PhD-FSTM-2024-079
The Faculty of Science, Technology and Medicine

DISSERTATION

Defence held on 30/09/2024 in Luxembourg

to obtain the degree of

DOCTEUR DE L'UNIVERSITÉ DU LUXEMBOURG

EN INFORMATIQUE

by

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MODELING AND DATA ANALYSIS FOR FLEXIBILITY OPTIMIZATION AND FORECASTING IN ENERGY SYSTEMS

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“As you start to walk on the way, the way appears.”

Rumi (1207 – 1273)

Acknowledgements

I would like to extend my sincere thanks to Prof. Gilbert Fridgen for his continuous support and guidance throughout my doctoral journey. His knowledge and encouragement have been crucial in shaping this thesis.

I am very grateful to Dr. Michael Schöpf, Dr. Ivan Pavić, and Dr. Mohammad Ansarin for their valuable feedback and continuous support on my final contributions. I also thank my colleagues and friends at FINATRAX for their collaborative spirit and enthusiasm, which have greatly contributed to this work.

I would like to thank Prof. Martin Weibelzahl and Prof. Yves Le Traon for their guidance as members of my Thesis Supervision Committee (CET). Their advice and support have been very important during my PhD.

This research was generously supported by the Kopernikus-project "SynErgie" by the German Federal Ministry of Education and Research (BMBF), by the Luxembourg National Research Fund (FNR) and PayPal, PEARL grant reference 13342933/Gilbert Fridgen. Their financial support has been essential for the successful completion of this study.

Abstract

The energy system is undergoing a significant transformation with the increasing penetration of renewable energy sources into the grid. This shift towards renewables introduces volatility due to the intermittent nature of sources like wind and solar power. To maintain power system stability and avoid unnecessary investments in new power generation or transmission infrastructure, stakeholders propose increasing flexibility within the energy system. Multiple energy sectors can contribute to this flexibility by optimizing their operations to balance supply and demand effectively. Enhanced coordination between these sectors can help mitigate the risks associated with the volatility of renewable energy sources. Additionally, data inputs such as time series of electrical load and renewable generation are essential for optimization, making data analytics crucial for enabling this integrated approach to energy management.

This doctoral thesis comprises six publications that investigate two primary research directions: flexibility optimization and time series analysis. The first four publications focus on developing flexibility optimization algorithms tailored for various energy sectors and market participants, including industrial companies, residential consumers, and electric vehicle (EV) aggregators. Specifically, two papers address industrial demand flexibility optimization, utilizing a generic data model to facilitate seamless data transfer. Another paper proposes a model for EV aggregator flexibility optimization that account for data uncertainty, ensuring reliable operation under uncertain conditions. The forth paper examines flexibility optimization within an energy hub, integrating electricity, gas, and heat as interconnected energy carriers. In addition to optimization strategies, the thesis delves into time series analysis, essential for effective flexibility optimization. Two publications in this domain investigate methods to enhance data quality and forecasting. One publication focuses on real-time spatiotemporal time series missing data imputation, offering solutions to manage and recover incomplete datasets crucial for real-time decision-making. The other publication reviews and evaluates various load forecasting methods, providing insights into their applicability and performance in forecasting future energy demands. Together, these studies contribute to a comprehensive understanding of how to optimize flexibility across different sectors and how time series analysis can support this optimization.

Declaration

I, Ramin Bahmani, declare that this thesis is solely my original work and has not been previously submitted for any other degree or professional qualification. I have acknowledged any contributions made by other authors in jointly-authored research papers and have provided accurate citations and references throughout the thesis. To improve the clarity and flow of my work, I have utilized various AI tools, such as ChatGPT and Grammarly. I have reviewed the output generated by these tools to ensure it accurately conveys my intended message and is free of grammatical errors.

Moreover, I have no financial interests to declare and adhere to the principles of transparency and integrity in both public and professional life. I fully understand and commit to ethical research practices and academic honesty. This thesis represents the culmination of my efforts, and I am open to addressing any questions or concerns regarding its content or veracity in an honest and forthright manner.

Luxembourg, 30/09/2024

Ramin Bahmani

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I Introduction

1 Motivation

The climate crisis poses a significant threat to the world, affecting every aspect of life on earth (Leahy et al., 2010). The continuous rise in global temperatures influences natural ecosystems, weather patterns, and human societies in profound ways (Kerr, 2007). This will affect agricultural productivity, leading to food shortages and increased prices, which could exacerbate hunger and malnutrition globally. Additionally, the climate crisis will cause more frequent and severe natural disasters, such as hurricanes, floods, and droughts, disrupting communities, displacing populations, and straining economies (Klinenberg et al., 2020). In response to this urgent issue, the Paris Agreement was established in 2015, bringing nations together in a shared commitment to combat climate change (Meinshausen et al., 2022). The primary goal of the Paris Agreement is to keep the global temperature rise well below 2°C. Furthermore, it aims to pursue efforts to limit the temperature increase even further to 1.5°C (Rogelj et al., 2016). This ambitious target is crucial for reducing the risks and impacts of climate change, preserving biodiversity, and ensuring a sustainable future for all.

To uphold the Paris Agreement, decisive action is essential. This includes significantly reducing carbon emissions and minimizing reliance on fossil fuels (Jackson et al., 2019). One major area of focus is electricity, a primary energy demand driver, playing a crucial role in decarbonization efforts (Arbabzadeh et al., 2019). Transitioning to renewable energy Sourcess (RESs) is vital in this process. RESs, such as solar, wind, and hydropower, offer sustainable alternatives to traditional fossil fuels, helping to cut carbon emissions (Jin and Kim, 2018). These interconnected sectors highlight the importance of a holistic approach to energy transition (Fridgen et al., 2020). By leveraging the potential of renewable energy, we can drive significant progress across multiple areas, ensuring a more sustainable and resilient energy system (Lund, 2007).

Traditional power systems are centralized with a unidirectional electric flow from bulk power plants to consumers. However, the shift to a modern power system, facilitated by information and communication technology (ICT) and driven by policies to mitigate global warming, has led to an increase in RESs, which are often distributed. These RESs rely on weather conditions for optimal performance, thereby heightening the challenge of maintaining power system stability. To overcome this challenge, energy systems require energy flexibility. (Union of the Electricity Industry - EURELECTRIC aisbl, 2014) defines flexibility as the *"[...] modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) to provide a service within the energy system "*. Energy flexibility provision can thus stem from various sources. While options such as upgrading transmission lines, constructing new electrical storage facilities, or building new power plants involve significant investment costs (Heffron et al., 2020b; Palensky and Dietrich, 2011), dadjusting electricity demand leverages existing assets and is therefore less capital intensive (Heffron et al., 2020b). The concept of demand response (DR), a component of demand side management (DSM), pertains to short-term modifications on the electricity consumption side (Palensky and Dietrich, 2011).

Flexibility in the power system spans various end-users, including industrial, residential, and commercial, each offering unique contributions to energy management (Dranka and Ferreira, 2020). In the industrial sector, flexibility is achieved through DR, where energy-intensive companies adjust their energy consumption based on grid needs, thereby enhancing stability and efficiency (Xu et al., 2020). Residential end-users contribute to flexibility through smart appliances and home energy management systems that optimize usage during peak and off-peak hours. The integration of RESs and battery storage in homes further aids in balancing supply and demand (Gottwalt et al., 2016). In the commercial sector, buildings equipped with advanced energy management systems can adjust heating, cooling, and lighting in response to grid signals, significantly reducing energy consumption during peak periods (Huang et al., 2021). Certain players can operate across multiple sectors of the power system. For instance, electric vehicle (EV) aggregators play a vital role in this ecosystem by managing fleets of EVs that serve as mobile energy storage units, benefiting both residential and commercial sectors (Deng et al., 2020). EV aggregators can coordinate charging and discharging times, providing valuable grid services and enhancing overall system flexibility. This coordination ensures a more resilient and adaptive power system (Lu et al., 2020).

In addition to providing flexibility in the electricity sector, multi-energy systems (MES) also offer flexibility across thermal and gas networks. Flexibility in MES is also vital for enhancing efficiency, reliability, and economic performance across interconnected energy networks (Corsetti et al., 2021). MES involves the integration of various energy carriers, such as electricity, heat, and gas. This approach allows for coordinated energy conversion and storage, optimizing resource utilization and enabling dynamic response to demand fluctuations and market conditions (Mancarella, 2014). MES flexibility supports participation in ancillary services, including frequency control, which improves grid stability. Technologies like combined heat and power (CHP) units and energy storages, such as thermal storage and batteries, are key components that facilitate MES's ability to adjust operations efficiently, ensuring technical and economic benefits across multiple energy sectors (Mancarella et al., 2018).

To integrate flexibility in electricity markets, decision-making systems are necessary (Abdin et al., 2019). Effective decision-making in flexibility provision programs depends on advanced optimization models, which maximize revenue for the participating parties and provide strong financial incentives to engage in flexibility activities. By using generic data formats, the decision-making process can seamlessly accommodate diverse stakeholders and technologies. These processes require a generic data model for inputs and outputs of the flexibility provision program to ensure interoperability and avoid user-specific constraints (Schott et al., 2019). Market-based flexibility mechanisms allow for the dynamic balancing of supply and demand, responding in real-time to fluctuating conditions (Wang et al., 2020).

In flexibility optimization, input data plays a critical role, particularly through the use of various time series data such as loads, electricity prices, and power system measurements (Khatami et al., 2019). Power system analysis necessitates high-quality time series data, making the use of imputation techniques to handle missing or incomplete data essential (Alamoodi et al., 2021). Additionally, predicting future values of these time series is vital for effective flexibility optimization, requiring robust time series forecasting methods to generate accurate and reliable future data points (Pinto et al., 2017). By incorporating advanced forecasting techniques, we can anticipate future load demands, price fluctuations, and system measurements, which serve as vital inputs for optimization models. These models then utilize the predicted data to optimize resource allocation, enhance grid stability, and maximize economic benefits (Zavala et al., 2009). Therefore, the integration of high-quality time series data, imputation, and forecasting is fundamental to the success of flexibility optimization in modern power systems.

2 Research aim

To successfully integrate flexibility into the power system, we need flexibility optimization models to optimize the profit derived from flexibility scheduling. Different energy consumers, such as commercial, industrial, and residential entities, each have their own requirements for flexibility optimization (Dranka and Ferreira, 2020). Therefore, there is no one-size-fits-all solution (Lind et al., 2024). However, there is a general flow of the optimization process demonstrated in Figure I.1. This flowchart illustrates the input-output process for flexibility optimization. It begins with potential flexibility quantification and time series analysis. In the potential flexibility quantification, we assess elements capable of participating in flexibility provision to determine their potential contributions. These elements include flexible loads, generation units, and storage systems. Additionally, various time series data, such as wind speed, solar radiation, and consumer load, require preprocessing steps like missing data imputation and time series forecasting before use in flexibility optimization. These inputs are formatted generically and fed into the flexibility optimization modeling stage. This stage considers factors such as electricity markets, uncertainty modeling, and optimization methods. Finally, the outputs include a schedule of flexible loads and storage, along with the profit derived from flexibility scheduling.

The main focus of this doctoral thesis is on flexibility optimization modeling for different energy consumers considering different electricity markets and uncertainty modeling approaches. Each energy system involves unique components, requiring different flexibility optimization models (Lund et al., 2015). Industrial processes include machines, energy and material storages, and interdependencies between machines within a plant, necessitating specific optimization strategies (Heffron et al., 2020b). This doctoral thesis also aims to deepen the insights presented by (Schott et al., 2019) by investigating the design of a industrial flexibility optimization model based on their generic data model applicable to various industrial companies. In contrast to the industrial flexibility which focuses on the large industrial machines, residential flexibility focuses on household appliances and their usage patterns, considering peak times and demand response programs (Yin et al., 2016). Additionally, there is a special attention to EV charging, as home EV charging is becoming increasingly popular. A further focus of this doctoral thesis is to design optimization algorithms for EV aggregators and incorporating uncertainty into the model. In a broader perspective, this thesis investigates how flexibility can be utilized in a multi-energy system. Therefore, this thesis also explores the availability and optimization of different types of energy, specifically focusing on heat electricity, and gas for enhancing system flexibility.

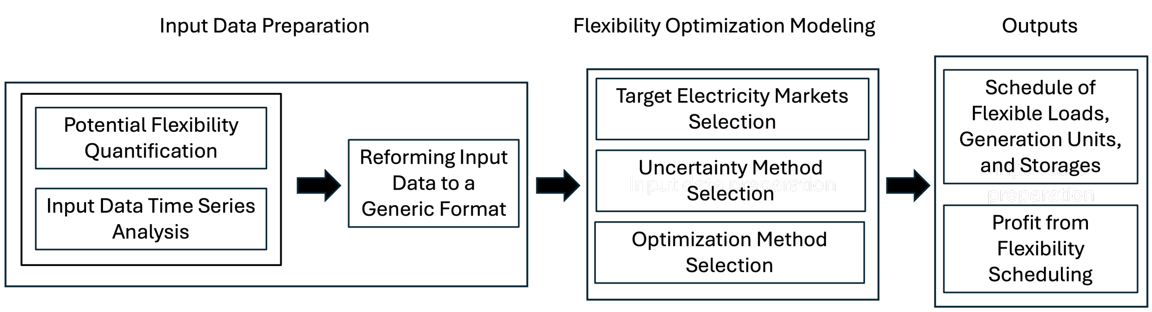


Figure I.1: Flexibility optimization input output flowchart (source: own demonstration)

Energy systems feature various flexibility sources, such as flexible loads and storages. Additionally, different time series, including weather data, electricity price signals, and measurement data, play crucial roles in the optimization process as inputs (Liu and Heiselberg, 2019). Consequently, an additional focus of this doctoral thesis is on forecasting and imputing the time series necessary for effective optimization.

The overall purpose of this thesis is to design and optimize flexibility models for various energy consumers, considering unique sector-specific requirements, uncertainties, and market influences. The research particularly focuses on integrating heat, electricity, and gas in multi-energy systems and improving time series forecasting and imputation.

3 Structure of the thesis

This doctoral thesis consists of a collection of six publications, each contributing to the overall research aim. Table I.1 lists these six publications and highlights their specific roles in achieving the thesis aims. The table outlines various aspects, such as load types, missing data imputation, forecasting, generic input format, electricity markets, and uncertainty modeling. Each publication is detailed based on these attributes, highlighting their specific focus and methods. Four of the publications focus on modeling and optimizing flexibility in different sectors and use cases, including multi-energy systems, industrial loads, and EV aggregators. The other two publications focus on time series analysis needed for the input data in flexibility optimization. Together, these publications provide a thorough exploration of the research topic, covering both theoretical and practical aspects.

After this introduction (Section I), Section II considers flexibility providers across various end users, including industrial, residential, and commercial sectors, detailing their specific characteristics. Additionally, it introduces flexibility in different energy sectors, such as heat and electricity.

Section III addresses the preparation of inputs for flexibility optimization. This process involves quantifying potential flexibility for electricity consumers and generators, conducting time series analysis, and converting input data into a standardized format.

Section IV discusses several key methods and approaches for enhancing the adaptability of energy systems. It emphasizes the importance of time series analysis for forecasting and understanding patterns in energy consumption and generation. Additionally, it highlights the need for generic data formats to ensure interoperability and efficient data integration across various systems. The chapter also explores different markets for flexibility optimization and the role of uncertainty modeling using stochastic optimization technique. Economic and mathematical models, including cost minimization and profit maximization approaches, are detailed to achieve optimal flexibility in energy systems.

Section V concludes this thesis by summarizing the key findings from the previous sections, identifying limitations, and providing an outlook on future research.

	Papers	Load Type	Energy Sectors	Missing Data Imputation	Forecasting	Generic Input Format
Flexibility optimization papers	RP1: Cooperative energy management of multi-energy hub systems considering demand response programs and ice storage	Residential, industrial, and commercial	Electricity, heat, and gas	-	-	-
	RP2: Optimal industrial flexibility scheduling based on generic data format	Industrial load	Electricity	-	-	Yes
	RP3: Energy flexibility scheduling optimization considering aggregated and non- aggregated industrial electrical loads	Industrial load	Electricity	-	-	Yes
	RP4: Impact of minimum energy requirement on electric vehicle charging costs on spot markets	EV aggregator	Electricity	-	-	-
Time series analysis papers	RP5: Noisy PMU data recovery in transient conditions through self-attention neural networks	-	-	Real-time time series imputation	-	-
	RP6: Federated learning for Energy Systems	-	-	-	Load forecasting	-

Table I.1: Research focus of the papers in this thesis

II Flexibility Providers in Energy Systems

Power systems require flexibility to maintain balance between supply and demand, especially as renewable energy sources become more prevalent. In the sections, we first describe flexibility provision by the electrical demand and generation side. These are loads and generations that are adjustable or shift-able to different times. Second, we discuss flexibility provision by multi-energy systems. These systems integrate different forms of energy such as electricity, heat, and gas, allowing us to convert and use one form of energy based on availability and demand. These strategies collectively enhance overall system resilience and efficiency, providing a stable and reliable energy system in the face of fluctuating supply and demand dynamics.

1 Flexibility provision in electrical demand and generation side

Flexible electrical loads and generation play a vital role in modern energy systems by allowing us to adjust power consumption based on real-time grid conditions. By integrating both flexible loads and generation, we create a more robust and adaptable energy system (Heggarty et al., 2020). As demonstrated in Figure II.1, both load and generation can participate in flexibility provision. Flexible loads comprise three primary types: load increase, load decrease, and load shifting. Load increase involves temporarily increasing the power consumption of certain loads to balance excess generation or stabilize the grid. For example, we can schedule EVs to charge during periods with cheaper electricity price (Alyami et al., 2022). On the other hand, load decrease involves reducing power consumption to prevent grid overloads or during periods of high demand. We can for instance turn off devices like electric water heaters, HVAC systems, and other non-essential loads or operate them at reduced capacity, contributing to downward flexibility in the grid (Tian et al., 2021). Load shifting aims to move energy consumption from peak periods to off-peak times. We can achieve this through dynamic pricing schemes like time-of-use (TOU) tariffs, which incentivize users to consume electricity during off-peak hours (Pallonetto et al., 2016). Appliances such as dishwashers and washing machines are often used in load-shifting strategies to align energy use with periods of lower demand or higher renewable generation (Sadeghianpourhamami et al., 2016).

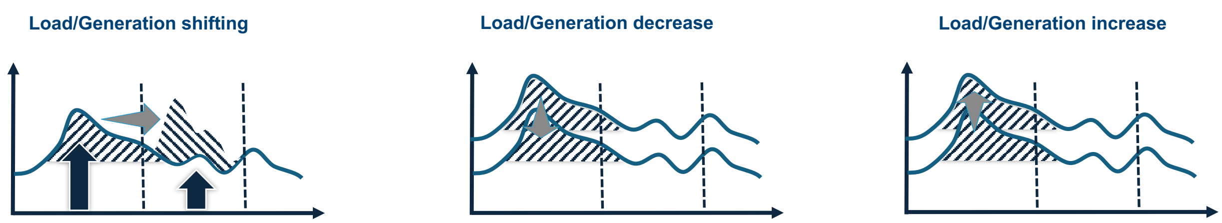


Figure II.1: Load/Generation flexibility types (source: own representation)

On the generation side, we also implement flexibility provision. For instance, we can adjust the output of flexible power plants, such as natural gas turbines, which can ramp up or down quickly in response to grid demands. Additionally, renewable energy sources like wind and solar farms can participate by curtailing production during periods of low demand or excess supply.

We can categorize these flexibility providers into several types, including industrial, residential, commercial, and agricultural providers (Yin et al., 2016). Each type uniquely enhances grid flexibility and stability. Notably, the industrial and residential sectors consume the most energy, which gives them significant potential to contribute to grid flexibility and stability (Dranka and Ferreira, 2020).

Industries are major consumers of electricity, making them critical players in demand-side flexibility RP3. The flexibility in industrial processes can significantly contribute to grid stability and efficiency. Several industrial processes possess substantial flexibility potential, particularly in energy intensive industries such as cement manufacturing, metal smelting, and oil refineries (Golmohamadi, 2022). These industries can adjust their energy consumption patterns to provide substantial grid support (Lee et al., 2020). For example, in cement manufacturing, we can operate crushers and mills during off-peak hours to reduce peak demand on the grid. Crushers, considered interruptible processes, can be switched off on short notice. Additionally, we can run raw and cement mills to provide power flexibility without interrupting production (Golmohamadi, 2022). To ensure that these adjustments are economically viable for the industries involved, we often suggest financial incentives to encourage participation in demand response programs (Marton et al., 2021).

