As part of the DD-EFMod sub-process of *energy flexibility model synthesis* the automatically determined EFKF was parameterized in the EFDM. Further, the deployment of the data streaming algorithms for power state determination in scenario one confirms research hypothesis number two, but the online clustering algorithms only achieved partial success in this scenario.

The second scenario showed the successful application of the DD-EFMod method to the EFDM class storage by considering the product storage of the EMAG GT. Therefore, the *energy flexibility modeling* step was applied with the deployment of storage-specific data analytics algorithms. This successful application for the EFDM class storage shows the modular applicability of the DD-EFMod method. This scenario also demonstrated the high flexibility potential of product and material storages in production systems.

In a third scenario, the transferability of the DD-EFMod method to other machine types or flexible loads was successfully validated, considering a cooling machine and the linked cold storage. The main challenge of this scenario is the continuous operation behavior of the cooling machine, which results in the machine not having defined power states. To address this, within the application of the DD-EFMod steps of *data verification* and *data preparation*, Equal-Width Binning was implemented. This leads further to the successful data-driven automated parameterization of the EFDM for this scenario within the *energy flexibility modeling* sub-processes. The successful implementation of this scenario confirms, therefore, the transferability of the DD-EFMod method.

In the fourth scenario, I validated the method for data-driven determination of the EFDM key figures for the class dependency between flexible loads. For this purpose, the machines machine tool EMAG GT from the first scenario and the cooling machine from the third scenrio was analyzed in combination following the DD-EFMod steps. In order to identify possible dependencies in the *data verification* step, a correlation analysis was implemented. This analysis did not identify any correlations in the available data at this point. Because of the operating behavior of the machine tool, however, simultaneous operation of the cooling machine is required. This dependency could be determined in the next step of *energy flexibility modeling* the *EFKF determination* sub-process by implementing a Boolean analysis algorithm. This made it possible to automatically determine the required key figures for the EFDM class dependency based on the available data.

Finally, I validate the economic potential of the detailed determination and application of the automatically parameterized EFDM. For this purpose, the automatically determined key figures of the scenarios were used to form concrete load profiles for the machines in the form of flexible load measures. Based on this, the first research hypothesis can be confirmed. Furthermore, I was able to show that the application of energy-flexibility measures based on detailed modeling of energy flexibility offers monetary advantages, especially when oriented toward the volatile Intraday energy market. However, this requires factories to be able to operate in an energy-flexible manner. As shown, this can be realized by the application of the DD-EFMod method I developed in this thesis. In the following summarizing section, I evaluate the prototypical implementation of the DD-EFMod method and the results achieved meet the requirements specified in Chapter 4. This is summarized in Table 7.26.

Table 7.26: Fulfillment of the requirements for the method and implementation as part of the validation (own table).

Criteria	Fullfilment
FR-M 1 Applicability	●
FR-M 2 Modularity	●
FR-M 3 Transferability	●
FR-M 4 Reproducibility	●
FR-EF 1 Feasibility	●
FR-EF 2 Accuracy	●
FR-EF 3 Maximization	◑
FR-EF 4 Explainability	●
FR-EF 5 Safty	◑
QR 1 Quality	◑
QR 2 Robustness	◑
QR 3 Explainability	●
QR 4 Scalability	●
QR 5 Real-time capability	●

FR-M 1 Applicability:
The method was implemented using an open-source software concept and real measured machine data. This ensures that the method is widely accessible and based on real data. The validation through the prototypical implementation in various scenarios with real machine data confirms the successful application of the DD-EFMod method for the data-driven determination of energy flexibility key figures and parameterization of the EFDM.

FR-M 2 Modularity
The modularity of the software concept makes it possible to determine only individual EFKFs if required. This increases the flexibility and adaptability of the method to specific requirements. The successful application and results in the scenarios clearly demonstrate the modularity of the DD-EFMod method.
FR-M 3 Transferability The method was successful tested consider different classes (flexible loads, storage, dependencies) of the EFDM of production infrastructure machine types. This confirms the versatile applicability and adaptability of the DD-EFMod method to different system components. The results fundamentally demonstrate the possibility of transfer to different machine types.
FR-M 4 Reproducibility
Several test runs with the same database using different scenarios underline the reproducibility of the DD-EFMod method. The consistency of the EFKF and other parameters when repeatedly applied to the same data confirms the reliability and repeatability of the method, which is essential for scientific and technical application.
FR-EF 1 Feasibility
The transfer of the automatically determined EFKFs of the EFDM in flexible load measures demonstrates the practical feasibility of the method. Validation by simulated flexible load measures not only shows the potential for energy and cost savings, and also the feasibility of transferring the method to real systems, as has already been demonstrated in my previous work Lindner *et al.* [30]
FR-EF 2 Accuracy
The accuracy of the method's results is based on measured values, which makes the parameterized EFKFs reliable. The validation process of the DD-EFMod method in the sub-process *energy flexibility model synthesis* including the *EFKF validation* and step *energy flexibility model validation*, is based on expert knowledge and defined metrics and therefore fulfills the implementation requirements.
FR-EF 3 Maximization

The implementation takes into account all theoretical power states and storage capacities in order to exploit the maximum energy-flexibility potential. The validation shows that the theoretically calculated maximum potential must be integrated into a flexible load measure within the technical operating limits to be technically feasible. Not all maximum operating limits could be utilized during the validation.

FR-EF 4 Explainability:
The methodology ensures the traceability and validity of the parameterized EFDMs, whereby this is achieved through the *algorithm selection* step by selecting explainable machine learning and data analysis algorithms. The machine learning and data analysis algorithms selected for validation in this thesis meet the explainability requirements.

FR-EF 5 Safty:
Technical operating limits are an essential aspect of both the validation of individual EFKFs and the validation of the entire EFDM in order to enable safe, energy-flexible operation. The automated determined EFKFs meet these requirements. In addition, it is necessary to check that the limits are fullfilied by the flexible load measures.

QR 1 Quality
The development of the DD-EFMod method includes the step *model quality sufficient*, which is crucial for the evaluation of the selected machine learning or data analytics algorithm for the automated determination of EFKFs, and ensures the quality of the method. The validation of the selected algorithms in this thesis shows a good model quality but with potential for improvement.

QR 2 Robustness
The selection and testing of efficient methods on different data sets shows that not every algorithm is suitable for every key figure, which requires an individual *algorithm selection* step for each key figure.

QR 3 Explainability
The method enables the selection of explainable algorithms through the *algorithm selection* step, which contributes to the transparency and comprehensibility of the results.

QR 4 Scalability
The applied algorithms in this work show asymptotic behavior and provide similar results even for larger data sets, which confirms the scalability of the selected algorithms.
QR 5 Real-time capability
Real-time requirements were considered in the *algorithms selection* step, with all tested algorithms being able to complete the calculations within the specified time frame of a maximum of 15 minutes.

In summary, the method for Data-Driven Energy Flexibility Modeling (DD-EFMod) and the prototypical implementation based on the software concept fulfills the defined requirements from chapter 4 well. However, there is still room for improvement in some technical details, especially in the evaluation and selection of machine learning or data analytics algorithms. The method represents a simplification in determining the energy flexibility key figures of the Energy Flexibility Data Model. It can support energy or production managers in implementing energy-flexibility measures. Due to the possibility of automated parameterization and processing of an EFDM and its key figures, the method I developed thus offers a good starting point for realizing the automated application of industrial energy flexibility.

8 Conclusion and Outlook

”I think the first and most important thing is that you’ve got to have a goal and a vision.”

Arnold Schwarzenegger

This chapter gives a summary of the main findings and achievements of this thesis. Finally, an outlook on possible further improvements and future research topics are given.

8.1 Summary and Conclusion

The efficient and sustainable operation of industrial production systems is associated with challenges. In addition to maintaining product quality and managing production schedules, adapting production to volatile energy prices and renewable energy sources is becoming more important. To achieve this, it is essential to consider all dependencies between production machines, supply systems, and storages. Therefore, industrial energy flexibility provides a strategic solution by enabling production systems to adjust to volatile energy prices or to renewable energy sources without sacrificing productivity. This can be realized by energy-flexibility measures. This adjustment has the potential to reduce energy costs and furthermore to reduce the CO_2 footprint of a company by leveraging the increased use of renewable energies. Furthermore, trading energy flexibility in future energy markets could generate additional revenues for a company while saving energy costs.
A core aspect of realizing energy flexibility is the modeling of energy-flexible systems within a generic data model, such th Energy Flexibility Data Model. Given the complexity of industrial systems and the extensive expert knowledge required, the correct modeling of each relevant system is a difficult task.
This thesis addresses these issues by proposing a data-driven method, to automate the parameterization of energy flexibility models, which is essential to realize energy-flexibility measures, particularly in dynamically changing market conditions. This method, called the Data-Driven Energy Flexibility Modeling (DD-EFMod) significantly streamlines the process of enabling energy-flexible factory operations. The research work and the the development of the DD-EFMod was therefore lead by the following research question:

> ”Is it possible to develop a method for automated parameterization of an energy flexibility model, based on data from a production system, to describe the energy flexibility of the production system?”

To answer this research question, two research hypotheses was derived from these central research question:

1. ”Data-driven automatically parameterized energy flexibility models of machines in production infrastructure can be used to enable energy-flexible operations.”
2. ”Machine learning and data stream mining algorithms can be used to automate the parameterization of energy flexibility models of machines from the production infrastructure.”

To adress the research question and the research hypotheses, this research work was carried out according to the Design Research Methodology. Based on the research scope in Chapter 1, a fundamental understanding of the state of the art in science and technology is established in the Descriptive Study I (Chapter 2 and 3). Therefore this work presents the fundamentals of industrial energy systems and energy flexibility in interaction with digital production. Furthermore, existing approaches to data analysis and modeling of energy flexibility are presented, and the research gap is identified through a systematic literature review and analysis.
This work focuses on the prescriptive study. Based on the identified research gap, the research questions, hypotheses, and requirements for the method for data-driven automated modeling of energy flexibility are formulated in Chapter 4. This is followed by the development of the Data-Driven Energy Flexibility Modeling (DD-EFMod) method in Chapter 5, which provides a structured procedure for the automated modeling of energy flexibility.
The DD-EFMod method, as shown in Figure 5.1, has been developed to facilitate the necessary modeling of energy flexibility through data-driven approaches. This method extends the process to enable factories to energy-flexible operation during the *application and implementation*

step. Therefore, the *application and implementation* layer of the DD-EFMod method specifically uses the different steps *data verification*, *data preparation*, and the *energy flexibility model setup* to describe energy flexibility, reducing the need for manual intervention. In the *energy flexibility modeling* layer of the DD-EFMod method, the automated determination of the individual energy flexibility key figures of the Energy Flexibility Data Model is realized by the implementation of suitable machine learning and data analytics algorithms in the sub-process *energy flexibility key figures determination*. These determined key figures are then parameterized, validated, and built to the Energy Flexibility Data Model within the *energy flexibility model synthesis* sub-process. These structured steps provide the DD-EFMod method to automate and simplify the task of modeling energy flexibility.