Metal smelting plants, such as those involved in aluminum and steel production, also offer significant flexibility potential (Molina-Garcia et al., 2010). Although the smelting process itself is generally uninterruptible, the power consumption of smelting pots is adjustable to provide flexibility (Golmohamadi, 2022). For instance, we can adjust transformers' taps to modulate the power consumption of electric arc furnaces, allowing these plants to participate in demand response programs (Zhang et al., 2016). In the oil refinery industry, which consumes substantial amounts of power, heat, and steam, we can offer considerable flexibility. These refineries often have self-generation facilities such as gas turbines and boilers that we can adjust to provide grid support. For example, during periods of high electricity prices or grid stress, refineries can increase their on-site power generation or reduce consumption (Golmohamadi and Asadi, 2020). Other industrial sectors also contribute to demand-side flexibility. Pulp and paper, textile, food and drink, ceramics, chemical, and glass manufacturers can adjust various processes to provide grid support. By participating in demand response programs, these industries can optimize their energy consumption, reduce emissions, and improve operational costs.

In addition to the industrial flexibility, residential flexibility can play an important role in demand side flexibility. Buildings are significant energy consumers, heavily burdening the modern power grid. In many developed countries, they account for 30%–40% of the total primary energy consumption (Jensen et al., 2017). Buildings are not only significant energy consumers but also major contributors to causing peak demands. For instance, buildings contribute to nearly 80% of peak demand in the United States (Center, 2020). Residential buildings alone represent 55% of this energy consumption in the U.S. Therefore, they have a crucial role in developing an efficient and reliable power grid (Administration, 2015). Residential EV charging significantly impacts residential load, often increasing peak demand and causing potential grid instability. According to (Golmohamadi, 2022), uncoordinated EV charging can increase the residential load by up to 25%, stressing the distribution system and leading to voltage and frequency imbalances, power losses, and reduced grid reliability (Das et al., 2020). EV aggregators can mitigate these issues by optimizing charging schedules and enhancing grid flexibility. They act as intermediaries between EV owners and grid operators, coordinating charging times to avoid peak load periods and integrating EVs as distributed energy resources RP4. This coordinated approach allows for load leveling and the provision of ancillary services such as frequency control and reactive power support, enhancing overall grid stability and efficiency (Torre et al., 2023). By leveraging advanced communication and control infrastructures, aggregators can facilitate real-time adjustments to charging patterns, thereby providing a crucial tool for grid management and energy optimization in residential areas RP4.

2 Flexibility in multi-energy systems

In addition to the flexibility lied in the electrical system, the flexibility in the heating demand is vital for optimizing multi-energy systems and enhancing their sustainability. This flexibility is achievable through the integration of various heat sources and aims to a more efficient energy use in the system (Corsetti et al., 2021). Figure II.2 illustrates an integrated multi-energy system that optimizes electrical, heating, and cooling operations by managing various energy flows. We use and store electricity from renewable sources and the grid, directing excess power to electric chillers for cooling. Natural gas powers CHP units and boilers, generating both electricity and heat. We store heat and supply it to absorption chillers for additional cooling. By adjusting loads based on grid conditions through electrical and thermal demand response units, we enhance the system's reliability, efficiency, and flexibility. By adapting to fluctuating demand and supply conditions, heating systems can optimize energy consumption and contribute significantly to a flexible energy system. This collaborative effort ensures that the heating sector can meet its efficiency and sustainability goals, providing a more reliable and efficient energy supply (Golmohamadi et al., 2021). The dynamic adaptation of heating systems to real-time conditions enhances their overall performance and supports broader environmental and economic objectives, making energy flexibility a cornerstone of modern energy management strategies.

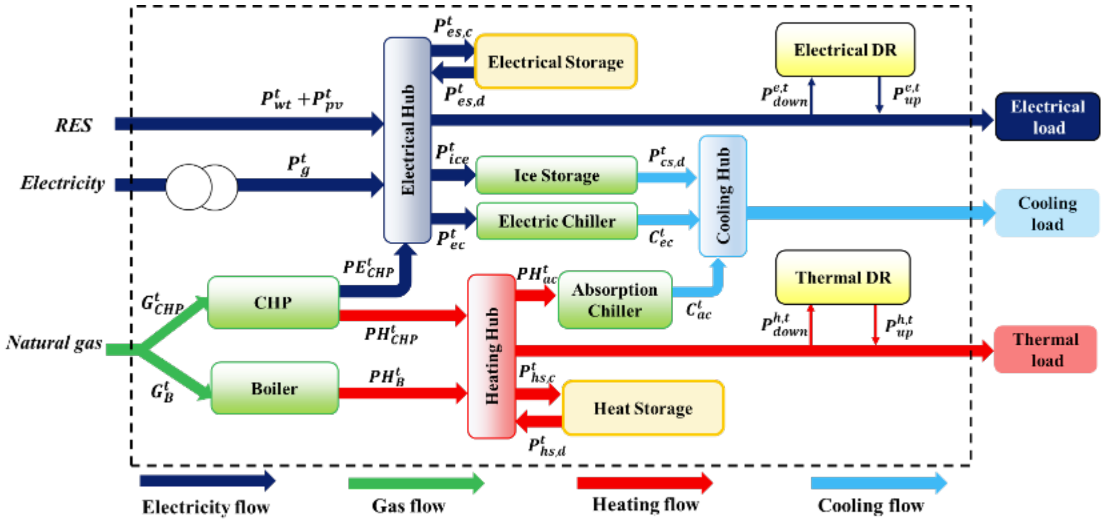


Figure II.2: The architecture of exemplary multi-energy system (RP1)

District heating (DH) exemplifies multi-energy systems by incorporating various energy sources and technologies, such as CHP plants, renewable energy, and electric boilers. District heating systems exhibit a high degree of flexibility by incorporating various heat sources and thermal units, ranging from traditional fossil fuels to modern renewable energy installations (Vandermeulen et al., 2018). In Nordic and Baltic countries, DH systems account for approximately 52%–62% of the heat supply, highlighting their critical role in these regions (Sneum et al., 2016). Renewable energy is used in DH to produce heat, such as solar thermal plants and biomass (Brand and Svendsen, 2013). The integration of renewable energy into DH systems enhances climate balance, with Denmark and Finland exemplifying this through their use of biomass and solar thermal plants, which are also economically supported by tax exemptions (Skytte and Olsen, 2016). Key thermal units in DH systems include CHP plants and boilers (Sayegh et al., 2017). CHP plants are pivotal as they cogenerate both heat and electricity, thereby enhancing energy efficiency and reducing greenhouse gas emissions. Common CHP technologies include steam turbines and fuel cells, which are often located near consumers to facilitate the recycling of waste heat RP1. The deployment of CHP in DH systems can reduce energy consumption by 20%–30% (Wu and Wu, 2013).

III Input Data Preparation for Flexibility Optimization

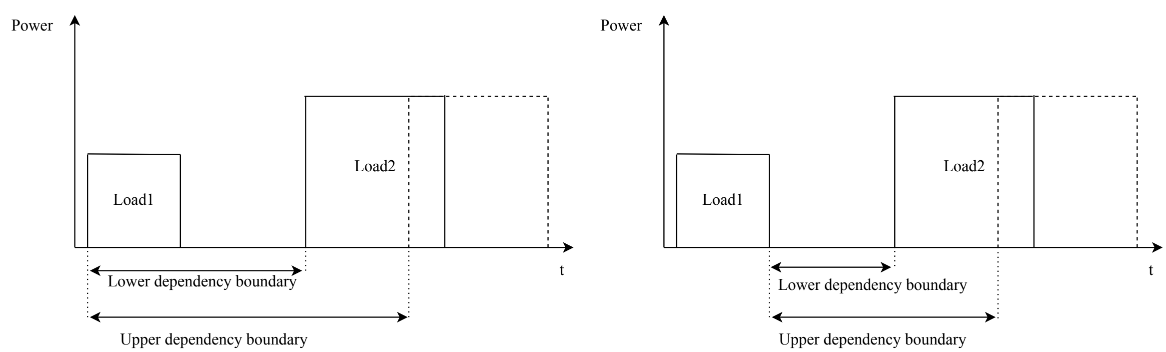
In this chapter, we discuss the input data preparation required for flexibility optimization. As illustrated in Figure I.1, the process of flexibility optimization begins with input data preparation, involving several critical elements. First, we quantify the potential flexibility within the system by identifying flexible loads and storage capacities. Next, we analyze the system inputs, which are in the form of time series data. Finally, we reform the input data into a generic data model suitable for optimization.

1 Potential flexibility quantification for electricity consumers and generations

We quantify potential flexibility for electricity consumers and generations by assessing unique load/generation characteristics and adjusting usage patterns in residential, commercial, and industrial sectors. In this sub-chapter, we first describe the flexibility quantification in the industrial sector. Second, we outline flexibility quantification of the EV aggregators. Finally, we discuss flexibility quantification for residential and commercial consumers.

1.1. Industrial flexibility quantification

By participating in demand response programs, industrial companies can adjust their energy consumption patterns in response to grid signals. Flexibility in industrial settings often involves complex dependencies between different processes and machines, which we must consider in any optimization model. To manage these dependencies, it's crucial to consider the interrelations between various loads. For example, the operation of one machine might depend on the completion of another task, or certain loads might need to be activated in a specific sequence. This approach involves scheduling and managing these inter-dependencies to ensure that the industrial processes remain efficient while providing the necessary flexibility to the grid. For instance, Figure III.1 illustrates the need for activating or deactivating one flexible load before or after another. In this figure, there can be a dependency between the activation and deactivation times of Load1 and Load2. On the left, Load1's activation necessitates the subsequent activation of Load2, with lower and upper dependency boundaries provided. Using these boundaries, rather than a specific time, extends flexibility options and increases the chances of capturing all possible flexibilities. On the right, the deactivation of Load1 requires the activation of Load2 afterward, within the allowed boundaries (RP2) .



(a) Dependency type start-start **(b)** Dependency type end-start

Figure III.1: Dependencies between different industrial loads (RP2)

1.2. EV Aggregators flexibility quantification

EV aggregators play a crucial role in managing the charging behaviors of multiple EVs to provide grid services. By aggregating the charging demands and flexibilities of a fleet of EVs, aggregators can respond effectively to electricity market signals, such as price variations in day-ahead and intraday markets. The flexibility offered by EVs is highly variable and depends on factors like the minimum state of charge (SOCmin) requirements, arrival and departure times, and user driving patterns RP4.

We can quantify the flexibility of EVs in terms of energy and power metrics over time. This quantification helps in optimizing the charging schedules to balance grid demands and user requirements. For instance, in RP4, a novel algorithm quantifies EV flexibility by evaluating both energy and power as functions of time, taking into account user needs and market conditions. This approach allows for an optimized charging strategy that minimizes costs while ensuring that EV users have sufficient charge when needed.

In Figure III.2, we illustrate a typical EV battery with different energy levels at the time of arrival. E^{max} represents the total battery capacity, E^{arr} is the energy level at the arrival time, E^{SOCmin} is the energy required to meet the desired state of charge, and E^{dep} is the energy level at the departure time. Based on these energy values, the summation of E^{arr} and E^{SOCmin} should be at least E^{dep}. Using this energy values, we quantify the EV aggregator flexibility in RP4.

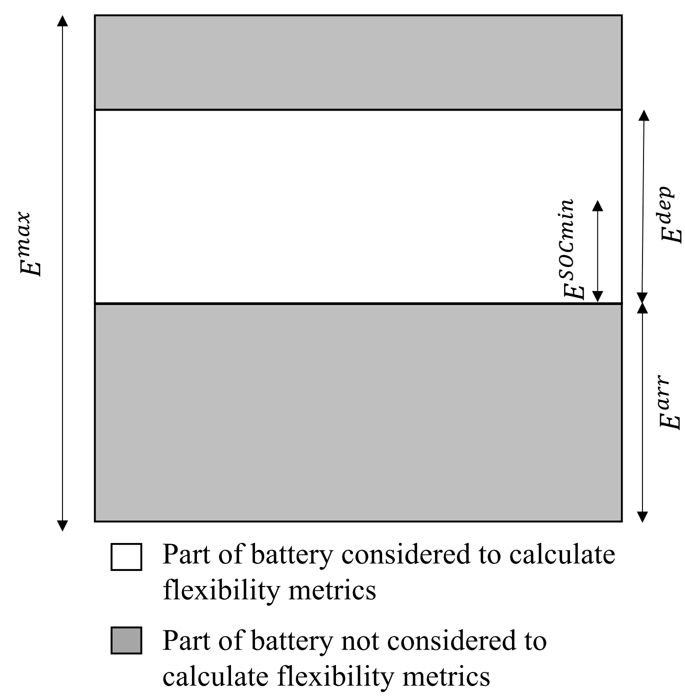


Figure III.2: Typical EV battery and different energy values derived from RP4

1.3. Residential and commercial consumers flexibility quantification

Other flexible loads, including residential and commercial consumers, significantly contribute to grid flexibility. We quantify this flexibility by understanding typical usage patterns and identifying opportunities to shift energy consumption. We start with detailed data collection, monitoring appliances, heating and cooling systems, and other devices over time. In residential settings, we analyze historical energy consumption data to identify peak usage times and potential for load shifting. We track the use of dishwashers, washing machines, and electric vehicles, estimating how much energy we can defer to off-peak hours (Sadeghianpourhamami et al., 2016). Smart meters and home energy management systems also provide valuable insights into daily and seasonal usage patterns.

In commercial buildings, the flexibility quantification process includes conducting energy audits and using advanced energy management systems to collect real-time data on HVAC operations and lighting. We model different load adjustment scenarios, such as reducing HVAC usage during peak hours or dimming lights in unoccupied areas (Tian et al., 2021). By doing so, we can quantify where and when in the building the energy consumption and change.

For both consumers, we employ statistical and machine learning techniques to predict future energy usage and determine flexibility potential (Pallonetto et al., 2022). We also consider consumer behavior and willingness to participate in demand response programs.

2 Time series analysis

Time series analysis is a critical component in the optimization and management of modern power systems. It involves statistical techniques that analyze time-ordered data points to extract meaningful statistics and characteristics. In the context of energy systems, time series data often include electricity consumption, renewable energy production levels, and various grid parameters, all recorded at consistent intervals (Teichgraeber and Brandt, 2022). The primary goals of time series analysis in energy systems are to forecast future values and to understand underlying patterns, trends, and seasonalities that can impact grid stability and efficiency (Severiano et al., 2021). Additionally, imputation plays a vital role in time series analysis by addressing missing or incomplete data points, ensuring the continuity and accuracy of the data used for analysis. Proper imputation techniques are essential for maintaining the integrity of the data, which is crucial for producing reliable forecasts and for making informed decisions in the management of power systems (Bülte et al., 2023). In this subchapter, we first discuss the concept of missing data imputation and its applications in power systems. Next, we describe the applications of time series forecasting in the power systems.

2.1. Missing Data Imputation

In contemporary systems, the utilization of measurement tools and sensors has become increasingly prevalent. These sensors gather data from various components within the system, resulting in a diverse array of data types and shapes (Liu et al., 2020). Ensuring the effective communication and transfer of this data is crucial for maintaining the integrity of the system's operations. Reliable and complete historical data are essential for performing accurate forecasts, which are integral for predictive maintenance and strategic planning (Saad et al., 2020). Moreover, incomplete data can severely impair decision-making processes, as accurate data is foundational for informed and effective decisions (Alamoodi et al., 2021). However, the reliability of this data can be compromised due to failures in sensors, equipment malfunctions, or disruptions in data transfer. These failures lead to gaps in the data, which must be addressed to maintain the utility of the dataset (Figure III.3). Imputation techniques play a vital role in mitigating the impact of these incomplete datasets, enabling the reconstruction of missing information and ensuring that the historical data remains robust and usable. By addressing these data gaps, systems can maintain their forecasting capabilities and continue to make well-informed decisions. Therefore, the implementation of effective imputation strategies is essential for sustaining the functionality and accuracy of systems that depend on sensor data.

Data imputation techniques are essential across various sectors to maintain the completeness and reliability of datasets, which is crucial for informed decision-making and operational efficiency. In healthcare, imputation addresses missing patient data in electronic health records, ensuring accurate diagnoses and effective treatments. Financial institutions use imputation to fill gaps in historical data, critical for risk assessment, fraud detection, and investment analysis. In manufacturing, imputation helps manage sensor data from machinery, facilitating predictive maintenance and quality control despite sensor failures (Fortuin et al., 2020). Retail businesses rely on imputation to maintain complete customer datasets, improving inventory management, sales forecasting, and personalized marketing strategies. Environmental science also benefits from imputation by ensuring continuous and accurate monitoring of air quality, water levels, and climate conditions, which is vital for analyzing environmental trends and developing policies (Erhan et al., 2021). Overall, imputation enhances the accuracy and reliability of data across these diverse fields, supporting better decision-making and operational effectiveness.

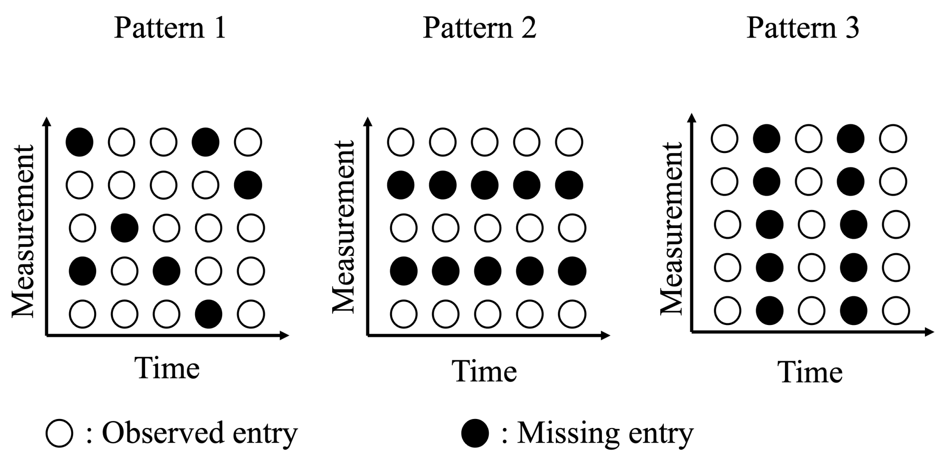


Figure III.3: Different common missing data patterns (RP5)

In power system applications, data imputation is crucial due to the reliance on precise and continuous data from various measurement tools such as Phasor Measurement Units (PMUs), smart meters, and other sensors. These tools collect vital data used for making both short-term and long-term decisions. In the short term, accurate data is essential for voltage control and power system stability assessment (Zhang et al., 2018). For long-term planning, data supports decisions regarding infrastructure development and maintenance strategies. Failures in sensors or data transfer can lead to incomplete datasets, which can compromise the reliability of these decisions (Sim et al., 2022). Imputation techniques help fill these gaps, ensuring that the data remains robust and reliable. This continuous and accurate flow of information is vital for maintaining the stability and efficiency of power systems, ultimately supporting the safe and efficient operation of the electrical grid.

Real-time imputation is essential in power systems, particularly for ensuring the integrity of high volumes of streaming data from sensors such as PMUs, smart meters, and other monitoring devices. These sensors generate extensive time-series data crucial for operators and controllers managing grid stability. Missing values due to malfunctioning devices, sensor failures, or data transfer errors can significantly impact real-time grid monitoring, leading to potential inaccuracies. Additionally, unexpected events like equipment failures or natural disasters can cause data loss at critical moments (Tan et al., 2020). Real-time imputation addresses these challenges by promptly filling in missing data, thereby maintaining a continuous and accurate data stream RP5. This process is vital for real-time security assessments, where complete data is necessary to identify and mitigate threats to the power grid quickly (Mostafanezhad et al., 2024). Another critical application is state estimation, which depends on accurate and complete data to provide a reliable snapshot of the grid's current state. By ensuring data completeness in real-time, imputation techniques enhance the reliability of grid monitoring and control, enabling better decision-making and improving the overall resilience and efficiency of power systems (Dahale and Natarajan, 2021).

Real-time imputation is essential for flexibility products with high resolutions due to the increasing variability and uncertainty in balancing generation and load (Wang et al., 2021). Flexible units often lack sufficient ramping capability, necessitating the use of real-time automatic reserves like spinning reserves and frequency containment reserves (FCR). Products such as automatic frequency restoration reserve (aFRR), frequency containment reserve (FCR), and manual frequency restoration reserve (mFRR) are critical for maintaining grid stability. These products rely on precise, real-time data to function effectively (Khodadadi et al., 2020). Huge amounts of data are transferred in real-time for these products, making accurate and immediate imputation crucial. Without real-time imputation, any missing or erroneous data could lead to inefficiencies and instability in the market.

In RP5, we proposed a real-time imputation algorithm where we impute spatiotemporal power system data. Since the real-time imputation is essential in power systems, the focus of this paper is on the real-time application of an imputation method based on neural network for having multivariant data recovery in case of missing data for various missing rates and different missing patterns (Figure III.3). The data used in this paper is the voltage magnitude and angle of IEEE 39 bus power system. However, this method is applicable for various real-time use cases such as fast load changes in power system that causes transient conditions and is vulnerable to missing data.