In the Descriptive Study II, the DD-EFMod is initially applied and validated on the use case presented in Chapter 6 with a focus on machines which represents electrical flexible loads. The validation was carried out as part of the work, and the resulting conclusions confirm the second research hypothesis. This was proven in particular by the successful implementation of DD-EFMod in the context of the use case. However, it was found that the various implemented machine learning algorithms delivered different results during the deployment. For example, the offline batch K-means clustering algorithm and the online batch incremental mini-batch K-means clustering algorithm produced good and reliable results, particularly when determining the key figure for power states. On the other hand, the data stream mining online learning instance incremental CluStream clustering algorithm for identifying the power states on the basis of the available data does not have the same performance as the K-means batch algorithms, but in principle, it is possible to use these algorithms.

The first research hypothesis can also be confirmed, as the simulative applied energy-flexibility measure *change processing sequence* and *shift start of job*, carried out as defined flexible load measures based on the automatically parameterized Energy Flexibility Data Model shows

good results.
In particular, it could be shown that the detailed modeling of the energy flexibility as EFDM of the machine tool and the cooling machine enables potentially higher cost savings, as a more specific machine operation, oriented to the energy market, is possible. The application of the energy flexibility measure *change processing sequence* as a EFDM based flexible load measure resulted in cost savings of 9.2 %. Additional cost savings of up to 69.4 % were achieved by combining the energy flexibility measures *change processing sequence* and *shift start of job* in regard to the Intraday energy market as part of the validation of the use case. The research question can be answered positively and confirmed by confirming the research hypotheses. This also shows that the DD-EFMod method developed as part of this work simplifies the enablement process for energy flexibilization of factories.

8.2 Outlook and Further Research

The implementation and the developed Data-Driven Energy Flexibility Modeling method proposed in this thesis form a starting point for filling an essential gap regarding the modeling and application of energy flexibility in manufacturing. While the proposed method demonstrates significant potential, it also presents several limitations that should be considered in its application and future developments:

- The parameterization of Energy Flexibility Data Models and machine learning models must be repeated for each new machine or system, as the models are not directly transferable.
- The approach assumes the availability of high-quality, consistent data as a prerequisite, which may not always be achievable in every production environment.
- Reliable access to machine data and the network infrastructure is critical. Network stability and data transmission issues can affect the quality of the datasets used for modeling and analysis.

- The dataset characteristics, including transient behaviors and specific operating conditions (e.g., in the ETA Research Factory), may limit the direct applicability of the findings to other production environments or machine types without additional adaptation efforts.
- The simulated dataset used for validation was tailored specifically for the machine tool EMAG GT under predefined operating conditions. This may restrict the generalization of results to other configurations or scenarios.

Despite these limitations, the DD-EFMod method provides significant opportunities for further development and enhancement. Addressing these challenges is not only crucial for reinforcing the robustness of the method but also serves as a foundation for exploring new research opportunities and practical applications in energy flexibility. Building on these insights, several potential areas of future work have been identified, focusing on expanding and refining the method's capabilities:

- Expanding the DD-EFMod method to include the parameterization of logistical and economic energy flexibility key figures, broadening the scope of energy flexibility assessment. In particular, the key figures of the Energy Flexibility Data Model are to be considered therefore.
- Developing automatic machine learning pipelines to fully automate the machine learning model selection and the method's application, thereby reducing manual intervention and expert knowledge.
- Integrating the energy flexibility models into asset administration shell submodels (given in [117]) and management systems for real-time decision-making and operational control. This can make a decisive contribution to standardized data exchange and thus enhance the automated use of energy-flexible systems [118, 38].
- Validation of the DD-EFMod method for different use cases and industries is crucial to ensure its robustness and applicability. In the context of this work, the focus was on electrical flexible

loads. Future research should therefore investigate the application to other types of flexibilities, e.g. heat supply, aggregation of multiple flexibilities [90], bidirectionally chargeable electric vehicles for factories [119, 120] or chemical processes, to confirm the method's applicability in a much larger range of industrial energy flexibility scenarios.

- Investigating alternative models, such as those proposed by [77] and [82], or further developing the EFDM to incorporate data exchange with external simulation and planning tools like [121] or [122], offers promising opportunities for expanding the dimensions of energy flexibility in manufacturing. These enhancements could facilitate more sophisticated optimization strategies, enabling real-time energy management and more precise alignment with market signals or operational constraints.

These research topics aim to address the current limitations and extend the potential of energy flexibility in manufacturing, contributing to achieving sustainable and adaptable industrial production.

A Appendix

A.1 Further Related Work

A.1.1 The EFDM GUI Service

The EFDM GUI is a web application tailored for creating energy flexibility data models (EFDM) that facilitate the standardized description of energy flexibility. The service was developed as an element of the Synergy project in the period from 2019 to 2023 and has since been provided by Institute of Production Management, Technology and Machine Tools (PTW) at the Technical University of Darmstadt [94].