2.2. Time series forecasting

Forecasting plays multiple crucial roles in power systems. Accurate demand forecasting helps utilities forecast electricity consumption. Renewable energy forecasting, particularly for solar and wind, is vital for integrating variable energy sources into the grid, reducing reliance on fossil fuels. Load forecasting assists in grid planning and maintenance, minimizing the risk of blackouts and ensuring a steady supply (Ahmed and Khalid, 2019). Additionally, price forecasting informs market participants, optimizing trading strategies and economic dispatch. Overall, robust forecasting supports operational decisions, strategic planning, and the transition to a more sustainable energy landscape. Moreover, accurate forecasting allows grid operators to plan and balance supply and demand effectively, minimizing the risk of blackouts and optimizing the use of energy resources.

Forecasting is essential for decision-making processes such as energy management, system cost minimization, and grid reliability. Accurate renewable energy forecasts, including solar and wind, are critical for integrating variable generation sources into the grid, ensuring stability and reducing reliance on fossil fuels. Load forecasting enables precise demand predictions, facilitating optimal resource allocation and preventing outages. It also aids in system cost minimization by allowing utilities to schedule generation efficiently and reduce operational expenses. Furthermore, accurate forecasts support market operations by informing trading strategies and economic dispatch, ultimately enhancing the overall efficiency and sustainability of power systems (Wang et al., 2018).

In RP6, we investigated various applications of Federated learning for time series analysis in power systems, including time series forecasting. FL is a decentralized machine learning approach where multiple participants train a model locally on their data and share only model updates, not the raw data, with a central server. This method preserves data privacy and security while enabling collaborative model training (Gholizadeh and Musilek, 2022).

This decentralized approach allows for real-time integration of data from various regions to improve operational efficiency. Additionally, FL ensures compliance with data privacy regulations and maintains data security and fosters innovation in load forecasting and overall power system management (Wei et al., 2020).

3 Reforming the inputs into a generic data model

In the context of power systems, generic data models for optimization inputs play a crucial role, even though they are not strictly required. The optimization models in RP2 and RP3 employ a generic data model known as the energy flexibility data model (EFDM), originally developed by (Schott et al., 2019). The EFDM is essential for outlining (1) the flexibility potential and (2) the specific power profile that flexible loads must adhere to, referred to as the flexible load measure. Moreover, the EFDM provides industrial companies with a comprehensive framework in javaScript object Notation (JSON) for managing flexibility descriptions. This data model provides a general way to represent various forms of data, enabling seamless communication, interoperability, and integration across different systems and platforms. The data model enables transferability across various sectors, offering a pathway to standardization. Consequently, it serves as a foundation for incorporating flexibility into information systems, thereby enhancing information exchange, increasing automation, and facilitating the automated utilization of flexibility.

IV Techniques and Models for Optimizing Flexibility in Energy Systems

After preparing the input data in a generic data format (Section III), we integrate it into the flexibility optimization modeling process. In the next sections, we describe the key components involved in flexibility optimization. The first section addresses the selection of various electricity markets for optimizing energy flexibility. The subsequent section examines the impact of uncertainty on energy flexibility. The third section explores economic and mathematical modeling within the context of flexibility optimization. Finally, we consider the outputs of flexibility optimization and interpret the results.

1 Selecting target electricity markets for flexibility optimization

Selecting target electricity markets for flexibility optimization is crucial for flexibility optimization. The main markets include spot markets, ancillary services markets, system balancing markets, and network congestion management markets (Jin et al., 2020).

Spot Markets involve immediate electricity delivery, requiring rapid response to price changes and demand fluctuations. **Ancillary Services Markets** support transmission reliability with services like frequency regulation and voltage support, demanding on-demand flexibility (Villanueva-Rosario et al., 2022). **System Balancing Markets** ensure real-time supply-demand matching, crucial for grid stability, involving adjustments in generation or consumption to address imbalances. **Network Congestion Management Markets** deal with insufficient transmission capacity, requiring quick responses to prevent overloads through demand response or distributed generation (Attar et al., 2022).

We can broadly categorize optimization approaches in for electricity markets into multi-stage optimization and single-stage optimization. **Multi-stage optimization** involves optimizing participation across multiple markets in a step-by-step manner, considering the interdependencies and cumulative effects of decisions made in each market. This approach can maximize overall benefits but requires sophisticated modeling to handle the complexities (Puglia et al., 2011). **Single-stage Optimization**, on the other hand, focuses on optimizing flexibility within a single market, simplifying the process but potentially missing out on synergistic benefits from other markets (Kraft et al., 2023).

Selecting appropriate markets involves analyzing market signals, resource characteristics, regulatory environments, and utilizing advanced forecasting and optimization models. Market signals and incentives guide economic advantages, while understanding resource capabilities ensures technical feasibility (Al-Lawati et al., 2021). Navigating regulatory frameworks ensures compliance, and forecasting models help predict market conditions and inform resource allocation.

In this thesis, we proposed methods for flexibility optimization by flexibility providers in single markets, namely day-ahead and intraday markets, or in two-stage optimization models. In RP4, we proposed flexibility methods to provide flexibility for EV aggregators in sequential spot markets, including day-ahead and intraday markets. As bidding decisions occur sequentially and price information gradually reveals itself, we formulate decision models as multi-stage programs and generate scenarios for realization of electricity price in RP4. On the other hand, in RP1, RP2, and RP3, we proposed methods for flexibility provision in a single electricity market, specifically the day-ahead spot market.

2 Uncertainty modeling for flexibility optimization

Uncertainty modeling in flexibility optimization involves quantifying and describing the volatility in load demand and renewable generation forecasts. We use stochastic optimization to optimize the dispatch of flexible resources. This method ensures grid stability and cost-efficiency under uncertain conditions (Najafi et al., 2021). Key sources of uncertainty include renewable energy variability, market price fluctuations and their impact on economic viability, and user behavior such as driving patterns, charging preferences, and the frequency of EV connections (Ye, 2018). We will describe this technique in the next section.

2.1. Scenario-Based Stochastic Optimization Models

Scenario-based stochastic optimization leverages generated scenarios to encapsulate various possible outcomes and uncertainties inherent in complex systems. This method is particularly useful in energy systems, where uncertainties arise from sources such as RESs variability, demand fluctuations, and market price volatilities (Leterme et al., 2014). By creating a diverse set of scenarios that reflect different possible future events, this approach allows for the optimization process to account for a wide range of potential conditions, enhancing the robustness of the solutions.

In practice, scenario-based stochastic optimization involves generating a large number of potential future states, each represented by a scenario. Analysts typically generate these scenarios using probability density functions (PDFs) derived from historical data and expert forecasts (Bahmani et al., 2020). For instance, in the context of electricity pricing, we analyze historical price data to produce a range of possible future price trajectories. These price scenarios then serve as inputs into the optimization model, ensuring that the model's solutions suit well for various market conditions.

This approach offers a key advantage by providing decision-makers with insights into the probability and impact of different risks. By evaluating the performance of different strategies across a broad set of scenarios, stakeholders can identify solutions that perform well under a wide array of conditions, thereby mitigating the risk of adverse outcomes (Al-Lawati et al., 2021). Furthermore, scenario-based stochastic optimization supports dynamic and adaptive decision-making processes. As new data becomes available, we can update the probability distributions and generate new scenarios, allowing the optimization model to remain relevant and accurate over time (Niknam et al., 2012). This adaptability is crucial for managing the evolving uncertainties in energy systems and markets. However, the effectiveness of stochastic optimization models is highly dependent on the accuracy of the probability distributions used. Despite this limitation, they remain a powerful tool for managing the inherent uncertainties in modern energy systems, supporting optimal operational strategies and enhancing overall system performance (Khatami et al., 2019).

In the context of EV charging, stochastic optimization helps schedule charging sessions by predicting market prices and user behaviors. In RP4, we developed a two-stage scenario-based stochastic optimization model to account for the price uncertainty in the intraday market. To address this uncertainty, we first generate scenarios for intraday electricity prices, which are then used as inputs for the optimization process. We capture the uncertainty of intraday prices by employing PDFs to generate scenarios based on historical data, thereby modeling the probabilistic behavior of the intraday market.

3 Economic modeling of flexibility provision

Economic models aim to simplify and abstract complex real-world economic phenomena, enabling a better understanding of the relationships between different economic variables. They help predict future economic conditions and outcomes of policy decisions (Gibbard and Varian, 1978). By testing economic theories, models provide a framework for hypothesis validation and guide policy analysis. These models are crucial for informed decision-making by businesses and governments and serve educational purposes by elucidating economic concepts. Economic models in energy flexibility provision aim to optimize the integration and operation of energy systems to enhance responsiveness to volatile supply and demand. These models simulate the behavior of various energy assets and evaluate the economic viability of different flexibility options like demand response and energy storage (Wang et al., 2020).

Economic modeling of flexibility optimization involves various approaches to achieve objectives such as cost minimization and profit maximization. Economically, flexibility optimization can focus on reducing operational costs or increasing financial returns (Forero-Quintero et al., 2022). We can achieve cost minimization using conventional methods that do not consider fairness among participants in the model, or through more complex approaches like Game-Theoretic Cooperative Cost Minimization, which ensures fair cost distribution among market participants RP1.

In RP4, we modeled the cost minimization for an EV aggregator, focusing on participating in both the day-ahead and intraday markets. Energy providers can motivate users to be flexible by offering incentives, which they can finance with the revenues generated from the users' flexibility.

Although RP4 primarily focuses on cost minimization without necessarily considering fairness, RP1 aims to minimize costs while ensuring a fair distribution of costs among market participants using cooperative cost minimization approach. This approach ensures that all participants share costs fairly and benefit from joint strategies. Key strategies include developing coalitions for joint investments and implementing shared infrastructure to achieve significant cost savings. The Shapley value, a concept used in this context, allocates the overall gain of the coalition among participants based on their contribution, efficacy, and bargaining power (Wu et al., 2017). This ensures that each participant's role is fairly assessed and rewarded, fostering a cooperative environment that maximizes overall efficiency and cost-effectiveness. By leveraging these principles, participants can achieve better outcomes than they would individually, promoting a more collaborative and financially sustainable energy market.

RP1 presents a cooperative flexibility optimization framework for multi-energy hub systems, where hubs collaborate to minimize costs and enhance system flexibility. Unlike traditional approaches, this cooperative model ensures optimal solutions for fair resource allocation based on hub contributions. Energy hubs integrate various sources such as CHP, boilers, renewables, and chillers, alongside energy storages to increase system flexibility. By sharing resources and forming coalitions, energy hubs achieve substantial cost savings and operational enhancements. The cooperative strategy not only guarantees optimal solutions but also provides a rational and fair profit allocation mechanism among the energy hubs. This comprehensive approach is well-suited for multi-owner systems, offering a structured method for enhancing system performance and reducing operational costs through collaborative optimization.

In addition to the previously mentioned papers in this thesis, we formulated industrial flexibility in RP2 and RP3. In RP2, we proposed a model aimed at maximizing profit through participation in flexibility provision. The evaluation of the optimization model indicates that it can effectively achieve its objectives across various scenarios. In RP3, we developed a model that addresses both aggregated and non-aggregated industrial flexible loads, taking into account the constraints inherent in industrial processes, which we modeled as economic factors.

4 Mathematical techniques for modeling flexibility optimization

After economic modeling (Section 3), we have a detailed understanding of the economic factors and constraints that influence flexibility optimization. This foundation enables us to perform mathematical modeling to optimize objective function effectively. Optimization techniques are crucial for achieving objectives in flexibility optimization. Various techniques cater to different aspects of the problem, providing solutions for both operational and strategic needs. Linear Programming (LP used in RP4) is a mathematical method for optimizing linear objective functions. It is highly efficient in handling large-scale problems, making it suitable for cost minimization and short-term operational planning in flexibility optimization. LP ensures optimal resource allocation while adhering to system constraints. Integer Linear Programming (ILP employed in RP3) extends LP by incorporating integer decision variables, making it apt for discrete decisions such as power plant operations and investment project selection. ILP is essential for scheduling and resource allocation, ensuring precise and practical solutions in flexibility contexts. Mixed-Integer Linear Programming (MILP modeled in RP1 and RP2) combines continuous and integer variables, offering flexibility for complex optimization problems. This method is suitable for both operational and investment decisions, making it ideal for strategic planning. MILP allows for more comprehensive and nuanced solutions, addressing the multifaceted nature of flexibility optimization challenges. These optimization methods are integral to maximizing efficiency and economic performance in modern energy systems.

V Conclusion

1 Contribution

My research significantly contributes to the field of energy system flexibility and optimization. Firstly, I developed specialized flexibility optimization algorithms tailored to various energy sectors, such as industrial companies (see RP2 and RP3), residential consumers (see RP1), and EV aggregators (see RP4). These algorithms enhance the ability of different stakeholders to adapt their energy consumption and generation in response to fluctuating market signals and grid conditions.

One of the major contributions is the enhancement of data models for seamless data transfer and integration across systems (see RP2 and RP3). This generic data model facilitates interoperability, ensuring that diverse energy stakeholders can effectively communicate and coordinate their flexibility efforts. This model is particularly beneficial for industrial companies, enabling them to standardize their data management and optimize their energy use more efficiently.

We also proposed a model for EV aggregator flexibility optimization that accounts for data uncertainty proposed in RP4. This innovation ensures reliable operation under uncertain conditions, enhancing the stability and efficiency of the energy system. By considering various uncertainties for market price fluctuations, this model provides a resilient framework for managing EV charging and discharging schedules.

Our research further integrates multi-energy systems, combining electricity, gas, and heat to optimize overall flexibility presented in RP1. This integration allows for coordinated energy conversion and storage, optimizing resource utilization and enabling dynamic responses to demand fluctuations and market conditions. The proposed models demonstrate significant potential in enhancing system flexibility and efficiency.

Another key contribution is the advancement of real-time spatiotemporal data imputation techniques developed in RP5. These techniques address the challenges of incomplete datasets, ensuring high-quality data for real-time decision-making. This development is crucial for maintaining the integrity of time series data used in flexibility optimization, thereby improving the reliability of forecasting and operational strategies.

We also evaluated and improved various load forecasting methods, providing insights into their applicability and performance in predicting future energy demands in RP6. These enhancements in forecasting methods are vital for effective flexibility optimization, as accurate predictions are essential for balancing supply and demand.

Furthermore, our research provided comprehensive methods for participating in day-ahead and intraday markets. These methods guide energy stakeholders on how to optimize their bids and schedules, ensuring maximum profitability and system stability. By addressing the specific requirements of different energy consumers and market conditions, these strategies offer practical solutions for real-world applications.

2 Limitations

Despite the significant contributions, our research has several limitations. Firstly, the limited access to real-world data constrained our validation efforts. While the models and algorithms developed show promising results in simulations, their performance in real-world scenarios remains partially untested. This limitation highlights the need for more extensive data collection and collaboration with industry partners.

Scalability of the proposed models in larger, more complex systems also remains untested. While the algorithms perform well in controlled environments, their applicability in larger-scale systems with higher complexity and variability needs further exploration. This aspect is critical for ensuring that the models can handle the demands of extensive energy networks.

The high computational requirements for real-time data imputation and optimization present another limitation. The advanced techniques developed require significant processing power, which may not be readily available in all practical applications. This limitation underscores the need for ongoing research into more efficient computational methods.

Our research also did not fully explore the economic impacts on small-scale energy consumers. While the focus was on larger industrial and aggregated systems, understanding the implications for smaller consumers is equally important for comprehensive energy system management.

Dependence on accurate forecasting models is another limitation. The effectiveness of flexibility optimization heavily relies on the precision of load and generation forecasts. Any inaccuracies in these forecasts can significantly impact the optimization outcomes. Therefore, continuous improvement of forecasting methods is necessary to enhance reliability.

Potential bias in the dataset used for model training and validation is also a concern. The data collected may not fully represent the diversity of real-world conditions, leading to skewed results. Ensuring a more representative dataset is crucial for developing universally applicable models.

Finally, the need for more extensive validation of the proposed algorithms in live energy markets remains. While theoretical and simulation-based validations are essential, practical validation through partnerships with industry players is necessary to confirm the effectiveness and robustness of the models.

3 Outlook

Looking ahead, there are several avenues for further research and development. Firstly, exploring the scalability of the algorithms in larger, more complex energy systems is essential. This exploration will ensure that the models can handle the increasing demands and complexities of modern energy networks.

Incorporating more diverse and extensive real-world datasets for validation will also be a priority. Collaborating with industry partners to access comprehensive data will enhance the robustness and applicability of the models. This collaboration will bridge the gap between theoretical research and practical implementation.

Improving the computational efficiency of real-time data imputation methods is another key area for future work. Developing more efficient algorithms and leveraging advanced computing technologies will make these techniques more accessible and practical for real-world applications.

Extending the research to include the economic impacts on small-scale energy consumers is also crucial. By understanding the specific needs and challenges of smaller consumers, we can develop more inclusive and equitable energy management strategies.

Developing enhanced forecasting models to reduce dependency on current ones is essential. Incorporating advanced techniques such as machine learning and artificial intelligence can improve the accuracy and reliability of forecasts, thereby enhancing the effectiveness of flexibility optimization.

Investigating geographic diversity in case studies will provide a broader understanding of different regional conditions and their impacts on energy system flexibility. This investigation will improve the generalizability of the findings and ensure that the models are applicable in diverse contexts.

Validating the proposed algorithms through partnerships with live energy markets will be a crucial step. Collaborating with industry players to implement and test the models in real-world scenarios will confirm their practicality and effectiveness.

Finally, integrating advancements in AI and machine learning into flexibility optimization will open new possibilities. These technologies can enhance the adaptability and efficiency of energy systems, providing innovative solutions to emerging challenges. By staying at the forefront of technological advancements, future research can continue to drive progress in energy system flexibility and optimization.

4 Recognition of previous and related work

The research presented in this thesis is the culmination of my collaborations with colleagues within the Digital Financial Services and Cross-Organisational Digital Transformations (FINATRAX) research group at the University of Luxembourg's Interdisciplinary Centre for Security, Reliability, and Trust (SnT), as well as with partners from other international institutes.

RP1 is the outcome of my collaboration with researchers from Center of Excellence for Power System Automation and Operation at Iran University of Science and Technology (IUST) on the multi-energy systems flexibility optimization(Esmaeili et al., 2019, Karimi and Jadid, 2020, and Amir et al., 2017).

The previous works of my professor and his network inspired us in the FINATRAX research group to develop industrial flexibility optimization models, as detailed in RP2 and RP3 (see Lindner et al., 2021, Heffron et al., 2020a, Bank et al., 2021, Roth et al., 2019, Fridgen et al., 2016, Heffron et al., 2021, Bhuiyan et al., 2022, Fridgen et al., 2017, Roesch et al., 2019, Bertsch et al., 2017, Schott et al., 2018, Fridgen et al., 2018, Jäckle et al., 2019, Bauer et al., 2017, Fridgen et al., 2014a, and Wederhake et al., 2022).

The collaboration between the FINATRAX research group and Enovos, Luxembourg's main energy supplier, resulted in RP4, which investigates the participation of EV aggregators in the spot market to share flexibility (see Fridgen et al., 2021, Fridgen et al., 2014b, Baumgarte et al., 2022, Keller et al., 2021, Baumgarte et al., 2021, Chen et al., 2024, Heffron et al., 2022, and Halbrügge et al., 2021).

Through the collaboration between the FINATRAX research group and the School of Energy Systems at Lappeenranta-Lahti University of Technology (LUT), we conducted RP5. This research paper leverages the expertise of both groups and focuses on the field of time series analysis, particularly on power systems time series imputation (see Mostafanezhad et al., 2023, Afrasiabi et al., 2022, Afrasiabi et al., 2020, and Afrasiabi et al., 2021).

Lastly, our collaboration within the FINATRAX group resulted RP6, building on the extensive knowledge we have developed over the past years in forecasting (see Fernández et al., 2022, Hornek et al., 2024 , Delgado Fernandez et al., 2023, and Amard et al., 2023).

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VII | Appendix

1 Publications

This section lists the various publications in this dissertation. It divides the publications into two main categories. The first category is the articles included in this dissertation. The second category contains other non-peer-reviewed publications not included in this dissertation.

1.1. Articles in this dissertation

- RP1-R. Bahmani, H. Karimi, and S. Jadid (2021). "Cooperative energy management of multi-energy hub systems considering demand response programs and ice storage". In: *International Journal of Electrical Power & Energy Systems* 130, p. 106904. Scopus percentile: **92th** (July 30, 2024).

- RP2-R. Bahmani, C. van Stiphoudt, S. P. Menci, M. SchÖpf, and G. Fridgen (2022b). "Optimal industrial flexibility scheduling based on generic data format". In: *Energy Informatics* 5.1, p. 26. Scopus percentile: **67th** (July 30, 2024)

- RP3-R. Bahmani, C. van Stiphoudt, M. Ansarin, and G. Fridgen (2022a). "Energy flexibility scheduling optimization considering aggregated and non-aggregated industrial electrical loads". In: *Energy Proceedings* 29. GGS rating: Not applicable. (July 30, 2024)

- RP4-R. Chemudupaty, M. Ansarin, R. Bahmani, G. Fridgen, H. Marxen, and I. Pavić (2023). "Impact of Minimum Energy Requirement on Electric Vehicle Charging Costs on Spot Markets". In: *2023 IEEE Belgrade PowerTech*. IEEE, pp. 01–06. GGS ranking: **B**. (July 30, 2024)

- RP5-R. Bahmani and M. Afrasiabi (2024). "Noisy PMU Data Recovery in Transient Conditions through Self-Attention Neural Networks". In: *2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*. IEEE. GGS ranking: **C**. (July 30, 2024).