This application supports energy managers in manually entering data related to storage systems, flexible loads, their dependencies, and specific energy flexibility measures into the system [5, pp. 255–260]. The DD-EFMod is used to automatically determine the energy flexibility key figures of the Energy Flexibility Data Model. These key figures are then transferred to the EFDM GUI, which facilitates their integration into the required JSON format for further use. The interface of the EFDM GUI, allows the input and management of this data through an HTML-based graphical user interface. Users can manually fill out various forms on the EFDM GUI to compile data, which can then be downloaded as a JSON file for (automated) marketing of energy flexibility [29].

The EFDM GUI is designed to ensure platform-independent, easily readable JSON formatted data that conforms to a uniform schema, enhancing (semi-)automated IT processing between industrial companies and energy markets. It includes multiple tabs for detailed editing of classes such as Flexible Loads, Dependencies, and Energy Storage, each contributing to a comprehensive representation of energy flexibility within an enterprise (see Chapter 2).

This tool also allows the integration and interaction with external energy management and market services, aligning with the Energy Synchronization Platform (ESP) to optimize energy-flexible operations across systems. The EFDM serves as a crucial basis for internal and external communications, enabling users to effectively manage and update energy flexibility data in line with industry standards.

A.1.2 The Energy Synchronization Platform (ESP)

The Energy Synchronization Platform [37] concept describes the architecture of components, interfaces and data models for the automation and standardization of energy flexibility trading as well as the integration of the relevant stakeholders. The Energy Synchronization Platform concept is implemented by the company platform and market platform.

The Energy Synchronization Platform is divided into two sub-platforms, the company platform and the market platform, which are able to exchange data and interact via an interface. The Energy Synchronization Platform thus describes the interaction of several company platforms on a central market platform to carry out transparent energy flexibility trading supported by information technology. A company platform offers the necessary functionalities for the IT connection and control of energy-flexible production processes and infrastructure in a service-oriented infrastructure. The market platform can be described as a multilateral platform that makes it possible to connect and control various energy flexibility markets and services .

The separation of the Energy Synchronization Platform into two logical platform types is necessary to securely encapsulate their specific domain knowledge, technologies, and methods without impairing the overall system's operation and performance. The Energy Synchronization Platform represents the overall framework for cooperation between the company platform and the market platform. In this global framework, stakeholders, technical interfaces, data flows, and regulations are defined for successful interaction and integration of the actual software platforms, namely the company platform and market platform [38].

The Energy Synchronization Platform provides for several company platforms existing in parallel, which, for example, provide the flexibility of connected energy-flexible systems and processes. Various services are required on the company platform for provision and orchestration. In contrast, a market platform that communicates with all company platforms via a uniform interface acts as an intermediary. By setting up the market platform as a multilateral platform, companies are given access to a large number of existing and future markets, platforms, and supporting services. To enable companies to market flexibility, various services are also provided and executed via the market platform. These support companies in various aspects of flexibility provision, flexibility assessment, and energy flexibility trading [123].

A.2 Additional Results

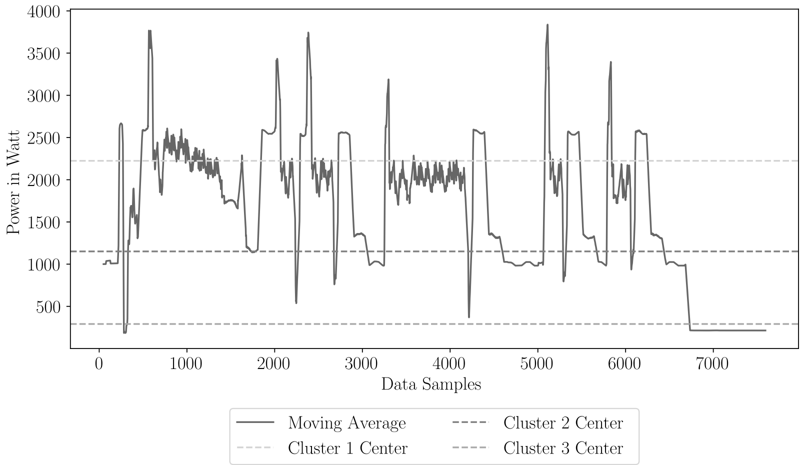


Figure A.1: Mini-batch K-means clustering results EMAG GT (own figure).

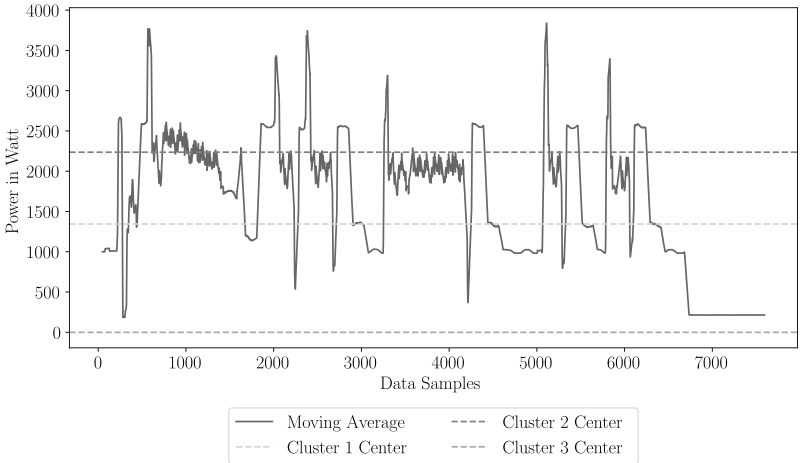


Figure A.2: CluStream clustering results EMAG GT (own figure).