- RP6-J. D. Fernandez, S. P. Menci, I. Pavi, R. Bahmani, and Q. V. Nguyen (2024). "Federated Learning for Energy Systems". In: *IEEE International Conference on Artificial Intelligence 2024 - Workshop on AI for Energy*. Ed. by Z. Vale, G. K. Venayagamoorthy, and J. Soares. Singapore: IEEE. GGS ranking: Not applicable (July 30, 2024).

1.2. Other non peer-reviewed publications not included in this dissertation

This subsection provides information on non peer-reviewed works such as commentaries, book chapters, and industry reports.

1.2.1. Industry reports

This section lists the industry reports written by me that are not included in the dissertation. Each entry will include the title of the report.

- J. Schlip, L. Bank, J. Köberlein, T. Bauernhansl, A. Sauer, G. Fridgen, R. Bahmani, S. P. Menci, M. Schoepf, C. van Stiphoudt, M. Weigold, and M. Lindner (2021). *Optimierung auf der Energiesynchronisationsplattform: Teil der Reihe Diskussionspapiere V4 Konzept der Energiesynchronisationsplattform*. Tech. Rep. University of Luxembourg. URL: https://orbilu.uni.lu/handle/10993/49772

2 Individual contribution to the included research papers

This section outlines specific contributions to each of the research papers included in this dissertation.

2.1. RP1 - Cooperative energy management of multi-energy hub systems considering demand response programs and ice storage

- **Contribution statement:** Original draft preparation, discussion and analysis, editing the manuscript preparation, editing the revised draft

As the lead author, I was primarily responsible for the major work of the paper. My co-authors contributed by assisting in refining and evaluating the results. My specific contributions included developing the methodology, data curation, conducting simulations, performing analysis, creating visualizations, drafting the original manuscript, and incorporating reviewer feedback.

2.2. RP2 - Optimal industrial flexibility scheduling based on generic data format

- **Contribution statement:** All authors contributed to the conception of the research. RB, MS and SPM contributed to the design of the work. RB, CvS and SPM drafted the first version of the paper. MS and GF supervised the research conception, provided feedback and participated in the paper revision. All authors read and approved the final manuscript.

As a co-author, my contributions primarily involved designing the optimization functions, shaping the conceptual framework by providing the structure, contributing to the research methodology, analyzing the results, drafting the original manuscript, and revising the final version based on peer-reviewed feedback.

2.3. RP3 - Energy flexibility scheduling optimization considering aggregated and non-aggregated industrial electrical loads

- **Contribution statement:** The published research paper does not have a contribution statement in its publication format.

As a co-author, my contributions were mainly focused on designing the optimization functions, structuring the conceptual framework, contributing to the research methodology, analyzing the results, drafting the original manuscript, and revising the final version based on peer-review feedback.

2.4. RP4 - Impact of minimum energy requirement on electric vehicle charging costs on spot markets

- **Contribution statement:** The published research paper does not have a contribution statement in its publication format.

As a subordinate author, my contributions to the paper were focused on developing the conceptual framework, refining the research methodology, creating scenarios, curating and analyzing data, assisting with visualizations, drafting the original manuscript, and revising the final version based on peer-reviewed feedback.

2.5. RP5 - Noisy PMU Data Recovery in Transient Conditions through Self-Attention Neural Networks

- **Contribution statement:** The published research paper does not have a contribution statement in its publication format.

As the lead author, I took on the primary responsibility for the major aspects of the paper. My co-author provided valuable support in refining and assessing the results. My key contributions encompassed developing the methodology, curating the data, conducting simulations, performing analyses, creating visualizations, drafting the original manuscript, and integrating feedback from reviewers.

2.6. RP6 - Federated Learning for Energy Systems

- **Contribution statement:** The published research paper does not have a contribution statement in its publication format.

As a subordinate author, my contributions to the paper mainly included developing the conceptual framework, refining the research methodology, creating scenarios, curating and analyzing data, assisting with visualizations, and drafting the original manuscript.

3 Appended Research Papers

3.1. Research Paper 1 – *Cooperative energy management of multi-energy hub systems considering demand response programs and ice storage*

Cooperative energy management of multi-energy hub systems considering demand response programs and ice storage

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Abstract

Energy hub systems integrate various energy sources and interconnect different energy carriers in order to enhance the flexibility of the system. In this paper, a cooperative framework is proposed in which a network of energy hubs collaborate together and share their resources in order to reduce their costs. Each hub has several sources including CHP, boiler, renewable sources, electrical chiller, and absorption chiller. Moreover, energy storages are considered for electrical, heating, and cooling systems in order to increase the flexibility of energy hubs. Unlike the methods based on Nash-equilibrium points, which find the equilibrium point and have no guarantee for optimality of the solution, the employed cooperative method finds the optimal solution for the problem. We utilize the Shapley value to allocate the overall gain of the hub's coalition based on the contribution and efficiency of the energy hubs. The proposed method is modeled as a mixed integer linear programming problem, and the cost of network energy hubs are decreased in the cooperative operation, which shows the efficiency of this model. The results show 18.89, 10.23, and 8.72% improvement for hub1, hub2, and hub3, respectively, by using the fair revenue mechanism.

Keywords: Integrated energy hubs, Demand response, Cooperative methods, Multi-carrier systems, Shapley value.

NOMENCLATURE

Indices		$P_g^{i,max}$	Imported power from upstream network limit
i	Index of energy hub	P_h^{max}	Heat pipe transmission limit
t	Index of time	OM_{CHP}	Maintenance cost coefficient of CHP units
Abbreviations		OM_B	Maintenance cost coefficient of Boilers
CHP	Combined heat and power	MR_{up}^e/MR_{down}^e	Maximum coefficient for up/down of electrical load
Boiler	Heat only boiler	λ_t^G	Natural gas price
AC	Absorption chiller	LHV	Low calorific value of natural gas
EC	Electrical Chiller	$\eta_{CHP}^e/\eta_{CHP}^h$	CHP gas to electricity/heat coefficients
CS	Ice storage	η_B	Boiler gas to coefficient
ES	Electrical storage	$COP_{ec}, COP_{ice}, COP_{ac}$	Performance coefficients of EC, CS, and AC
HS	Heat storage	CO_{curt}	Coefficient of maximum curtailed load
DR	Demand response	PEN_{curt}	Penalty of load curtailment
Parameters		**Variables**	
π_g	Price of purchasing power from the main grid	$P_g^{i,t}$	Purchased power from the upstream network
λ_t^G	Price of purchasing gas from the gas network	$G_{CHP}^{i,t}$	Consumed gas in CHP unit
$E_{es}^{max,i}/E_{es}^{min,i}$	Minimum/maximum capacities of ES	$PE_{CHP}^{i,t}/PH_{CHP}^{i,t}$	Output power/heat from CHP units
$P_{es,c}^{max,i}/P_{es,d}^{max,i}$	Maximum charging/discharging rate of ES	$G_B^{i,t}$	Consumed gas in boiler
$\eta_{es,c}^i/\ \eta_{es,d}^i$	Charging/discharging efficiency of ES	$PH_B^{i,t}$	Output heat from boiler
$E_{hs}^{max,i}/E_{hs}^{min,i}$	Minimum/maximum capacities of HS	$P_{curt}^{e,i,t}$	Curtailed load
$P_{hs,c}^{max,i}/P_{hs,d}^{max,i}$	Maximum charging/discharging rate of HS	$P_{up}^{e,i,t}/P_{down}^{e,i,t}$	Shift up/down of electrical load by DR
$\eta_{hs,c}^i/\eta_{hs,d}^i$	Charging/discharging efficiency of HS	$P_{up}^{h,i,t}/P_{down}^{h,i,t}$	Shift up/down of heat load by DR
$E_{cs}^{max,i}/E_{cs}^{min,i}$	Minimum/maximum capacities of CS	$I_{up}^{e,i,t}/I_{down}^{e,i,t}$	Binary variable for shift up/down of electrical load by DR
$P_{cs,c}^{max,i}/P_{cs,d}^{max,i}$	Maximum charging/discharging rate of CS	$I_{up}^{h,i,t}/I_{down}^{h,i,t}$	Binary variable for shift up/down of heat load by DR
$\eta_{cs,c}^i/\eta_{cs,d}^i$	Charging/discharging efficiency of CS	$E_{es}^{i,t}, E_{hs}^{i,t}, E_{cs}^{i,t}$	Stored power in ES,HS,CS
δ_{cs}^i	Energy loss constant of CS	$P_{es,c}^{i,t}/P_{es,d}^{i,t}$	Power charging/discharging rate of ES
$G_{CHP}^{max,i}$	Maximum purchasable natural gas of CHP units	$P_{hs,c}^{i,t}/P_{hs,d}^{i,t}$	Heat charging/discharging rate of HS
$G_B^{max,i}$	Maximum purchasable natural gas of Boiler	$P_{cs,c}^{i,t}/P_{cs,d}^{i,t}$	Cooling charging/discharging rate of CS
$PH_{ac}^{max,i}$	Maximum heat input of AC	$k_c^{e,i,t}/k_d^{e,i,t}$	Binary variable for ES charging/discharging constraint
$P_{icc}^{max,i}/P_{ec}^{max,i}$	Maximum electricity input of CS/ES	$k_c^{h,i,t}/k_d^{h,i,t}$	Binary variable for HS charging/discharging constraint
$P^{el,i,t}$	Electrical load	$k_c^{cs,i,t}/k_d^{cs,i,t}$	Binary variable for CS charging/discharging constraint
$P^{hl,i,t}$	Heat load	$P_{ice}^{i\ \ i,t}/P_{ec}^{i,t}$	Input power of CS/EC
$CL^{i,t}$	Cooling load	$PH_{ac}^{i,t}$	Input heat of AC
$P_{pv}^{i,t}$	Generated power from Photovoltaic	$C_{ec}^{i,t}, C_{ac}^{i,t}, P_{cs,d}^{i,t}$	Cooling output from EC, AC, and CS
$p_{wt}^{i,t}$	Generated power from wind turbines		

I. Introduction

Today, energy consumption is increasing rapidly around the world, which encourages researchers to find novel ways to solve this issue. There are various energy sources to supply energy for the consumption sector such as electricity, gas, and renewable energy sources (RES). In recent years, electricity and gas are employed simultaneously in scheduling and operating energy systems which are investigated as multi-carrier energy systems. Using gas and electricity for energy optimization enhances the reliability and efficiency of the system, since they can increase the flexibility of the system in both the normal and critical conditions. One of the frameworks that are used to integrated energy management in multi-carrier energy systems is the energy hub. Energy hub consists of different energy sources and demands such as electrical, heating, and cooling, which are interconnected by several units. Energy hubs have various units, namely power generation, RES, and storage units, which cooperate to serve the demands and achieve the optimal operation scheduling [1]. Nowadays, energy hubs are investigated vastly and are modeled for distinct systems such as residential, commercial, and industrial sector.

By interconnecting energy hubs, the concept of networked energy hubs (NEH) is formed, from which the system gains many benefits. In this context, NEH includes several energy hubs that increase the flexibility of the system significantly by having access to different units and sources [2]. Moreover, NEH can use the strength of each hub to overcome the weakness of other hubs, resulting in more appropriate energy management in the system. Also, NEH employs local energy sources more effectively, enhancing the reliability of the system and reducing the required power from the main grid. Therefore, NEH not only provides the whole system considerable benefits but also improves the performance of each energy hub individually.

In order to increase flexibility, energy storage systems play a crucial role in the system. These facilities store the energy so that the overall performance of the system enhances. For instance, the electrical storage saves energy at low price intervals and discharge it in peak hours [3]. A stochastic day-ahead bidding strategy for energy hub is proposed in [4], considering the presence of various energy storages including battery energy storage, heating storage, and ice storage while neglecting the cooperation of various hubs and demand response programs. A networked energy hub system is proposed in [5], which aims to maximize the profit of the system by using the alternating direction method of multipliers (ADMM) method. However, the demand response programs and cooling system modeling are not considered. In [6], a cooperative framework is proposed in the multi-energy systems that integrate the renewable energy resources and energy storage systems in the energy hubs. However, the impacts of ice storage systems and the electrical and thermal demand response programs were not studied. The operation scheduling of energy hub is considered in [7] and uncertainty of the inputs and various storage systems such as electrical, heat, and ice storage are taken into account. However, the cooperation of different energy hubs and heat demand response are not investigated.

The authors in [8] presented a stochastic model for a multi-carrier energy hub in which the demand response program, electricity market, and thermal energy market are taken into account. In contrast, the network of energy hubs and cooling system are not considered. In [9], optimal day-ahead scheduling of an active distribution system including multiple energy hubs is investigated wherein the transacted energy between the participants is calculated using their bids and offers. However, the fair cost allocation for participants and maintenance cost are ignored. Economic optimization of a multi-carrier system using the coupling matrix and virtual nodes insertion is proposed in [10]. Although this study considers several energy sources for energy carriers and the effect of demand response programs is taken into account, the cooling system and the cooperation of different energy hubs in a fair condition are not studied. In [11], multi-carrier networked microgrids are investigated which can exchange energy with each other, but the fair cost allocation and demand response programs are not discussed.

From the cooperation perspective, networked systems are separated into cooperative and non-cooperative systems. In the cooperative methods, the objective is to find the Pareto optimal solution of the problem, but finding the equilibrium point is the objective in the non-cooperative models. The authors in [12] proposed a cooperative model including power to gas (P2G) devices for integrated power and gas networks and considered the demand smoothness and cost reduction in the network. Nevertheless, the effect of cooling system, demand response program, and fair allocation of costs are not investigated. A multi-objective model is proposed in [13] to optimize cost savings and carbon emissions in NEH using ε -constraint technique and max-min fuzzy decision making. This paper considers the cooperation of energy hubs while neglecting the fair cost allocation and cooling system. In [14], a congestion game is modeled, guaranteeing the existence of the Nash equilibrium. However, demand response and cooling system are not modeled in this paper. An optimal planning framework is presented in [15], which explores the effect of allocation and sizing of the hubs in optimal design of networked energy hubs.

The authors in [16] and [17] proposed a non-cooperative game in which gas and electricity demand response are employed in order to maximize the profit of the utility companies. However, the fair cost-sharing and the cooling system are ignored in this study. An exact potential game is proposed in [18] to design an online distribution algorithm and explore the existence of the Nash equilibrium while ignoring the demand response programs and heat energy storage. A non-cooperative framework is presented in [19] for networked energy hubs in which the interaction among energy hubs is studied. However, the fair cost allocation and cooling system are not taken into account. Li et al. [20] proposed a decentralized optimization framework for the energy scheduling of multiple energy hubs. The proposed model integrates the electric distribution and natural gas systems to improve the performance of multi-carrier systems. Although the role of electrical and gas storage systems had been studied, the impact of the ice storage system was ignored. However, the impact of the electrical and thermal DR programs on the operation scheduling of the energy hubs was not investigated. Authors in [21, 22] suggest the bi-level game theory to model the energy scheduling of the energy hubs.

The impact of energy storage systems on the market mechanism was investigated in [21]. Although the uncertainty of demand loads had been applied to the model, the role of the DR programs and ice storage on the control of uncertainty was not studied. In [22], the interaction among distribution company and energy hubs had been formulated as the leader multi-follower optimization. At the upper-level, the distribution company tries to minimize its total cost, while the cost of the energy hubs had been considered at the lower-levels. Although the impacts of the renewable resources on the operation of energy hubs had been investigated, the role of storage systems and demand response programs were not studied. Also, the cooperation among the energy hubs at the lower-level was not investigated.

In the non-cooperative games, the Nash equilibrium points (NEPs) are the solution to the problem. The NEPs provide stable solutions, while there is no guarantee of optimality. In other words, in the NEPs, no player has anything to gain by changing only his own strategy. If the optimization problem has a better unstable solution, it cannot be chosen by the non-cooperative games. The bi-level approaches are non-cooperative games (Stackelberg games) that find the NEPs by iteration. Therefore, they cannot ensure the best plan from an economic point of view. Also, in the non-cooperative games, each actor only considers its objectives. Unlike non-cooperative games, the total cost/profit of the system had been optimized in the cooperative games. The cooperative games focus on the predicting that forming coalitions will form, the joint actions that players take and the resulting collective payoffs. When energy hubs cooperate, they can share their electrical, thermal, and cooling resources. Compared to the non-cooperative games, cooperation enhances the flexibility of the system because the energy hubs can use the surplus capacity of the other resources. Therefore, the cooperative games ensure the optimal solution for the system. Also, the emission of greenhouse gasses and power losses in the cooperative model is less than the non-cooperative model.

According to the above, we propose a cooperative framework for the energy scheduling of multiple energy hubs, which considers fair energy sharing between energy hubs by using Shapley value. Furthermore, energy hubs contain electrical, heating, and cooling load, and they can employ both the electrical and heating demand response programs. In this regard, a

Mixed Integer Linear Programming (MILP) model is used in order to achieve the global optimum solution for the problem. Various energy sources and generation units such as PV, WT, CHP, heat only boiler, electrical chiller, and absorption chiller are also employed. In the proposed model, the energy hubs form a coalition and share their resources to optimize the cost of the system. The overall gain of the coalition should be divided among the hubs trough a fair mechanism. We utilize the Shapley value and consider the contribution of each energy hub for cost minimization to allocate the benefit of coalition among each hub. A summary of the recently published paper on the energy hubs is provided in Table 1.

***Table 1**. Summary of literature in energy hub systems*

Ref.	Proposed model	Pros	Cons
[7]	• Stochastic optimization	• The role of ice storage has been studied • The impact of the electrical demand response program was investigated • A comprehensive structure of energy hub consists of heating, and cooling system is introduced	• The connection among energy hubs was not investigated • The role of thermal DR programs has not studied
[13]	• Cooperative approach	• The energy scheduling of the multi-energy hubs had been studied • The role of electrical and thermal DR programs was deliberated	• The fair cost allocation was not investigated • The cooling system was not considered • The impact of ice storage was not studied
[15]	• Cooperative approach	• The role of electrical and heat storage systems was studied • The absorption chiller was considered in the hub structure • The optimal planning of the multi-energy hubs had been studied	• The impact of ice storage was not studied • The effect of renewable resources was not investigated • The electrical and thermal DR programs were not considered • The fair cost allocation for the cooperator energy hubs was not investigated
[18]	• Non-cooperative approach	• The energy scheduling of multiple energy systems had been modeled • The uncertain nature of market prices and demand loads had been applied to the model	• The electric chiller and absorption chiller were not considered • The impacts of renewable resources were ignored • The efficiency of the thermal and ice storage systems had not been studied
[20]	• Non-cooperative approach	• Considering the electrical and natural gas networks for the optimal energy scheduling of integrated energy hub • The role of electrical and heat storage was investigated	• The role of ice storage was not deliberated • The cooling systems were not applied to the proposed structure • The cooperation among energy hubs was not studied
[21]	• Non-cooperative approach	• The impact of the energy storage systems had been investigated • The natural gas network had been modeled • The interaction among the distribution company and energy hubs had been modeled as the bi-level optimization framework	• The role of electrical and thermal DR programs was not studied • The cooling systems were not integrated into the hub structure • The performance of ice storage was not deliberated • The cooperation and fair cost-allocation among energy hubs had not studied
[22]	• Non-cooperative approach	• The role of static VAR compensator had been studied • The renewable resources had been considered	• The energy storage systems were not considered • The impacts of electrical and thermal DR programs were not investigated • The cooperation among energy hubs at the lower-level of optimization had not been studied

[23]	• Deterministic optimization	• The renewable energy resources had been integrated to the energy management of the energy hub • The role of the electrical, thermal, and cooling storage systems was considered	• The connection among energy hubs was not studied • The effects of thermal DR programs were ignored • The uncertainty of demand loads, market prices, and renewable resources had been ignored
[24]	• Probabilistic optimization	• The efficiency of the cooling storage had been investigated • The electrical DR program was considered • The absorption chiller and electric chiller had been applied to the model	• The energy scheduling of a single energy hub is investigated • The role of thermal DR had been ignored • The natural gas network was not considered
This paper	• Cooperative approach	• Presenting a comprehensive structure of the energy hub considering cooling systems such as absorption and electric chiller, and ice storage • Modeling of the interconnected energy hubs by the cooperative approach • The impacts of electrical and thermal DR programs had been investigated • The overall gain of the coalition has been divided as a fair solution	• The natural gas network will be studied in future work

The main advantage of the proposed model is that it guarantees the optimal solution for the system and can be easily used for multi-owner systems.