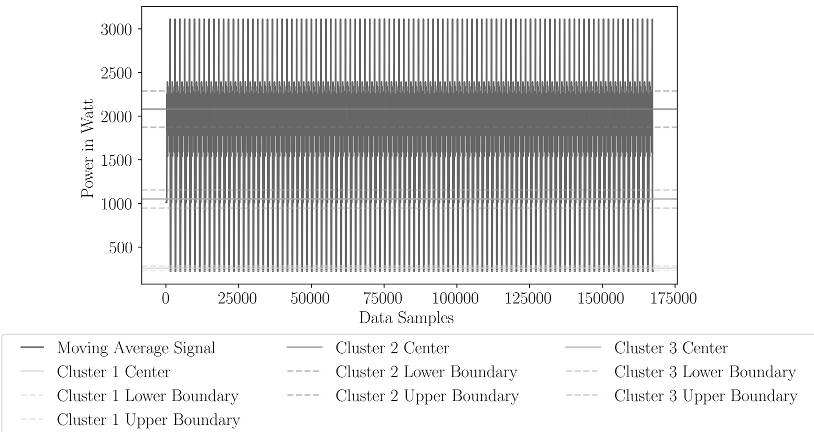


Figure A.3: Batch K-means clustering results EMAG GT simulated data set (own figure).

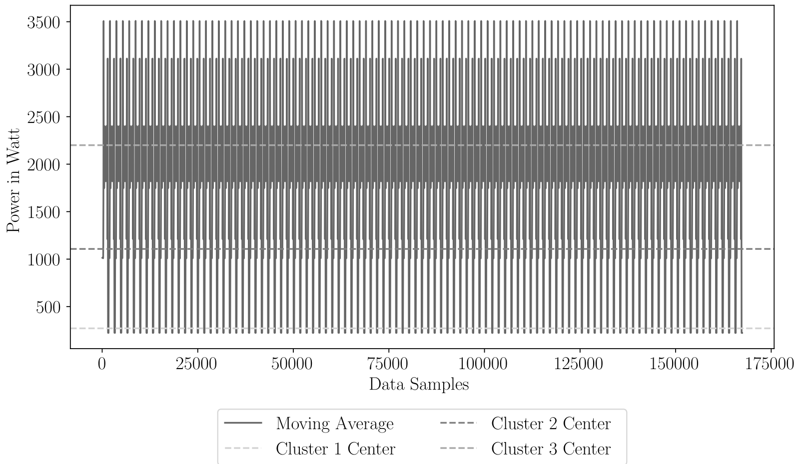


Figure A.4: Mini-batch K-means clustering results EMAG GT simulated data set (own figure).

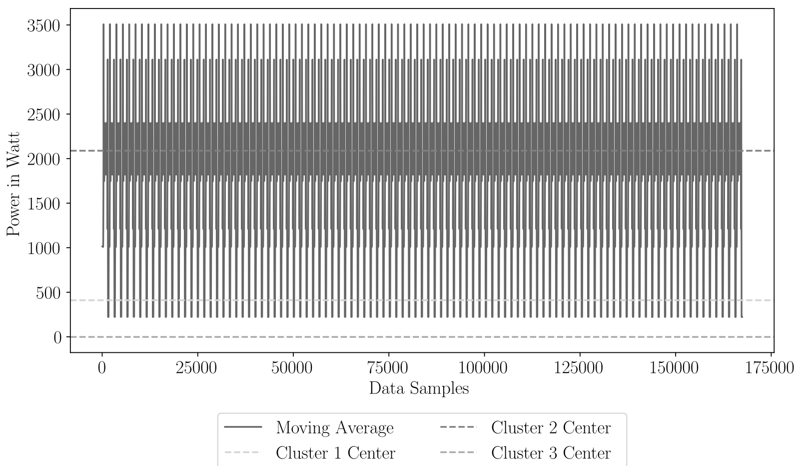


Figure A.5: CluStream clustering results EMAG GT simulated data set (own figure).

A.3 Detailed Description of the EFDM

The Energy Flexibility Data Model (EFDM) developed within the SynErgie-Project serves for the generic and standardized description and modeling of energy flexibility [29]. It describes energy flexibility in form of a flexibility space and concrete *flexible load measure*. The goal is not to create a completely realistic representation of a flexibility, but the mapping of technically and energetically relevant information in a granularity that enables the communication of flexibility between industrial companies and energy markets on the basis of the Energy Synchronization Platform [37]. It is represented in the form of a JSON schema [29].

Table A.1: Detailed description of the class flexible load of the EFDM (mandatory).