The main contributions of this paper are summarized as follows:

- We model the interaction among multi-carrier microgrids as a comprehensive energy hub that considers various electrical, heating, and cooling resources. Unlike [11], [15], [18], [19] and [25], we integrate the ice storage into the energy hub to improve the performance of the energy hubs.
- Presenting a cooperative model to ensure the best plan for the operation of multi-energy hubs. Unlike [7], [18], [19], [25], and [26] in the proposed model, the energy hubs are able to share their resources to use the surplus capacity of other hubs as the back-up. Therefore, the amount of shortage of power will be decreased which enhances the social welfare of the customers.
- The overall gain of the coalition is divided among cooperator energy hubs based on their contribution, efficiency, and bargaining power. Unlike, [7], [11], [13], [18], [19], and [25-29], the proposed model proposes a rational and fair solution to allocate the profit of the coalition among the energy hubs. Therefore, this comprehensive structure can be applied for multi-owner systems, where each operator tries to increase their efficiency.

- The proposed scheme enhances the flexibility of the studied system because the energy hubs can utilize the dispatchable resources of other hubs with different ramp-rates.

The rest of this paper is organized as follows: The mathematical formulation of the model is presented in section II. Section III describes the cooperative strategy and cost allocation of the proposed model. Simulation and results are presented in section IV. Finally, the conclusion is provided in section V.

II. MATHEMATICAL FORMULATION OF THE MODEL

Several energy sources including WT, PV, CHP, boiler, electrical chiller, absorption chiller in addition to DR programs and energy storage systems are employed in this paper. Each energy hub can import natural gas and electricity from the main grid. The energy hub model is illustrated in Fig.1.

The objective function and constraints of the problem are as follow:

1. Objective Function

The objective function of the presented model is the cost minimization of energy hubs as follows:

$$min\left\{\sum_t\left(\sum_i P_g^{i,t}\pi_g^t + G_{CHP}^{i,t}\lambda_t^G + (PE_{CHP}^{i,t} + PH_{CHP}^{i,t})OM_{CHP} + G_B^{i,t}\lambda_t^G + PH_B^{i,t}OM_B + P_{curt}^{e,i,t}PEN_{curt}\right)\right\} \quad (1)$$

In the objective function, the cost of imported electricity from the power grid, consumed natural gas for CHP units, operation and maintenance of the CHP units, consumed natural gas for boilers, operation as well as maintenance cost of the boilers, and the penalty for the curtailed load are included, respectively.

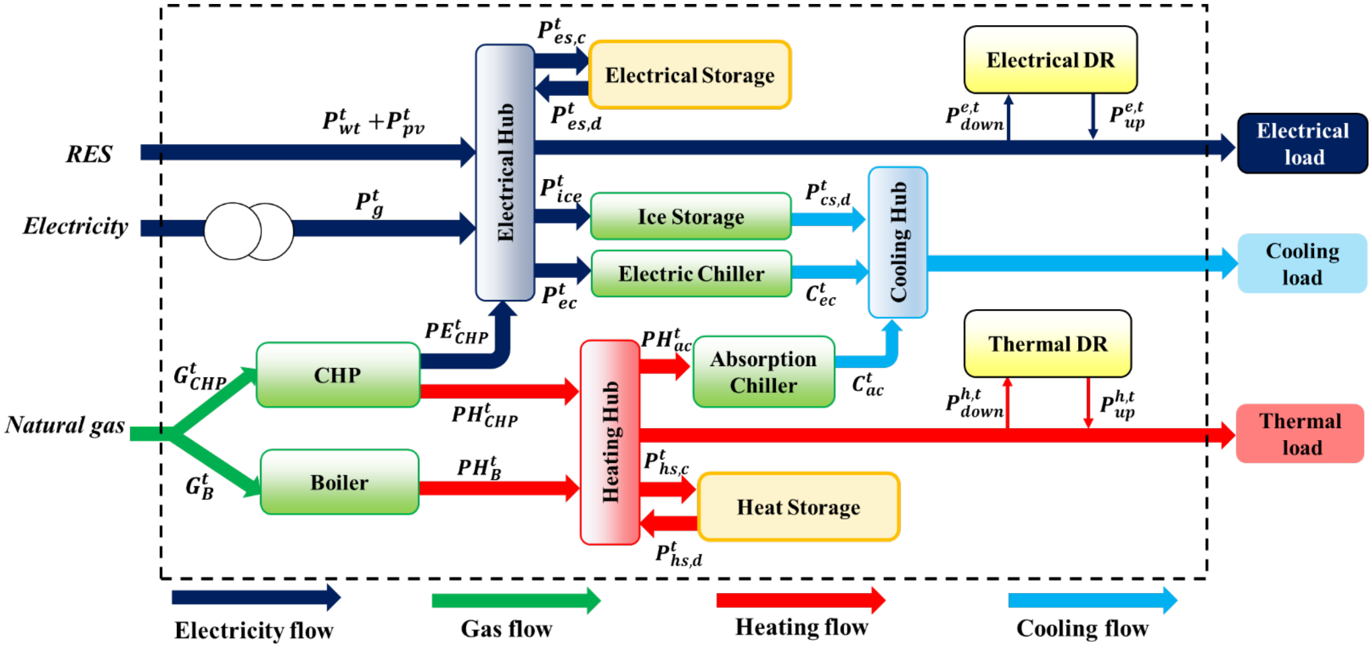

Fig. 1. *The architecture of energy hubs*

2. Constraints of the DR programs

In the DR programs, the loads are shifted or curtailed to decrease the costs. In the price-based DR programs, consumers shift their loads from peak hours so as to decrease their dependency on the power grid to buy energy. Also, consumers can use incentive-based demand response programs which curtails the loads in peak hours.

In this paper, price-based and incentive-based demand response programs are employed for electrical and thermal loads. The formulation of electrical DR is presented as follows:

$$\sum_t P_{up}^{e,i,t} = \sum_t P_{down}^{e,i,t} \qquad \forall\, i \tag{2}$$

$$0 \le P_{up}^{e,i,t} \le MR_{up}^{e} P^{el,i,t} I_{up}^{e,i,t} \qquad \forall\, i,t \tag{3}$$

$$0 \le P_{down}^{e,i,t} \le MR_{down}^{e} P^{el,i,t} I_{down}^{e,i,t} \qquad \forall\, i,t \tag{4}$$

$$0 \le I_{up}^{e,i,t} + I_{down}^{e,i,t} \le 1 \qquad \forall\, i,t \tag{5}$$

Eqs. (2)-(5) represent the price-based DR program, in which the total decreases in loads in the operation interval is equal to the total increased load. Eqs. (3) and (4) demonstrate the maximum allowed load shifting, and Eq. (5) prevents a simultaneous change in load. Similarly, Eq. (6) is used for modeling the load curtailment, which imposes a penalty to the energy hub.

$$0 \leq P_{curt}^{i,t} \leq P^{el,i,t} CO_{curt} \quad \forall\, i, t \tag{6}$$

In addition to electrical DR, heat DR is also used in this paper as follows:

$$\sum_t P_{up}^{h,i,t} = \sum_t P_{down}^{h,i,t} \qquad \forall\, i \tag{7}$$

$$0 \leq P_{up}^{h,i,t} \leq MR_{up}^{h} P^{hl,i,t} I_{up}^{h,i,t} \qquad \forall\, i, t \tag{8}$$

$$0 \leq P_{down}^{h,i,t} \leq MR_{down}^{h} P^{hl,i,t} I_{down}^{h,i,t} \quad \forall\, i, t \tag{9}$$

$$0 \leq I_{up}^{h,i,t} + I_{down}^{h,i,t} \leq 1 \qquad \forall\, i, t \tag{10}$$

Eq. (7) represents the equality of decrement and growth in the price-based DR program for heat load. Eqs. (8)-(9) show the highest quantities for heat load shifting, and the Eq. (10) is employed for simultaneous load shifting prevention.

3. Energy storage systems

Energy storages effectively enhance the performance of the system by storing the energy in the low load hours and discharging it when required. In this paper, the storage is used for electrical, heat, and cooling systems, which will be discussed more precisely. The following relations illustrate the operation of the electrical energy storage system:

$$E_{es}^{i,t+1} = E_{es}^{i,t} + P_{es,c}^{i,t} \eta_{es,c} - \frac{P_{es,d}^{i,t}}{\eta_{es,d}} \qquad \forall\, i, t \tag{11}$$

$$E_{es}^{min,i} \leq E_{es}^{i,t} \leq E_{es}^{max,i} \qquad \forall\, i, t \tag{12}$$

$$0 \leq P_{es,c}^{i,t} \leq P_{es,c}^{max} k_c^{e,i,t} \quad \forall\, i, t \tag{13}$$

$$0 \leq P_{es,d}^{i,t} \leq P_{es,d}^{max} k_d^{e,i,t} \quad \forall\, i, t \tag{14}$$

$$0 \leq k_c^{e,i,t} + k_d^{e,i,t} \leq 1 \quad \forall\, i, t \tag{15}$$

$$E_{es}^{i,0} = E_{es}^{i,24} \quad \forall\, i \tag{16}$$

The electrical energy balance for the energy storage system is described in the Eq. (11). Eqs. (12) - (14) restrict the value of $E_{es}^{i,t}$, $P_{es,c}^{i,t}$, and $P_{es,d}^{i,t}$ because of technical issues. Eq. (15) guarantees that the storage will not be charged and discharged at the same time. As given in the Eq. (16), the stored energy in the first and final hours of operation should be equal. The model for the heat storage system is described as follows:

$$E_{hs}^{i,t+1} = E_{hs}^{i,t} + P_{hs,c}^{i,t}\eta_{hs,c} - \frac{P_{hs,d}^{i,t}}{\eta_{hs,d}} \qquad \forall\, i,t \tag{17}$$

$$E_{hs}^{min,i} \leq E_{hs}^{i,t} \leq E_{hs}^{max,i} \qquad \forall\, i,t \tag{18}$$

$$0 \leq P_{hs,c}^{i,t} \leq P_{hs,c}^{max,i} k_c^{h,i,t} \quad \forall\, i,t \tag{19}$$

$$0 \leq P_{hs,d}^{i,t} \leq P_{hs,d}^{max} k_d^{h,i,t} \quad \forall\, i,t \tag{20}$$

$$0 \leq k_c^{h,i,t} + k_d^{h,i,t} \leq 1 \quad \forall\, i,t \tag{21}$$

$$E_{hs}^{i,0} = E_{hs}^{i,24} \quad \forall\, i \tag{22}$$

According to Eq. (17), the stored heat depends on the charging rate, discharging rate, and efficiency parameters. The limits of stored energy, charging power, and discharging power are represented in (18) – (20). Eq. (21) is used for prohibiting simultaneous charge and discharge. Eq. (22) is employed to have equal quantity for the accessible heat in the heat storage in the first and the last hour of the operation planning.

Using ice storage systems will have significant impacts on the operation of the cooling system and the costs, since they will be charged when the electricity price is low and discharge when the cooling load in the peak. Ice storage cooling systems use electric power to make ice during the low price hours, and melt the ice when required. They consist of an ice storage tank and an ice storage conditioner. The following relations illustrate the ice storage modeling:

$$E_{cs}^{i,t+1} = E_{cs}^{i,t}(1 - \delta_{cs}) + P_{cs,c}^{i,t}\eta_{cs,c} - \frac{P_{cs,d}^{i,t}}{\eta_{cs,d}} \qquad \forall\, i,t \tag{23}$$

$$E_{cs}^{min} \leq E_{cs}^{i,t} \leq E_{cs}^{max} \qquad \forall\, i,t \tag{24}$$

$$0 \leq P_{cs,c}^{i,t} \leq P_{cs,c}^{max} k_c^{cs,i,t} \quad \forall\, i,t \tag{25}$$

$$0 \leq P_{cs,d}^{i,t} \leq P_{cs,d}^{max} k_d^{cs,i,t} \quad \forall\, i,t \tag{26}$$

$$0 \leq k_c^{cs,i,t} + k_d^{cs,i,t} \leq 1 \quad \forall\, i,t \tag{27}$$

$$E_{cs}^{i,0} = E_{cs}^{i,24} \quad \forall\, i \tag{28}$$

Eq. (23) shows the energy balance for the ice storage system. Eqs. (24) – (26) demonstrate the technical constraints of ice storage. Eq. (27) is imposed to have either charging or discharging mode for the ice storage in each time. Eq. (28) is employed so as to have equal cooling energy stored in the storage in the first and last hour of the operation.

4. Energy balance of the system

The energy balance in the proposed model in the electrical and heat section is as follows:

$$P_g^{i,t} + P_{pv}^{i,t} + p_{wt}^{i,t} + PE_{CHP}^{i,t} + P_{es,d}^{i,t} + P_{down}^{e,i,t} + P_{curt}^{i,t} = P^{el,i,t} + P_{es,c}^{i,t} + P_{up}^{e,i,t} + P_{ice}^{i}{}^{i,t} + P_{ec}^{i,t} \quad (29)$$

$$PH_{CHP}^{i,t} + PH_B^{i,t} + P_{hs,d}^{i,t} + P_{down}^{h,i,t} = P^{hl,i,t} + P_{hs,c}^{i,t} + P_{up}^{h,i,t} + PH_{ac}^{i,t} \quad (30)$$

$$PH_B^{i,t} = G_B^{i,t} LHV \eta_B \quad (31)$$

$$PE_{CHP}^{i,t} = G_{CHP}^{i,t} LHV \eta_B^e \quad (32)$$

$$PH_{CHP}^{i,t} = G_{CHP}^{i,t} LHV \eta_B^h \quad (33)$$

$$0 \le G_{CHP}^{i,t} \le G_{CHP}^{max,i} \quad (34)$$

$$0 \le G_B^{i,t} \le G_B^{max,i} \quad (35)$$

$$-P_g^{i,max} \le P_g^{i,t} \le P_g^{i,max} \quad (36)$$

$$0 \le PH_{CHP}^{i,t} + PH_B^{i,t} + P_{hs,d}^{i,t} - P_{hs,c}^{i,t} \le P_h^{max} \quad (37)$$

The balance between supply and demand in the electrical as well as heat section of the hubs are demonstrated by Eq. (29) and (30), respectively. The produced heat from the boiler is described in Eq. (31). The output of electricity and heat of the CHP units are respectively shown in Eq. (32) and (33). The constraints of the purchasable natural gas for CHP units, and boilers are represented in Eq. (34) and (35), respectively. The constraints of the imported power from the main grid and the heat pipes are respectively demonstrated in Eq. (36) and (37). In order to meet the energy balance in the cooling section, the following relations are proposed:

$$C_{ec}^{i,t} + C_{ac}^{i,t} + P_{cs,d}^{i,t} = CL^{i,t} \quad (38)$$

$$P_{cs,c}^{i,t} = P_{ice}^{i,t} COP_{ice} \quad (39)$$

$$0 \le P_{ice}^{i,t} \le P_{ice}^{max,i} \quad (40)$$

$$C_{ac}^{i,t} = PH_{ac}^{i,t} COP_{ac} \quad (41)$$

$$0 \le PH_{ac}^{i,t} \le PH_{ac}^{max,i} \quad (42)$$

$$C_{ec}^{i,t} = P_{ec}^{i,t} COP_{ec} \quad (43)$$

$$0 \le P_{ec}^{i,t} \le P_{ec}^{max,i} \quad (44)$$

Eq. (38) shows the cooling system balance between supply and demand for each hub. According to Eq. (39), the charging energy for the ice storage depends on the COP_{ice} and the amount of input electricity which makes the ice. The power input limit for the ice storage is described in Eq. (40). Another cooling production unit in this paper is the absorption chiller, which receives heat and produces cooling energy for the system, and is illustrated in Eqs. (41) and (42). The last cooling supply unit is the electrical chiller in which the input electricity provides cooling energy for the system, which is demonstrated in Eqs. (43) and (44).

III. Cooperative strategy and fairly cost allocation

In this paper, we propose cooperative energy management for integrated energy hubs. Unlike non-cooperative games, cooperative strategies guarantee the optimal solution for the system. A coalition is formed when a group cooperates together. The overall gain of the coalition should be divided fairly among participants. Shapley value is a classic cooperative solution concept that allocates a unique distribution to the participants. The Shapley value allocates the overall gain of the coalition between participants based on their contribution, efficacy, and bargaining power of participants [30], and [31]. The amount that hub i gets given in a coalitional game is achieved as (45):

$$\varphi_i(v) = \frac{1}{N!} \sum_{S \quad N/\{i\}} |S|!\,(N-|S|-1)!\,(v(S \cup \{i\}) - v(S)) \tag{45}$$

Where N is the total number of hubs and the function v maps subsets of hubs to the real numbers. The S shows a coalition of hubs and $v(S)$ called the worth of coalition S. The Eq. (45) can be replaced by (46) and (47):

$$\varphi_i(v) = \frac{1}{N!} \sum_{R} \left[v\left(P_i^R \cup \{i\}\right) - v\left(P_i^R\right) \right] \tag{46}$$

$$\varphi_i(v) = \frac{1}{N!} \sum_{S \quad N/\{i\}} \frac{(v(S \cup \{i\}) - v(S))}{\binom{N-1}{|S|}} \tag{47}$$

Where P_i^R is the set of hubs in N, which precede i in order R. It should be noted that for a single-owner system, we can utilize the proposed cooperative model, but we do not need the cost allocation.

IV. Simulations and results

In this section, the simulation parameters and input power data are represented. Afterward, the results are analyzed and discussed. The proposed model includes several energy hubs, which have various generation units and demands. The parameters of the electrical, heat, and ice storage systems are shown in Table 2 [25, 26]. The parameters of the ice storage system and CCHP are described in Table 3 [25, 26]. The other simulation parameters are described in Table 4 [25, 26]. The input power from the PV and WT units are taken from [25]. The hourly electricity price is illustrated in Fig.2 .The electrical, heat, and cooling loads of the hubs are depicted in Figs. 3-5, respectively [25, 26] and [7].

Table 2. *Parameters of electrical and heat storage system*

Electrical storage parameters				**Heat storage parameters**			
Parameter	Hub1	Hub2	Hub3	Parameter	Hub1	Hub2	Hub3
$E_{es}^{max,i}$ (kWh)	90	130	100	$E_{hs}^{max,i}$ $(kW$h)	160	100	-
$E_{es}^{min,i}$ (kWh)	9	15	10	$E_{hs}^{min,i}$ (kWh)	30	20	-
$P_{es,c}^{max,i}$ (kW)	15	30	20	$P_{hs,c}^{max,i}$ (kW)	40	25	-
$P_{es,d}^{max,i}$ (kW)	15	30	20	$P_{hs,d}^{max,i}$ (kW)	40	25	-
$\eta_{es,c}^{i}$	0.9	0.9	0.9	$\eta_{hs,c}^{i}$	0.9	0.9	-
$\eta_{es,d}^{i}$	0.9	0.9	0.9	$\eta_{hs,d}^{i}$	0.9	0.9	-

Table 3. *Parameters of ice storage and CCHP units*

Ice storage parameters				**CCHP parameters**			
Parameter	Hub1	Hub2	Hub3	Parameter	Hub1	Hub2	Hub3
$E_{cs}^{max,i}$ (kWh)	320	-	300	$G_{CHP}^{max,i}$ (m^3/h)	60	75	50
$E_{cs}^{min,i}(kWh)$	60	-	60				
$P_{cs,c}^{max,i}(kWh)$	120	-	120	$G_{B}^{max,i}(m^3/h)$	30	35	30
$P_{cs,d}^{max,i}(kWh)$	140	-	140	$PH_{ac}^{max,i}$ (kW)	-	-	180
$\eta_{cs,c}^{i}$	0.97	-	0.97	$P_{icc}^{max,i}$(kW)	50	-	50
$\eta_{cs,d}^{i}$	0.95	-	0.95	$P_{ec}^{max,i}$(kW)	100	-	80
δ_{cs}^{i}	0.02	-	0.02				

Table 4. *Simulation Parameters*

Parameter	Value	Parameter	Value
OM_{CHP} $(cent/kWh)$	2	η_{CHP}^{e}	0.35

OM_B $(cent/kWh)$	2.7	η_{CHP}^{h}	0.45
MR_{up}^{e}	0.5	η_B	0.8
MR_{down}^{e}	0.2	COP_{ec}	4
MR_{up}^{h}	0.5	COP_{ice}	3.5
MR_{down}^{h}	0.2	COP_{ac}	1.2
λ_t^G $(cent/m^3)$	22	CO_{curt}	0.25
LHV (kWh/m^3)	9.7	$PEN_{curt}(cent/kWh)$	20