<table>
<tr><th>Key figure
JSON object
Symbol</th><th>Attributes</th><th>Value range</th><th>Data type</th><th>Unit</th><th>Required</th><th>Implicit default value</th></tr>
<tr><td rowspan="2">Flexible Load ID
flexibleLoadId
ID_{Load}</td><td></td><td></td><td>String Format: UUID</td><td></td><td>yes</td><td></td></tr>
<tr><td colspan="6">The ID of a flexible load for unique identification. The Universally Unique Identifier (UUID) is generated automatically and is used for identification and assignment within an IT system in a company and for further processing by external, market-side services.</td></tr>
<tr><td rowspan="2">Reaction Duration
reactionDuration
T_{Rea}</td><td></td><td>$\mathbb{R}_{0+}$</td><td>Number</td><td>s</td><td>no</td><td>0</td></tr>
<tr><td colspan="6">Time required by a technical system between the call-up and the start of a flexible load measure. The call must therefore be made at least with this lead time before the start. This key figure is important for the correct and timely execution of flexibility calls and is dependent on the communication partner. Thus, the reaction duration of a machine itself is shorter than the reaction duration that includes a communication chain via several upstream IT systems.</td></tr>
<tr><td rowspan="4">Validity Period
validity
T_{V}</td><td>temporalType</td><td>start; end; total</td><td>String Format: enum</td><td></td><td>no</td><td>total</td></tr>
<tr><td>from</td><td>$\mathcal{H}$</td><td>String Format: DateTime (ISO 8601)</td><td></td><td>no</td><td>constant availability</td></tr>
<tr><td>until</td><td>$\mathcal{H}$</td><td>String Format: DateTime (ISO 8601)</td><td></td><td>no</td><td>constant availability</td></tr>
<tr><td colspan="6">Subset of the company-internal planning horizon in which the flexible load is available. The beginning and end of this validity period are specified with the attributes from and until. If this period is not specified, continuous availability of the flexible load is assumed. The temporalType start specifies that the start of each flexible load measure belonging to this flexible load must lie within the validity period. end specifies that the end of each flexible load measure belonging to this flexible load must lie within the validity period. Total specifies that the total duration of each flexible load measure belonging to this flexible load must lie within the validity period.</td></tr>
<tr><td>Power States
power
$\mathbf{P}$</td><td>min;max</td><td>$\mathbb{R}$</td><td>Number</td><td>kW</td><td>yes</td><td>0; inf</td></tr>
<tr><td>Duration
duration / type
T_{H} / T_{type}</td><td>min;max; durationType</td><td>$\mathbb{R}^{+}$; deliveryDuration; holdingDuration</td><td>Number; Enum</td><td>s</td><td>no</td><td>holdingDuration</td></tr>
</table>

Order *order* P_O	*order*	chronological; arbitrary	Enum		no	arbitrary
	A set of *power states* with which the *flexible load* can run during each of the (number of changes + 1) holding periods. A positive sign means that the *flexible load* causes an increase in power consumption. Negative Power States represent a decrease in power consumption. Non-linear states can be approximated by corresponding pairs of values. The time period the *flexible load* runs in its *power states*. Duration corresponds to the time of a constant *power state* (*holdingDuration*) OR a constant *power state* with initial power modulation (*deliveryDuration*). Specifies whether *power states* can be retrieved in any order OR whether a chronological activation of the next *power states* must occur when the first *power state* is activated. This enables the modeling of a defined load profile.					
UsageNumber *usageNumber* N_{Use}	*min;max*	$\mathbb{N}_0$	Integer		no no	0;inf
	The allowed number of uses of the *flexible load* within the *validity period*. By specifying a minimum value, the necessity of calling a *flexible load* can be described. By specifying a maximum value, a limitation of the call frequency can be described.					
Modulation Number *modulationNumber* N_{Mod}		$\mathbb{N}_0$	Integer		no	inf
	The maximum number of *power state* changes (modulations) allowed within one use of a *flexible load*. The two modulations corresponding to the initial activation and the final deactivation are not counted.					
Power Gradient *powerGradients* ∇ $\nabla P_{\mathrm{Act}} / \nabla P_{\mathrm{Mod}} / \nabla P_{\mathrm{Dea}}$	**activationGradient** (*min*;*max*)	$\mathbb{R}_{0+}$	Number	$\frac{\mathrm{kW}}{\mathrm{s}}$	no	0;inf
	modulationGradient (*min*;*max*)	$\mathbb{R}_{0+}$	Number	$\frac{\mathrm{kW}}{\mathrm{s}}$	no	0;inf
	deactivationGradient (*min*;*max*)	$\mathbb{R}_{0+}$	Number	$\frac{\mathrm{kW}}{\mathrm{s}}$	no	0;inf
	The absolute value of the power gradient of a *flexible load* indicates how fast the power can be increased or decreased. The *activation gradient* describes the possible power gradient during the initial activation of a *flexible load*. The *modulation gradient* describes the power gradient during a change of power states. The *deactivation gradient* describes the possible power gradient during the final deactivation period.					
Regeneration Duration *regenerationDuration* T_{Reg}		$\mathbb{R}_{0+}$	Number	s	no	0
	The (minimum) time for which no (other) measure of the same *flexible load* may be activated after the deactivation of a *flexible load measure* has ended. This time is only to be taken into account if a deactivation is carried out. If another measure follows seamlessly, no deactivation takes place between the measures. This is therefore not a violation of the prescribed regeneration time.					
Costs *flexibleLoadCosts* c_{Load}	*variableCost*	$\mathbb{R}$	Number	$\frac{€\,\mathrm{h}}{\mathrm{kW}}$	no	0
	costPerUsage	$\mathbb{R}$	Number	€/usage	no	0
	fixedCost	$\mathbb{R}$	Number	€	no	0
	The costs associated with the use of the *flexible load*, excluding electricity costs. The *costs* of a *flexible load* consist of variable cost, usage cost and fixed cost: Variable costs refer to the total amount of energy converted. Usage costs are incurred per use of a *flexible load*. Fixed costs incurred during the *validity period* regardless of the call of a *flexible load* (example: standby costs of a power generation plant).					

Order Confirmation Deadline *orderConfirmationDeadline* t_{OCD}	*deadline-Type*	*absolute*;*relative*	String Format: enum	$\frac{\text{€ h}}{\text{kW}}$	no	relative
	dead-lineValue	$\mathbb{R}_0^+$ (relativ) $\mathcal{H}$ (absolut)	Number(relative) String Format: DateTime (ISO 8601) (absolute)	s	no	reaction-Duration
	Latest possible time by which confirmation of an accepted offer of the *flexible load* must have been received. By this time, the flexibility provider needs to know whether the *flexible load* must be held ready. After the *booking confirmation deadline* is exceeded, the *flexible load* offer is removed from the market. The *order confirmation deadline* can be specified either absolutely with a fixed time or relative to the start time of the *flexible load measure* (e.g. 100 seconds before the start of a *flexible load measure*). If no value is specified, constant availability for offering is assumed until the latest possible start time within the *validity period* minus the *reaction duration*.					
Prices *prices* p	*vari-ablePrice*	$\mathbb{R}$	Number	$\frac{\text{€ h}}{\text{kW}}$	no	0
	pricePe-rUsage	$\mathbb{R}$	Number	€/usage	no	0
	fixedPrice	$\mathbb{R}$	Number	€	no	0
	Prices to be realized on the market as a minimum for offering the *flexible load*. The *prices* of a *flexible load* are composed of a variable price, a usage price and a fixed price analogous to the *costs*. *Prices* are only needed if the *flexible load* is to be actively offered on the market.					
Location *location* L	*meterLoca-tion*		String		no	
	volt-ageLevel	$\mathbb{R}^+$	Number	kV	no	
	Meter point designation for the geographical and power grid topological location of a *flexible load*. The unambiguous allocation is made by means of the meter point designation known in the energy industry / in market communication. In Germany, it corresponds to a 33-digit alphanumeric code number. The specification of the grid voltage level to which the *flexible load* is connected. The voltage level at the grid connection point is to be used, independent of deviating voltage levels in any company grid.					

Table A.2: Detailed description of the class storage of the EFDM (optional).

Key figure *JSON object* **Symbol**	**Attributes**	**Value range**	**Data type**	**Unit**	**Required**	**Implicit default value**
Storage ID *storageId* ID_{Stor}			String Format: UUID		yes	
	The ID of a storage for unique identification. The *Universally Unique Identifier (UUID)* is generated automatically and is used for identification and assignment within an IT system in a company and for further processing by external, market-side services.					
Usable Capacity *usableCapacity* C_{S}	$(min; max)$	$\mathbb{R}$	Number	kW h	yes	
	Lower and upper limit of the storage energy content. These limits must never be exceeded or fallen short of. Depending on the choice of reference point, it is also possible to specify negative storage capacities, e.g. if it possible to exceed or fall below storage limits.					
Initial Energy Content *initialEnergyContent* E_{t_0}	$(min; max)$	$\mathbb{R}$	Number	kW h	yes	
	Energy content of the storage at the start time of the *validity period* of the associated *flexible load* (*suppliers*). If the storage is connected to several *flexible loads*, the *initial energy content* refers to the earliest start time of the *validity periods* of all *flexible loads*. If the initial energy content cannot be quantified exactly, the predicted range can be specified via *min* and *max*.					
Target Energy Content *targetEnergyContent* E_{Tar}	$(min; max)$	$\mathbb{R}$	Number	kW h	no	minimum *Usable Capacity* maximum *Usable Capacity*
	Energy content that the storage must have at the end time of the *validity period* of the associated *flexible loads* (*suppliers*). If the storage is connected to several *flexible loads*, the *target energy content* refers to the latest end time of the *validity periods* of all *flexible loads*. If the target energy content is flexible, the desired target range is specified can be specified via *min* and *max*.					
Energy Loss *energyLoss* E_{Loss}		[0,100]	Number	%/h	no	0
	Proportion of the energy content that is continuously lost, e.g. through exchange with the environment. The percentage refers to the actual energy content and not to the storage capacity.					
Suppliers *suppliers* S_{S}	*flexibleLoadId*		String Format: UUID		yes	
	conversion efficiency	$\mathbb{R}^+$	Number	%	no	100
	One or more *flexible loads* supplying the storage. The *flexible loads* must be defined in the same *flexibility space*. The conversion efficiency is specified for each supply system.					
Drain *drain* E_{Drain}	*power*	$\mathbb{R}$	Number	kW	no	0
	timestamp	$\mathcal{H}$	String Format: DateTime		no	total Validity Period
	A non-influenceable energy demand in the form of a load profile that must be met. The interpolation between the *power states* is linear.					
Costs *storageCosts* c_{Stor}	*variableCost*	$\mathbb{R}$	Number	$\frac{€}{\text{kWh}}$	no	0
	costPerUsage	$\mathbb{R}$	Number	$\frac{€}{\text{usage}}$	no	0
	fixedCost	$\mathbb{R}$	Number	€	no	0
	The costs associated with the use of the energy storage, which depend only on the (time-dependent) energy content of the storage. The *costs* of a storage facility consist of variable cost, usage cost and fixed cost. Variable costs refer to the total amount of energy converted. Usage costs arise per use of a storage tank. Fixed costs arise from keeping a storage facility on standby.					

Table A.3: Detailed description of the class dependency of the EFDM (optional).