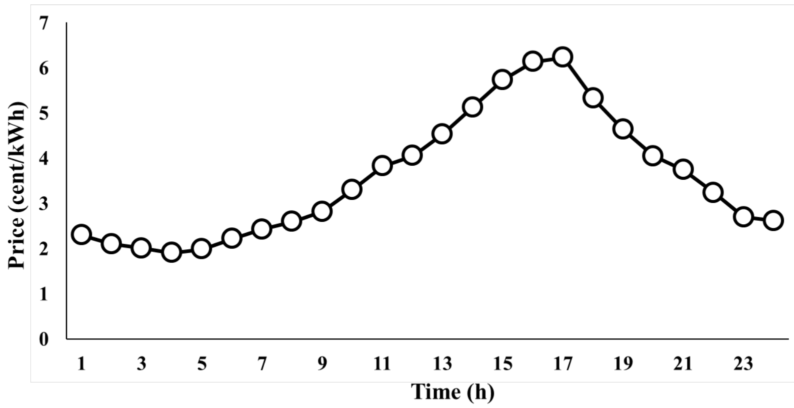

Fig. 2. *Wholesale electricity market prices*

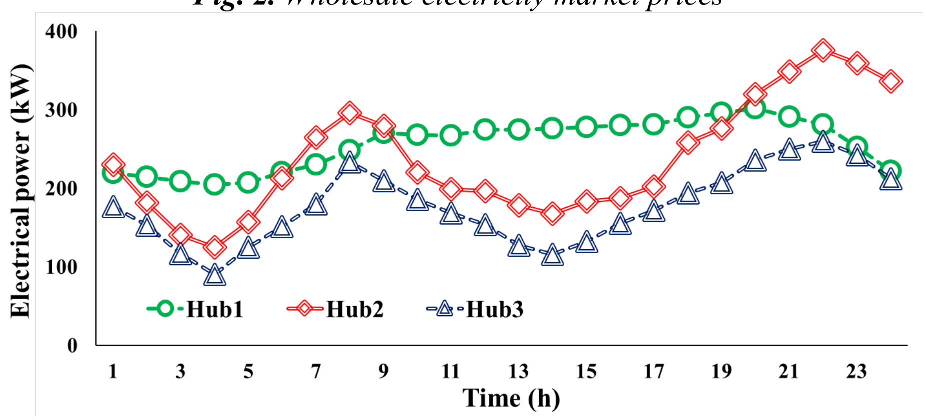

Fig. 3. *The electrical demand of energy hubs*

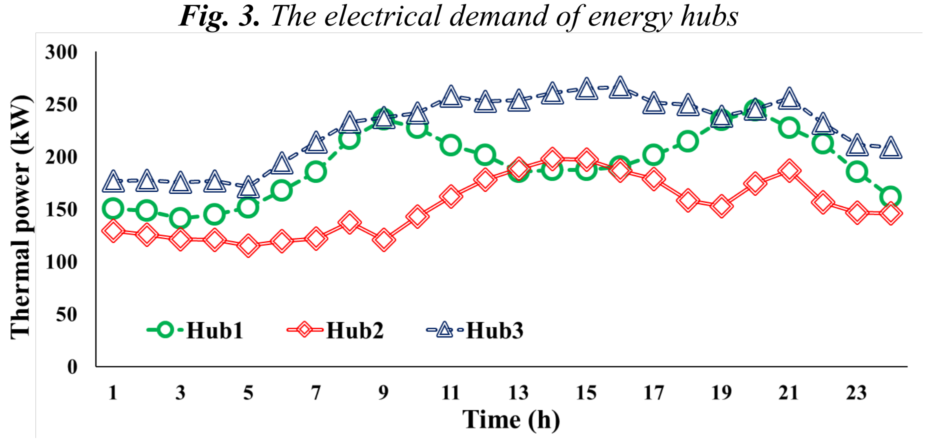

Fig. 4. *The thermal demand of energy hubs*

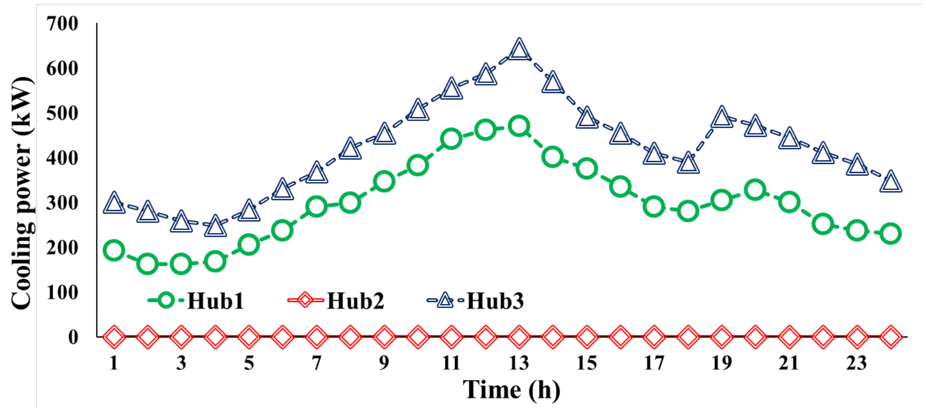

Fig. 5. *The cooling demand of energy hubs*

In order to show the efficiency of the proposed cooperative approach, two following case studies have been studied:

- Case I: In this case study, the energy hubs perform an autonomous operation scheduling to minimize their operation costs. Similar to this case study had been presented in [7], [23], [24], [25], and [26]. This case study is a base case and the energy hubs cannot cooperate to share their resources.
- Case II: The proposed cooperative approach has been investigated in this case study. The energy hubs cooperate together to form a coalition. In this case, the energy hubs can share their local resources to provide a back-up for other energy hubs. The overall profit of the coalition is divided among the energy hubs based on their efficiency, bargaining power, and contribution. The Simulation results of case studies are presented in Table 5.

Table 5. *The optimal results of case studies*

Case study	**Cost (cents)**			**Energy not supply**	**Interrupt**
	Hub1	**Hub2**	**Hub3**	**(kWh)**	**(times)**
Case I	73103.24	33574.75	50323.25	1205.37	24
Case II	59290.7	30140.68	45934.82	0	0
Improvement (%)	+18.89	+10.23	+8.72	+100	+100

The results of Table 5 show that the operating costs of the energy hubs have been improved by the proposed cooperative model. Compared to the case I, the operation cost of energy hub1 has been improved from 73103.24 cents to 59290.7 cents. Also, the operation costs of the energy hubs2 and 3 reach from 33574.75 cents and 50323.25 cents to 30140.68 cents and 45934.82 cents, respectively. Actually, the proposed model improves the operation costs of the energy hubs 1, 2, and 3 by 18.89%, 10.23%, and 8.72%, respectively. When energy hubs cooperate and share their resources, the total cost of the energy hubs had been reduced by 21635.04 cents. Based on the contribution and the efficiency of each energy hub, the profit of the coalition is divided among them that most of the overall gain goes to hub 1. In the proposed model, the energy hubs are able to use the local resources of the other energy hubs as the back-up. Therefore, the amount of curtailed load and the number of interrupts significantly have been improved by the proposed cooperative model. In the autonomous operation scheduling, the amount of the curtailed load is 1205.37 kWh, while in the proposed model all of the required loads have been supplied by the local resources. The analysis of each case study is presented as follows:

1. The electrical, heating, and cooling results of case I

In this section, the results of case I are analyzed in details.

i) The electrical results of energy hubs in case I

In Fig. 6-8, the amount of each electric production and demand including power resources, energy storages, DR programs, and electricity consumers such as ice storage and electrical chiller is demonstrated. As illustrated, hub1 faces a serious electrical energy shortage, since it has restrictions to import energy from the main grid. Thus, hub1 employs its own resources as much as possible to provide the required power for the demands, and it uses CHP unit to produce most of the required power in most of the operation time. Furthermore, this hub uses DR programs to shift and curtail the loads, resulting in enhancing its ability to serve the demands. Hub1 also possesses electrical chiller and ice storage, which consume a large part of the accessible electricity.

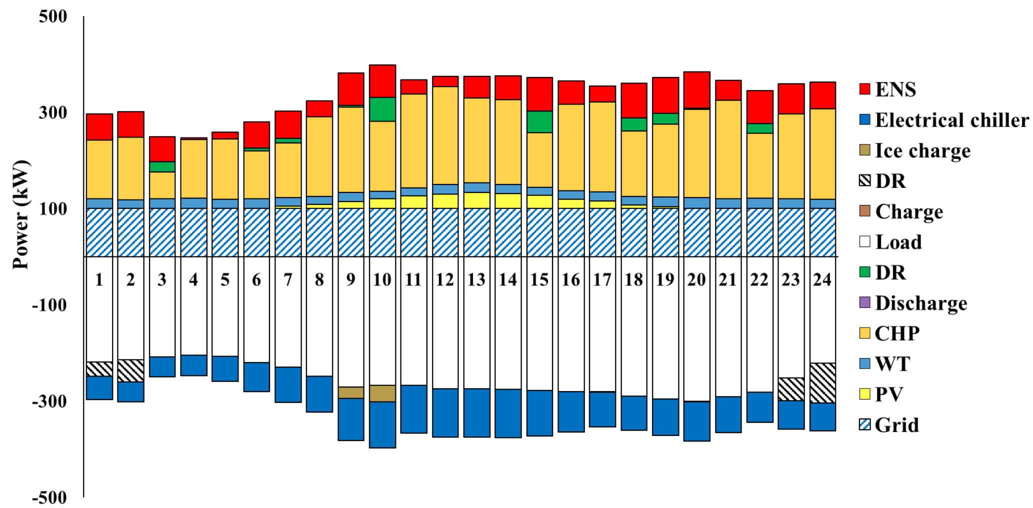

Fig. 6. *The electrical balance of energy hub 1*

As shown in Fig. 7, hub2 can import more power from the main grid, and it has not cooling loads to serve. With this in mind, it imports power in the low price hours and sells the extra power in the high price moments, which reduces its dependency on the CHP unit, and use CHP unit mostly to make profit during the high price hours and sell the power to the grid. Moreover, hub2 has shifted its loads from the peak load hours to low load hours using demand response programs to reduce the required energy in peak hours.

Hub3 contains various production units and demands, which has increased its flexibility in serving the demands. As depicted in Fig. 8, hub3 has shifted the loads from peak hours to low load periods, which results in a reduction in its operation cost. Also, it has injected power to the main grid during hours 11-18, since it has a large amount of renewable energy, enabling hub 3 to produce a large amount of energy.

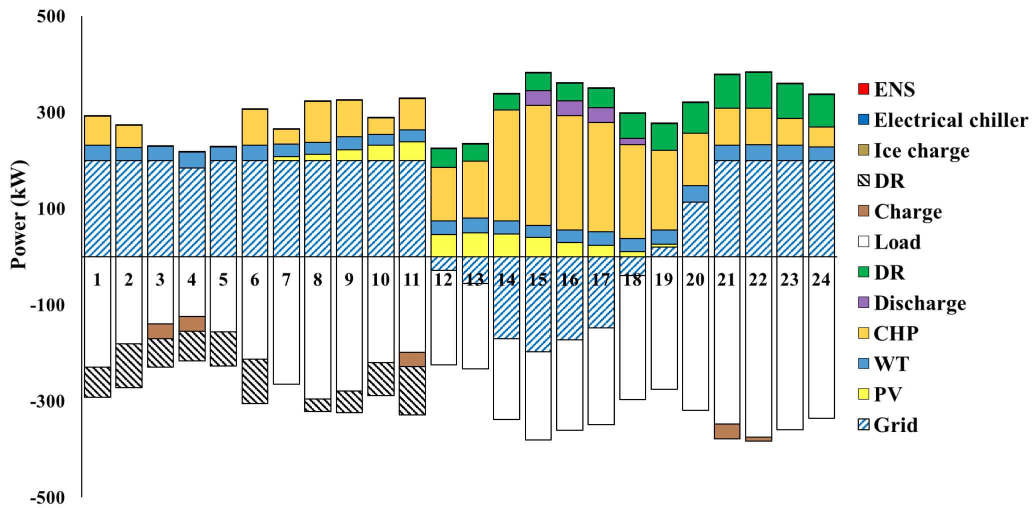

Fig. 7. *The electrical balance of energy hub 2*

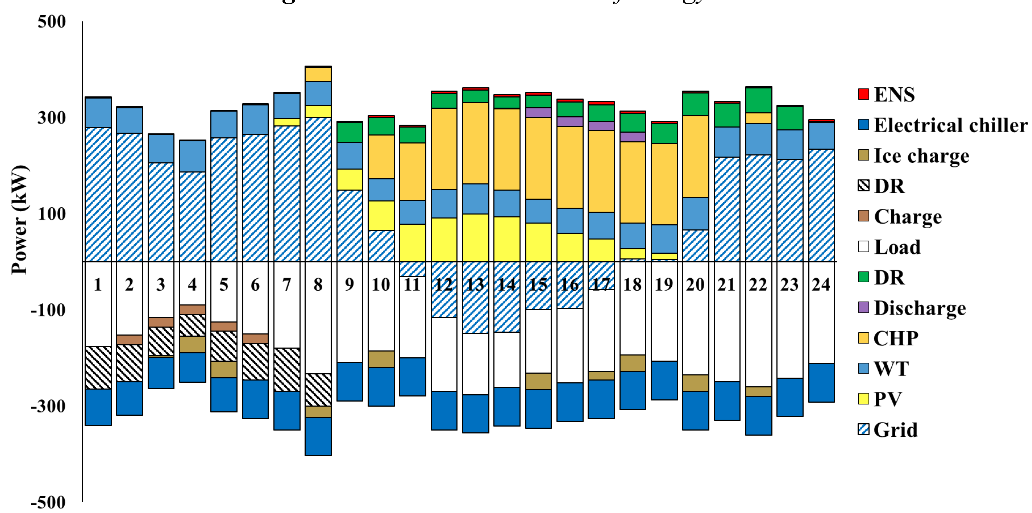

Fig. 8. *The electrical balance of energy hub 3*

ii) The heating results of energy hubs in case I

Figs. 9-11, shows an overview of the heat energy in hubs, in which the production and demands of each are described. Since hub1 should utilize its CHP to provide the required electrical power, its CHP is employed all over the operation period, and the boiler unit is not used in case I. Moreover, using the heat storage and DR programs, hub1 provides the required heat for the demands and shifts the heat load in order to decrease the operation costs. Furthermore, because of the limited flexibility in this case, hub1 is unable to use its absorption chiller and boiler.

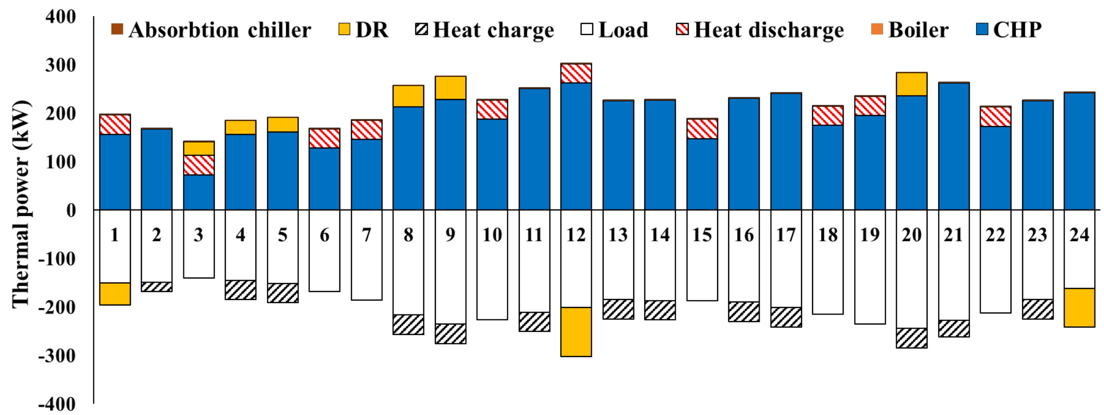

Fig. *9. The heating balance of energy hub 1*

According to Fig. 10, regarding the smaller quantity of the required electric power in hub2, less heat is produced by CHP, and boiler as well as DR program have provided the required heat for the hub. As mentioned earlier, hub2 uses its CHP to produce electrical power in the high price hours and sell the power to the main grid. Therefore, the only heat provider in the high price hours is the CHP unit. Also, the CHP unit supplies the required heat for charging the heat storage and the shifted heat loads from other intervals.

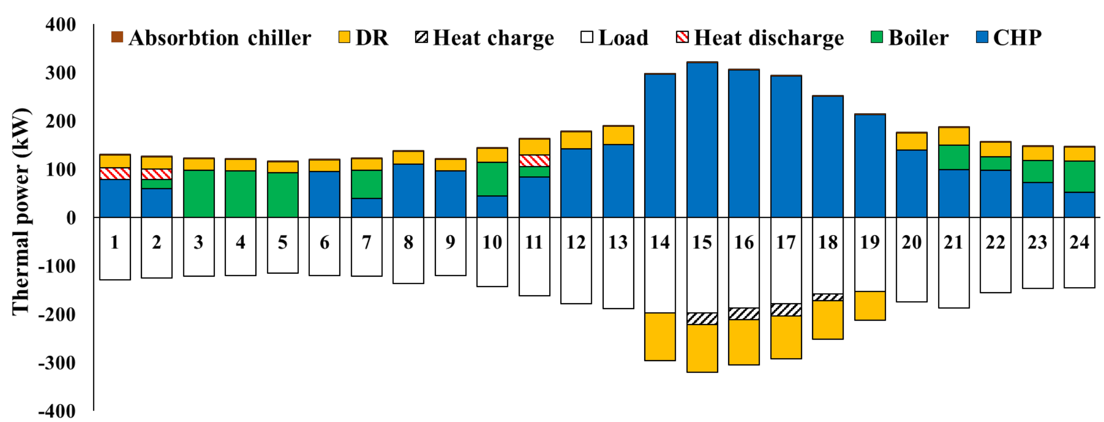

Fig. 10. *The heating balance of energy hub 2*

The main heat source of hub3 is the boiler, since it has less amount of electrical load and it can import more power from the main grid; thus it needs less electricity from the CHP units and most of the required heat is generated using boiler (see Fig. 11). Boiler and CHP provide heat together between hours 8-20, because the absorption chiller is employed during this period. During hours 9-21, CHP unit provides heat for hub3, since the generated power in these hours will reduce the imported power in the high price hours.

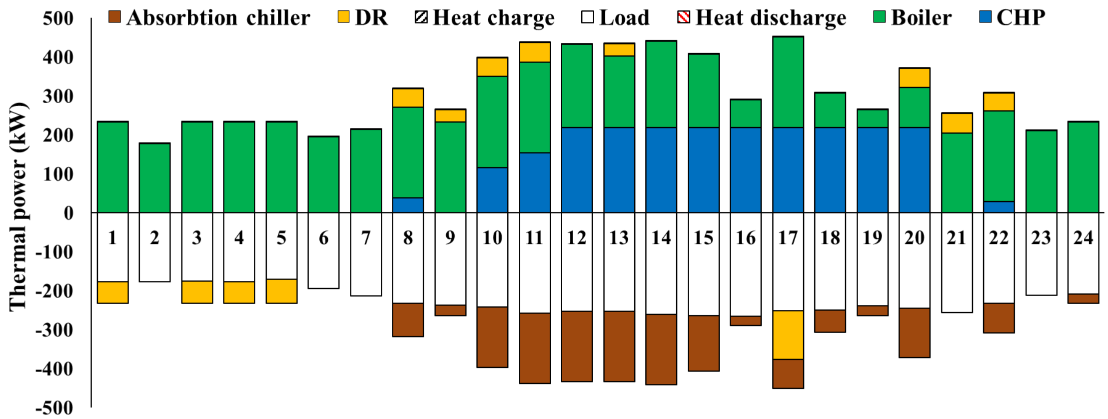

Fig. 11. *The heating balance of energy hub 3*

iii) The cooling results of energy hubs in case I

The main supplier of cooling energy in hub1 is the electrical chiller as illustrated in Fig. 12. Moreover, the ice storage system has provided more cooling energy between 11-13 when is the peak period of the cooling load.

According to Fig 13, hub3 owns absorption chiller, enabling it to have more options for cooling energy provision, although the main cooling energy provider is the electrical chiller. During the peak cooling load period, the absorption chiller and ice storage system support the electrical chiller to supply the required cooling energy for hub3. Furthermore, the ice storage supplies cooling energy in hours 19, 21, and 23 in which more cooling load is required.