Key figure *JSON object* **Symbol**	**Attributes**	**Value range**	**Data type**	**Unit**	**Required**	**Implicit default value**
Dependency ID *dependencyId* ID_{Dep}			String Format: UUID		yes	
	The ID of a dependency for unique identification. The *Universally Unique Identifier (UUID)* is generated automatically and is used for identification and assignment within an IT system in a company and for further processing by external, market-side services.					
Triggering Flexible Load *triggeringFlexibleLoad* ID_{Tri}	*triggeringFlexibleLoadId*		String Format: UUID		yes	
	temporalType	*start; total; end*	String Format: Enum		yes	
	The ID of the *flexible load* that triggers the dependency. The ID must correspond to a *flexible load ID* in the same *flexibility space*. In addition, one time parameter (*start*, *total* or *end*) of the *triggering flexible load* affected by the dependency is to be indicated. The *temporalType*... - ...*start* specifies that with the activation of a *flexible load measure* belonging to this *flexible load*, the dependency *applicability duration* of the *target flexible load* begins. - ...*end* specifies that at the deactivation end of a *flexible load measure* belonging to this *flexible load*, the dependency *appicability duration* of the *target flexible load* begins. - ...*total* specifies that during a *flexible load measure* belonging to this *flexible load*, the dependency *applicability duration* of the *target flexible load* is valid.					
Target Flexible Load *targetFlexibleLoad* ID_{Tar}	*targetFlexibleLoadId*		String Format: UUID		yes	
	temporalType	*start; total; end*	String Format: Enum		yes	
	The ID of the *flexible load* that is affected by the *triggering flexible load.* The ID must correspond to a *flexible load ID* in the same *flexibility space*. In addition, one time parameter (*start*, *total* or *end*) of the *target flexible load* that are affected by the dependency is to be indicated. The *temporalType*... - ...*start* specifies that the start of a *flexible load measure* of the *target flexible load* is affected by the dependency *applicability duration.* - ...*end* specifies that the deactivation end of a *flexible load measure* of the *target flexible load* is affected by the dependency *applicability duration.* - ...*total* specifies that the *flexible load measure* of the *target flexible load* is affected by the dependency *applicability duration* starting at activation until the end of deactivation.					
Logical Type *logicalType* Typ_{Log}		*implies; excludes*	String Format: Enum		yes	
	Specifies whether a use of the *triggering flexible load* requires (implies) or prevents (excludes) the activation of the *target flexible load* within the *applicability duration.*					
Applicability Duration *applicabilityDuration* T_{App}	*min*	$\mathbb{R}$	Number	s	no	Excludes:0 Implies:-inf
	max	$\mathbb{R}$	Number	s	no	Excludes:0 Implies:+inf
	The time period for which the *target flexible load* must be activated at least once (implies) or may not be activated at all (excludes) after the *triggering flexible load* has been used. The respective time linkage must be taken into account.					
Applicability Conditions *applicabilityConditions* A_{C}	*formulaLeft*		String		no	None
	formulaRight		String		no	None

	comparator	*equals; less; lessEqual; greater; greaterEqual*	String Format: Enum		no	None
	Additional conditions that must be met for the dependency to be considered fulfilled. In other words, an activation of the *triggering flexible load* implies or excludes a corresponding activation of the *target flexible load* in a configuration (measure), so that the applicability conditions are fulfilled. The *triggering flexible load* metrics are incorporated on the left side of the formula. The *target flexible load* metrics are incorporated on the right side.					

Table A.4: Detailed description of the class flexible load measure (FLM) of the EFDM (mandatory).

Key figure *JSON object* **Symbol**	**Attributes**	**Value range**	**Data type**	**Unit**	**Required**	**Implicit default value**
Load Measure ID *flexibleLoadMeasureId* ID_{FLM}			String Format: UUID		yes	
	The ID of the load measure for unique identification. The Universally Unique Identifier (UUID) is generated automatically and is used for identification and assignment within an IT system in a company and for further processing by external, market-side services.					
Flexible Load ID *flexibleLoadId* ID_{Load}			String Format: UUID		yes	
	The ID of the Flexible Load to which the *flexible load measure* is directed.					
Load Change Profile *loadChangeProfile* $\mathbf{P}_{\mathrm{FLM}}$	*power*	$\mathbb{R}$	Number	kW	yes	
	timestamp	$\mathcal{H}$	String Format: DateTime (ISO 8601)		yes	
	Load profile that represents the power reduction or increase of the *flexible load*. Positive power states mean that the *flexible load measure* requests an increase in power consumption from the *flexible load*. Negative power states require a decrease in power consumption. Interpolation between *power states* is linear; a step change in power can be mapped by specifying two equal timestamps with different power values.					
Reward *reward* r		$\mathbb{R}$	Number		no	0
	Total revenue received by a company for executing the *flexible load measure*.					

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Own Publications

The following publications have been published while working on this thesis:

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Curriculum Vitae

Experience

05/2019 – 04/2024	**Institute of Production Management, Technology and Machine Tools** Technical University of Darmstadt | Darmstadt | Germany Research associate | Head of Research Unit Cyber-physical production systems (since 04/2023)
11/2018 - 04/2019	**Institute of Process Measurement and Sensor Technology** TU Ilmenau | Ilmenau | Germany Research assistant
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05/2019 - today	**PhD student at the Department of Mechanical Engineering** Technical University of Darmstadt | Darmstadt | Germany
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10/2012 - 03/2016	**Bachelor of Engineering - Electrical and Computer Engineering** Hochschule Anhalt University of Applied Sciences | Köthen | Germany Bachelor thesis: „Analyse und Optimierung einer analogen Signalverarbeitung für Staubmessgeräte“
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