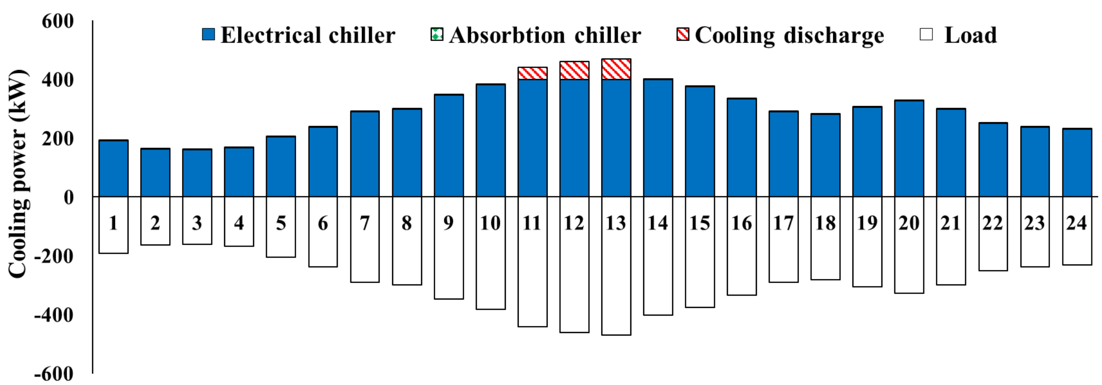

Fig. 12. *The heating balance of energy hub 1*

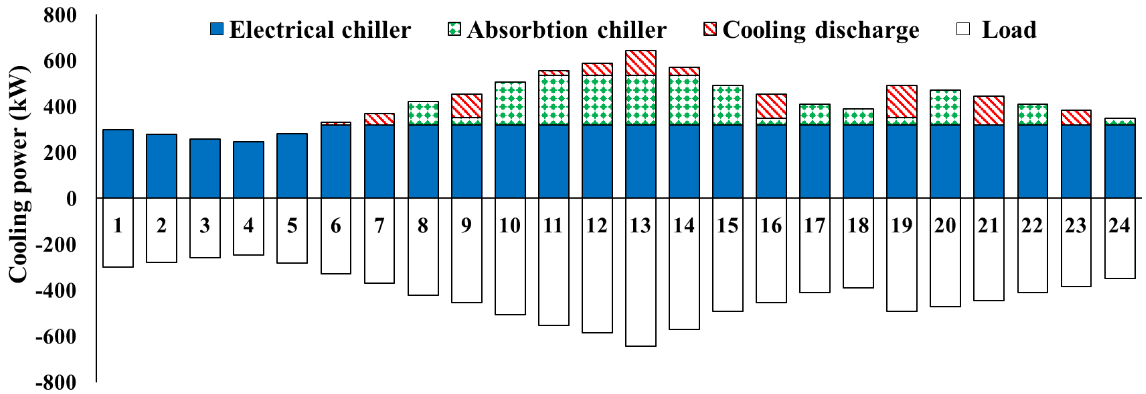

Fig. 13. *The heating balance of energy hub 3*

2. The electrical, heating, and cooling results of case II

The results of the electrical, thermal, and cooling energy of case II have been investigated in this section.

i) The electrical results of energy hubs in case II

The cooperative operation of energy hubs is investigated in case II. In the cooperative operation, the total imported power from the main grid for energy hubs is restricted to 600 kW instead of restricting purchasing power from the main grid for each of the energy hubs. According to Fig. 14, hub1 imports more amount of energy from the main grid in the cooperated operation in comparison with case I, since it has more loads to serve. Moreover, hub1 has decreased the output of CHP to increase the flexibility of the electrical and heat section. Furthermore, load curtailment is not required for hub1 in case II, because it can import sufficient power from the main grid. Unlike case I, the demand response program has been used more frequently in case II, because of the ability to import more power from the main grid.

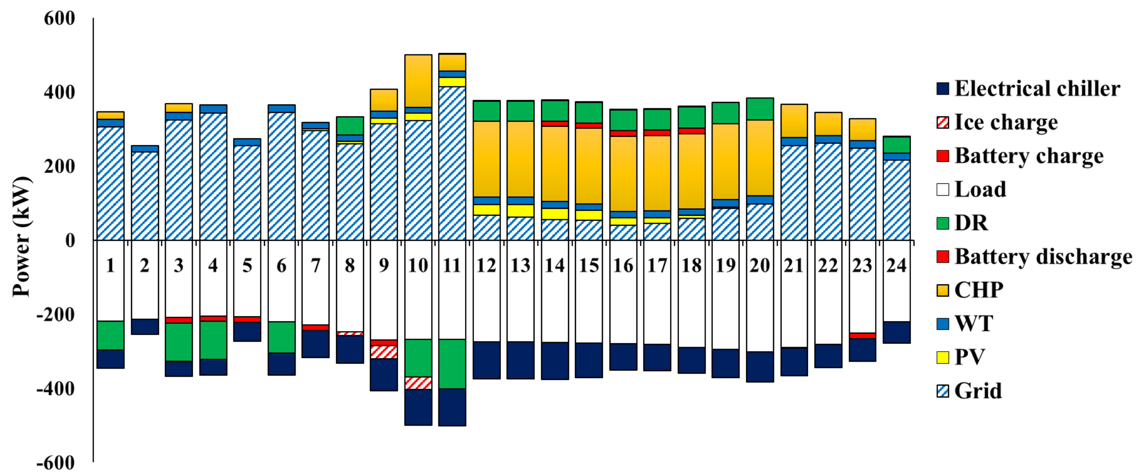

Fig.14. *The electrical balance of energy hub 1*

As we can observe from Fig. 15, hub2 is also able to import more power from the main grid in case II, resulting in decreasing the use of CHP during the operation period. However, during the high price hours, the CHP is still employed, because the obtained revenue from selling power to the grid overcomes the CHP shut down.

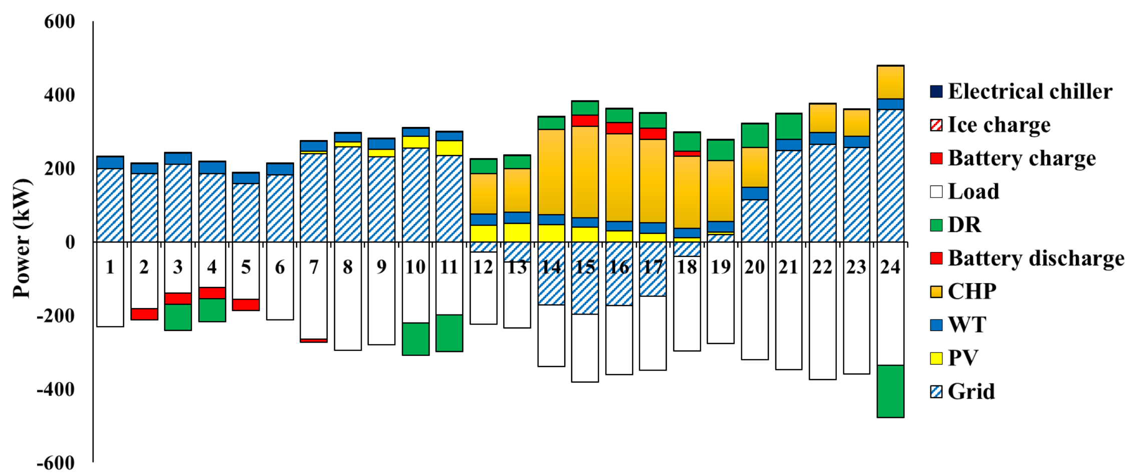

Fig.15. *The electrical balance of energy hub 2*

Hub3 has decreased the imported power from the main grid in the first hours of the operation and has used CHP units to produce the rest of required power, since energy hubs have shared the capacity of imported power from the main grid, and more capacity for importing power from the main grid is dedicated to hub1 in case II (Fig. 16).

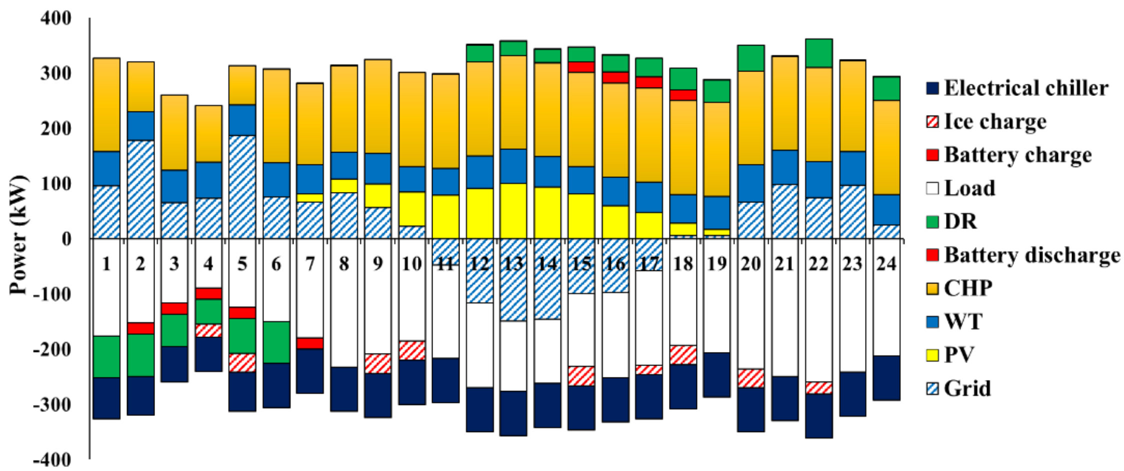

Fig. 16. *The electrical balance of energy hub 3*

ii) The heating results of energy hubs in case II

The output power of heat resources and heating load of energy hubs are presented in Figs. 17-19. The generated heat from the CHP in hub1 is decreased in case II, since hub1 needs less electricity from the CHP. Accordingly, less heat is generated from CHP, resulting in the growth in heat production from the boiler in case II. Moreover, using less amount of heat from the CHP has enabled hub1 to use more DR programs and shift the loads more appropriately. During the high price hours, CHP produces power and heat, and the boiler is not used in this interval.

Likewise, hub2 is also able to produce more heat from the boiler, because it has diminished the output of CHP during the first period of the operation. Nevertheless, the CHP heat output is the same as case I in the high price hours, as hub3 prefers to sell the generated power from the CHP to the grid. Hub3 has reduced the output of the boiler and increased the output of CHP, since it has to decline the imported power from the main grid by using its own CHP more frequently. The absorption chiller generates as same cooling energy as case I, but the heat DR program has changed in order to match with the power transmission restrictions.

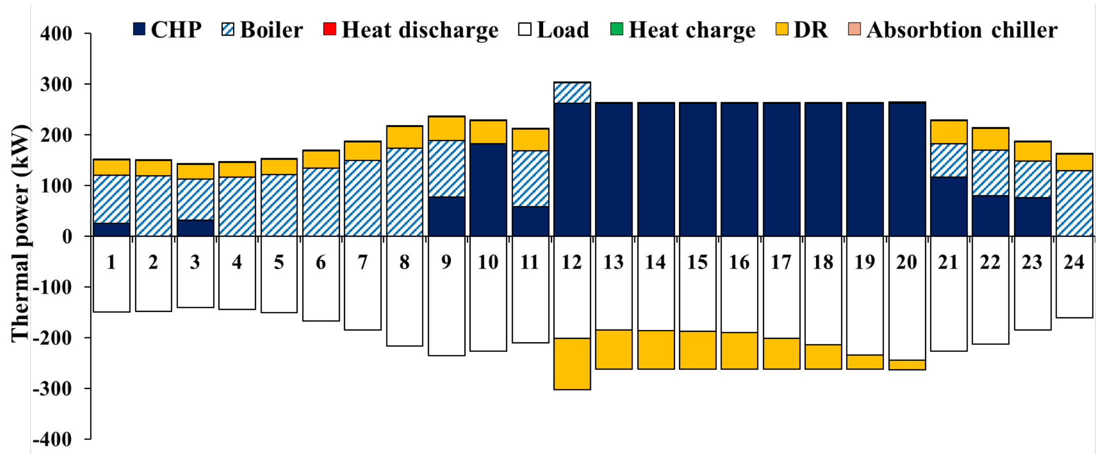

Fig. 17. *The heating balance of energy hub 1*

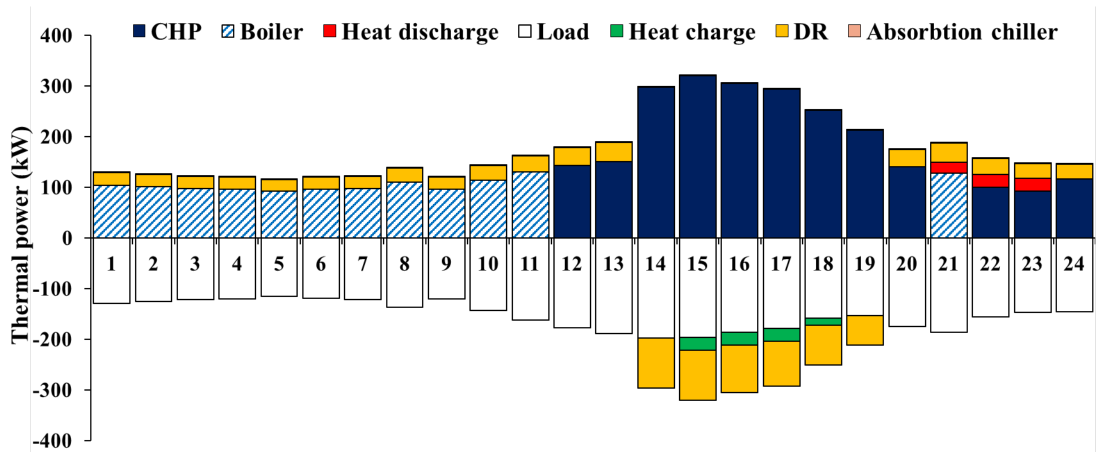

Fig. 18. *The heating balance of energy hub 2*

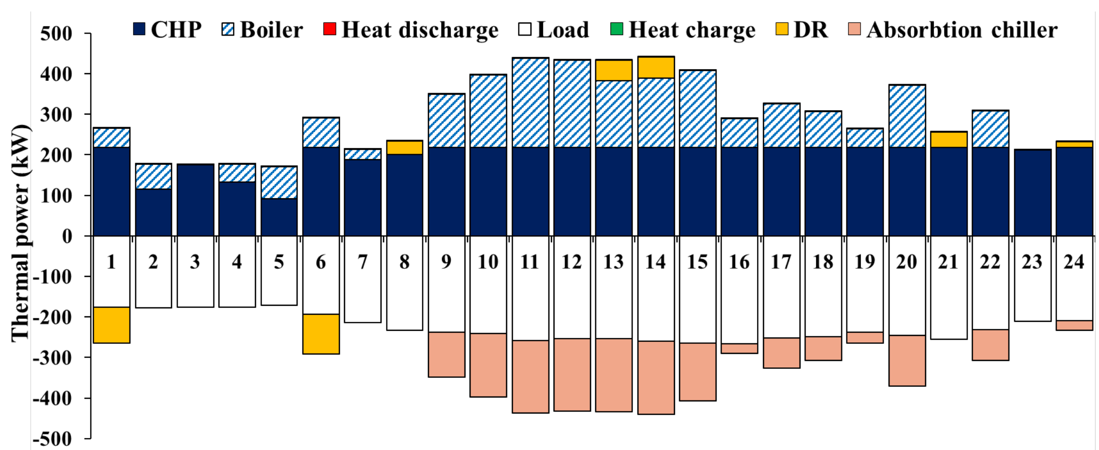

Fig. 19. *The heating balance of energy hub 3*

iii) The cooling results of energy hubs in case II

The cooling system results of case II are illustrated in Figs. 20-21 , in which the role of ice storage systems have increased in some hours, which is the result of more flexibility in the system by working in the cooperative condition. As previously mentioned, the main cooling supplier in hub1 is the electrical chiller, and ice storage collaborates in the cooling peak hours. The absorption chiller in addition to the electrical chiller is the main cooling energy supplier in hub3.

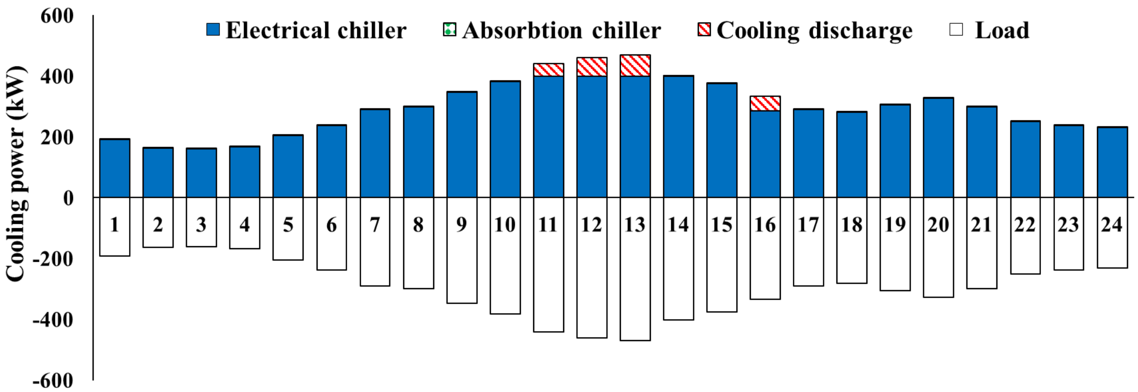

Fig. 20. *The cooling balance of energy hub 1*

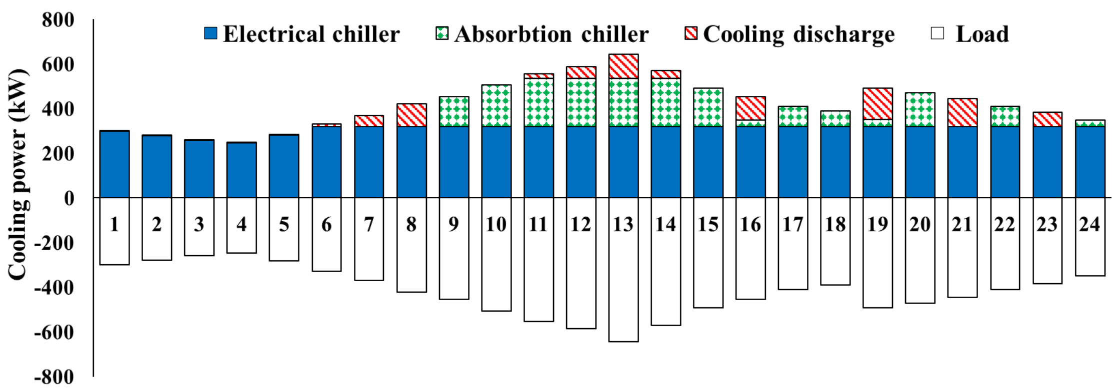

Fig. 21. *The cooling balance of energy hub 3*

V. Conclusion

In this paper, a cooperative model for networked energy hubs is proposed based on the fair cost allocation using the Shapley value. Several energy sources for different energy sections are used so that the optimal solution for the problem can be calculated. Energy storage systems as well as heat and electrical demand response for energy sectors are exerted in order to increase the flexibility of the system. The cooperation between energy hubs adds more flexibility to the problem, and they share their strength to reduce their weakness. The simulation results show when the energy hubs form a coalition, the total cost of the system improves by 13.78 percent. Considering the contribution of each energy hub and fairly cost allocation, the mechanism introduced in case II reduces the cost of hub1, hub2, and hub3

18.89, 10.23, and 8.72 percent, respectively. Moreover, the energy not supplied and interrupt times have improved significantly. A bi-level model considering demand response programs as well as storage systems and the ability to participate in the heat and gas market in addition to the electricity market will be investigated for networked energy hubs in our future works.

Acknowledgment:

The authors gratefully acknowledge the financial support of the Kopernikus-project "SynErgie" by the Federal Ministry of Education and Research BMBF and the project supervision by the project management organization Projektträger Jülich (PtJ) (Grant number 03SFK3G1).

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3.2. Research Paper 2 – *Optimal industrial flexibility scheduling based on generic data format*

Bahmani *et al. Energy Informatics* 2022, **5**(Suppl 1):26
https://doi.org/10.1186/s42162-022-00198-4

Energy Informatics

RESEARCH **Open Access**

Optimal industrial flexibility scheduling based on generic data format

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From The 11th DACH+ Conference on Energy Informatics 2022 Freiburg, Germany. 15-16 September 2022

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Abstract

The energy transition into a modern power system requires energy flexibility. Demand Response (DR) is one promising option for providing this flexibility. With the highest share of final energy consumption, the industry has the potential to offer DR and contribute to the energy transition by adjusting its energy demand. This paper proposes a mathematical optimization model that uses a generic data model for flexibility description. The optimization model supports industrial companies to select when (i.e., at which time), where (i.e., in which market), and how (i.e., the schedule) they should market their flexibility potential to optimize profit. We evaluate the optimization model under several synthetic use cases developed upon the learnings over several workshops and bilateral discussions with industrial partners from the paper and aluminum industry. 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. However, the optimization model computation time grows as the complexity of use cases grows.

Keywords: Industrial flexibility optimization, Mixed-integer linear programming, Generic flexibility description, Load dependency

Introduction

Traditional power systems are centralized since the electric flow is unidirectional, from bulk power plants to consumers. However, the transition into a modern power system enabled by Information and communication technology (ICT) and enacted policies to combat global warming increase Renewable Energy Sources (RES), distributed in many cases. These RES depend on weather conditions for their optimal operation and thus increase the challenge of sustaining power system stability. To meet this challenge, the energy system needs energy flexibility. Union of the Electricity Industry—EURELECTRIC aisbl (2014) defines the term flexibility as the *"[...] modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) to provide a service within the energy system"*. Energy flexibility provision thus can have many different sources. Whereas options such as the enhancement of transmission lines or the building of new electrical storages or power plants are cost-intensive to implement (Palensky and Dietrich 2011; Heffron et al. 2020) (i.e., high investment costs), the adjustment of electricity demand has the advantage that the energy flexibility providing assets already exist (Heffron et al. 2020). The so-called DR, as one part of Demand Side Management (DSM), describes short-term changes at the electricity consumption side (Palensky and Dietrich 2011).

In Germany, the industrial sector has the highest share of final electricity consumption at 41% (Energiebilanzen 2021). Thus, it offers a high potential to impact a change of demand using DR. However, the identification and application of industrial energy flexibility are challenging tasks. Industrial companies have complex and a variety of industrial processes where industrial energy flexibility is not a core business for most of them. Hence, most industrial companies use tailored decision support systems to help them determine their optimal adjustment of electricity demand in terms of time and characteristics that require customized scheduling models. Thus, these tailored solutions pose a threefold challenge. First, they might require a relatively high investment, especially hurdling small and medium-sized companies (Bauernhansl et al. 2019). Second, they tend to lack interoperability features, notably in using a single, specific model to describe their energy flexibilities (Bauernhansl et al. 2019). This specific model instantly creates vendor lock-in problems (unable to switch between service providers easily) (Potenciano Menci et al. 2021; van Stiphoudt et al. 2021). Third, tailored models and existing literature tend to be use-case-specific, resulting in case-dependent models (Helin et al. 2017; Zhou et al. 2017; Xu et al. 2020) and the consideration of single processes (Howard et al. 2021). Therefore, industrial companies find several barriers to realizing their energy flexibility potential. To address these challenges, there is a need for a holistic, interoperable, and generic use-case-independent model, which industrial companies can use to support their decision of where (i.e., which market) and when (i.e., which times) they can market their industrial energy flexibility.

We propose an optimization model for calculating an optimal adjustment of electricity demand for industries that is generic, holistic, and interoperable for a given horizon. We achieve generality by building upon a generic data model that describes energy flexibility, introduced by Schott et al. (2019). This generic data model allows us to decouple model generation (flexibility description) and optimization, letting industrial companies specify their level of detail in their model's description. In addition, it enables us to consider in the optimization model the inclusion of connected systems, including a wide range of storage types (e.g., energy, heat, compressed air, electric) and dependencies between different processes and/or machines. We consider the model holistic because it allows industrial companies to run the optimization for various scenarios considering different optimization horizons, energy markets, or flexibility descriptions to compare potential benefits. Thus, it can assist industrial companies in selecting where and when to market their flexibility using the optimal schedule. By using defined and generic inputs and outputs to describe flexibilities, the model becomes interoperable: Companies that describe their energy flexibilities with the data model introduced in Schott et al. (2019) can apply this optimization model. Furthermore, industrial companies could combine the optimization model we propose with other solutions which already use the same generic data model (Lindner et al. 2022; Bank 2021).

The paper is structured as follows. The "Related Work" section provides a brief overview of related work in energy flexibility optimization and scheduling. The "Model" section introduces the optimization and scheduling model formulation based on a mixed-integer linear programming approach. The "Use cases and results" section focuses on implementing the model under different use cases to evaluate its output. The "Discussion" section focuses on the discussion about the features of the proposed model based on the simulation results from the previous section. Finally, the "Conclusions" section summarizes the results but also acknowledges the limitations of the proposed model in addition to the research outlook.

Related work

Energy flexibility optimization focused on demand (household, industrial, etc.) or in combination with supply is a widely investigated topic within literature. In this context, DR applied to industrial energy flexibility refers to the deviation in the consumption patterns of an industrial consumer to take part in energy flexibility markets (any market trading power and capacity) (Fridgen et al. 2017; Commission et al. 2022; Shoreh et al. 2016). In this regard, a production plant can shift its production plan to make a monetary profit by taking part in current electricity markets (e.g., wholesale) and in new potential markets (e.g., local flexibility markets) with its energy flexibility (Bauernhansl et al. 2019).

Industrial companies mostly optimize their industrial processes focusing on efficiency regarding other production inputs than energy, which often prevents their industrial processes from being energy flexible. Additionally, industrial processes have different characteristics, limiting the availability of complete generic models (i.e., any model that can accept any process) (Schott et al. 2019).

One characteristic of industrial processes and their energy flexibility is the connection between industrial processes and/or machines (Shoreh et al. 2016). Each link creates a dependency. There is a need to consider these dependencies between processes and/or machines to create generic models for industrial energy flexibility. Nevertheless, for simplification purposes, many authors do not consider dependencies in their models and thus limit their models' general application. For instance, in Angizeh et al. (2019), authors propose an energy flexibility scheduling method for industrial consumers considering on-site generation. However, they do not consider the dependency between loads. Likewise, the models proposed in Shrouf et al. (2014) and Varelmann et al. (2022) focus on optimizing the production scheduling and participating in different markets considering a single industrial machine, respectively. Therefore, they contribute to considering aspects such as different power states, load shifting, and participating in different markets but do not consider the dependencies within the industrial process.

Other authors employ material flow models to tackle such dependency problems in their optimization. Material flow models are one possible way to model dependencies. For example, using a material flow model, authors in Mitra et al. (2012) investigate an optimal production planning method for energy-intensive industrial plants (e.g., air separation plant and cement plant). Similarly, authors in Wanapinit et al. (2021)

present a modular energy flexibility model for industrial end-users using a material flow model. Their model covers energy flexibility features such as ramp rates and time limits for energy flexibility activation. Authors in Ashok and Banerjee (2001) proposed a method to minimize the electricity costs considering the process, storage, and manufacturing constraints. In Ruohonen et al. (2011), the authors present a model for cost-effective scheduling of paper pulp mill. The authors in Ramin et al. (2018) investigate the DSM of industrial processes considering production constraints. Authors in Khatri et al. (2021) propose a coupled generic modeling library and optimal control to react and control based on fixed or variable price signals. Their generic modeling library enables industrial companies to model down to individual machines and how to control them. Their optimization provides a schedule allowing the control model to act accordingly. Similarly, authors in Castro et al. (2009) proposed a resource-task-network approach to schedule continuous production plants based on electricity price. Nevertheless, their optimizations in many cases using material flow models could hurdle the generality of their model. This is because material flow modeling needs a detailed description of each industry. Thus, it might result in case-specific models.

Further improvement of generic industrial energy flexibility modeling has to do with the inherent features of the industrial energy flexibility such as ramping of the machines, energy storage modeling, and limited run-time of the machines, which the authors in Moon and Park (2014) and Barth et al. (2018) considered in their proposed model.

Moreover, there are contributions in the optimization domain that employ heuristic approaches (Gong et al. 2019). Heuristics' ability to calculate fast solutions has increased their application mostly in large-scale problems (Küster et al. 2021). Although heuristics might be a fast solution, they cannot guarantee the global (optimal) solution and might result in a locally optimal solution.

Nevertheless, demand modeling requires data transfer regardless of the feature selection and optimization model. To enable the data transfer between various sectors and provide standardization, having a data model is highly important but imposes a challenge. For instance, authors in Huber (2018) briefly explored the necessary parameters to describe a flexible data model for DSM. More extensively, authors in Schott et al. (2019) propose a generic data model which can describe various energy flexibility aspects, improve the information exchange, and enhance energy flexibility automation. This generic data model enables cross-sectoral usage (i.e., residential and industrial), facilitating targeted cross-sectoral optimizations. They challenged their proposed data model against the feature-checklist developed by Barth et al. (2018) and were able to include all features in the proposed data model. Authors in Lindner et al. (2022) for instance, leverage the potential of the generic data model to propose a possible merging service that could combine various descriptions into one. Authors in Bank (2021) propose a conceptual step step-wise approach to integrating the generic data model for production planning.

In summary, many authors solve their optimizations in a simplified yet efficient and fast manner, considering specific use cases. Within these specific use cases, many authors select a limited number of relevant features for their models to solve their optimization problems and thus, develop tailored solutions. These specific use cases face a threefold problem (Bauernhansl et al. 2019). First, they limit the holism of their model due to their selection of relevant features for simplification and fast optimization solutions. Second, their models tend to lack interoperability across different demand types. Since their models usually only focus on one demand-type, it delimits the feature selection and optimization method. Third, they hurdle their model's replicability since it is a tailored solution across the same industry. This tailored model would require, in some cases, extensive modifications to adjust to other boundary conditions. Therefore, many demand models, even those focused on industrial demand flexibility, face holistic, interoperable, and replicable (transferable) limitations. According to Helin et al. (2017), such attributes are necessary for industrial flexibility modeling.

Model

The proposed optimization model (artifact) takes three different inputs and produces two different outputs, depicted in Fig. 1. The optimization uses a generic data model, the Energy Flexibility Data Model (EFDM) from van Stiphoudt et al. (2021); Schott et al. (2019). The EFDM is the core for describing (1) the flexibility potential and (2) the specific power profile the flexible loads have to follow, known as flexible load measure. Therefore, the EFDM offers companies an entire framework in JavaScript Object Notation (JSON) to work with flexibilities descriptions (Schott et al. 2019). We considered the guidelines proposed in Hevner et al. (2004) to design the optimization model. Moreover, we followed the iterative methodology for developing and evaluating the model proposed by Peffers et al. (2007). However, we only describe in this manuscript the final optimization model and not the multiple iterations needed for the model development. Hereafter, each subsection covers the inputs the optimization model uses, the mathematical description of the optimization model, and the optimization output. We coded the model in Python using the Gurobi solver (Gurobi Optimization 2022) and tested it on a computer with a Core i7 CPU @ 2.6 GHz processor and 32 GB RAM.

Inputs

Energy market prices

The first input to our optimization model is the energy market prices (i.e., electricity markets). Notably, the optimization can use the power exchange prices (i.e., European Power Exchange (EPEX)) from the spot market contained in the wholesale market as well as price forecasts expressed as time series. It supports data intake from the day-ahead and intraday (auction and continuous) since it allows for different time resolutions

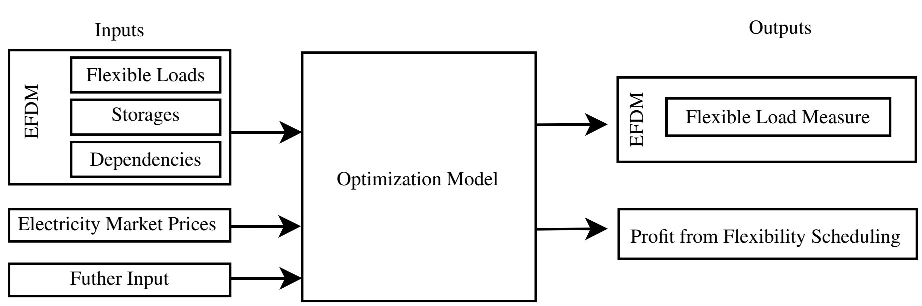


Fig. 1 Input and outputs of the optimization model

Table 1 Key figures of the EFDM as used by the optimization model

Key	Value (type)	Description
Validity	Integer ≥ 0	The interval where using the flexible load is allowed for flexibility purposes
Power states	Continuous ≥ 0	The deviation offlexible load from the normal operating point. The deviation ispositive in the load increase type,and it is negative in the loaddecrease type
Holding duration	Integer ≥ 0	The time length that flexible loads operate per usage
Usage numbers	Integer ≥ 0	The allowed number of usages in the optimization period
Modulation number	Integer ≥ 0	The number of permitted changes in the power state value per usage (without counting the power state change related to activation and deactivation)
Activation gradient	Continuous ≥ 0	The power change rate during the activation
Deactivation gradient	Continuous ≥ 0	The power change rate during the deactivation
Regeneration duration	Integer ≥ 0	The time limitation to activate a load after deactivation
Costs	Continuous ≥ 0	The cost of using flexible load, excluding the electric costs

Table 2 Storage key figures of the EFDM as used by the optimization model

Key	Value (type)	Description
Maximum capacity	Continuous ≥ 0	Maximum capacity of the storage
Initial energy content, including the timestamp	Continuous ≥ 0	Value of energy content stored at specified timestamp
Target energy content, including the timestamp	Continuous ≥ 0	Value of energy content that storage should reach at a specified timestamp
Energy loss	Continuous ≥ 0	Lost energy from storage because of exchange with the environment
Suppliers	String	Flexible loads that are filling the storage. Suppliers and stored value in the storages are linked using conversion efficiency
Drain	String	Loads that storage must serve in the specified time interval

(i.e., 15-min and 1-h values). The data input enables the analysis of price volatility in the electricity markets and the identification of the best possible marketing time, which may include times with negative prices.

EFDM: flexible loads, storages and dependencies

The second input of the optimization model is the flexibility description. Industrial companies can and are responsible to describe their flexibility using the EFDM developed in Schott et al. (2019) through its three main categories with any any level of detail they chose. These categories are the *flexible loads*, *storages*, and *dependencies*.

The *flexible load* category is the main flexibility description. It contains several key figures for the description, provided in Table 1.

Industrial companies might use a wide range of *storage* systems in their processes, such as heat, cold, compressed air, and electrical energy storage (EES). They can describe these *storages* using the *storage* category within the EFDM, utilizing several key figures, as described in Table 2.

Industrial companies can have complex processes. Their industrial processes involve machines that depend on one another. To capture industrial processes' complexity, industrial companies can describe these dependencies in the EFDM using the category *dependencies* between flexible loads. However, using the EFDM as inputs to describe the flexibility restricts the use of a material flow for our model. The EFDM can cover a dependency between two flexible loads. Dependencies internally in the EFDM have different types. This constitutes the necessity of activation/deactivation of one flexible load before/after another. There can be a dependency between the activation/deactivation time of *Load1* and *Load2*, as we depict in Fig. 2 in two examples. On the left, *Load1* imposes the activation of *Load2* after activation of *Load1*. It additionally provides lower and upper dependency boundaries. Using lower and upper boundaries and not one specific time for the dependencies can extend the flexibility options and result in more chances to capture all possible flexibilities. On the right, the deactivation of *Load1* requires the activation of *Load2* after and within the allowed boundaries.

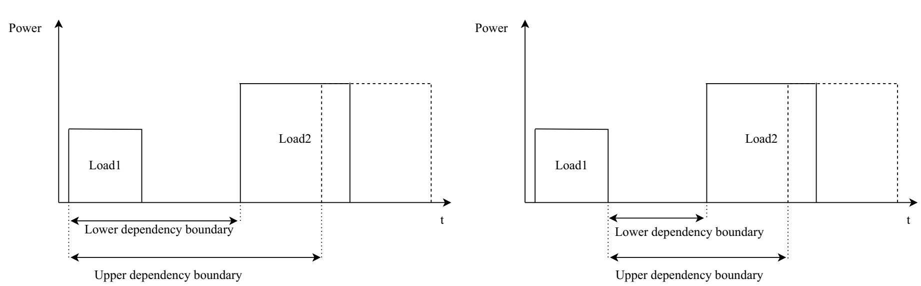
Further input

The third input to our optimization model includes additional information required for the optimization. The first additional input required is an optimization period. In addition to the validity time of the flexible loads passed with the EFDM, the optimization model requires an optimization period for which the optimization should perform the calculation. The second additional input is a selection of the electricity markets that the optimization model should consider. If no further input is selected, the optimization model considers all electricity markets for which electricity prices are available in the Electricity Market Prices input. The third additional input is the physical limitation of the grid connection point. The consideration restricts the power exchange to fulfill this grid constraint.

Mathematical model

Objective function

The core of the mathematical model is the objective function, which aims to maximize the profit by exploiting the market price differences and marketing industrial flexibility by either increasing or decreasing loads (i.e., modifying their power state). Equation (1) provides the objective function. L_{Neg}, L_{Pos}, L, and T are sets for load decrease flexibilities, load increase flexibilities, all the loads (union of L_{Neg} and L_{Pos}), and optimization horizon. The first term in the objective function (in the left) represents the profit obtained by decreasing the flexible loads. The second term (in the middle) represents the influence of increasing



(a) Dependency type start-start

(b) Dependency type end-start

Fig. 2 Dependencies between different loads the flexible loads. The third term (in the right) represents the costs associated with using the flexibilities (ac_l). In this objective function, $p_{l,t}$ is the variable expressing the magnitude of the power deviation, and $y_{l,t}$ is the binary variable which is equal to 1 in case flexible load l is activated at time t and is 0 otherwise. The parameters λ_t and ac_l express the electricity price at time t and the activation cost of flexible load l for flexibility purposes, respectively. Therefore, the objective function is as follows:

$$\max \left(\underbrace{\sum_{l \in L_{Neg}} \sum_{t \in T} p_{l,t} \lambda_t}_{load\ decrease\ profit} - \underbrace{\sum_{l \in L_{Pos}} \sum_{t \in T} p_{l,t} \lambda_t}_{load\ increase\ profit} - \underbrace{\sum_{l \in L} \sum_{t \in T} y_{l,t}\ ac_l}_{load\ activation\ cost} \right). \quad (1)$$

Power state constraints

The power state constraint forces the optimization to operate under a lower and an upper power deviation ($p_{l,t}$) is as follows:

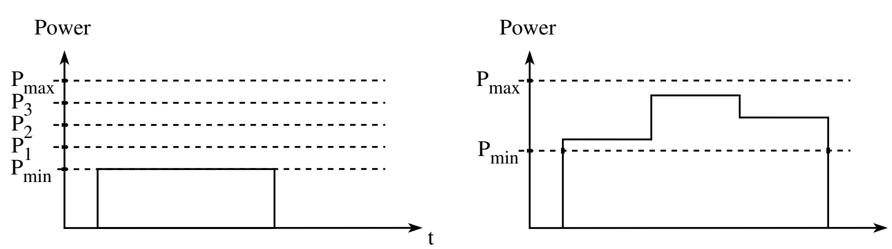
$$p_{l,min} I_{l,t} \le p_{l,t} \le p_{l,max} I_{l,t} \qquad \forall\, l \in L,\ t \in T \quad (2)$$

where $I_{l,t}$ is the current status binary variable of the flexible load l. In case the flexible load l is active at time t, the binary variable $I_{l,t}$ is 1 and $I_{l,t}$ is 0 otherwise.

Nevertheless, some flexible loads might require to only operate at specific power states. In such an event requiring discrete power states, Eqs. (3) and (4) are necessary. The term $states_l$ equals the number of permissible power states of load l between $p_{l,min}$ and $p_{l,max}$. $Int_{l,t}$ is the integer variable controlling the power state value in case the power state is discrete, and $p_{l,min}$ and $p_{l,max}$ are minimum and maximum power deviation of flexible load l. Figure 3a provides an example of one flexible load l with 5 possible power states. Therefore, we have:

$$p_{l,t} = p_{l,min} I_{l,t} + \frac{p_{l,max} - p_{l,min}}{states_l + 1}\, Int_{l,t} \qquad \forall\, l \in L,\ t \in T \quad (3)$$

$$0 \le Int_{l,t} \le (states_l + 1)\, I_{l,t} \qquad \forall\, l \in L,\ t \in T. \quad (4)$$



(a) Representation of 5 discrete power states of a flexible load.

(b) Case without discrete power states and restriction on modulation number.

Fig. 3 Representation of power states

Some flexible loads might only be able to operate in one unique power state. For these type of flexible loads, we propose two equations as follows:

$$p_{l,t} - p_{l,t-1} \leq p_{l,max}\, y_{l,t} \qquad \forall\, l \in L,\ t \in T \tag{5}$$

$$p_{l,t-1} - p_{l,t} \leq p_{l,max}\, s_{l,t} \qquad \forall\, l \in L,\ t \in T. \tag{6}$$

They impose only one value for the power state during the activation period and model loads with 0 modulation numbers—the number of changes of the power state value during the holding duration. In this regard, only one increase and one decrease in the power are allowed in the flexibility's start-up and shut-down time, resulting in only one power state during the flexibility activation. The binary variable $s_{l,t}$ is equal to 1 if flexible load l shuts down at time t, and it will be 0 otherwise.

For those flexibility loads, which can freely operate under any power state, for example, as Fig. 3b depicts, only require the constraint given by Eq. (2).

Activation and deactivation constraints

Another set of constraints we subject the optimization function to are the activation and deactivation of the flexibilities which additionally cover other aspects. For instance, Eq. (7) provides the holding duration constraint for a given load l between the step limits $IT_{min,l}$ to $IT_{max,l}$ as follows:

$$y_{l,t} \leq \sum_{h=IT_{min,l}}^{IT_{max,l}} s_{l,\ t+h} \qquad \forall\, l \in L,\ t \in T. \tag{7}$$

Moreover, each flexible load can have a regeneration time (DT_l) impeding the reactivation of the flexibility during that time, expressed as the following:

$$\sum_{h=t}^{t+DT_l-1} (1 - I_{l,h}) \geq DT_l s_{l,t}\ \ \forall\, l \in L,\ t \in T. \tag{8}$$

Furthermore, flexibilities might be constrained to a specific time for their activation representing its validity for operation as follows:

$$I_{l,t} \leq validity_{l,t} \forall\, l \in L,\ t \in T \tag{9}$$

where the $validity_{l,t}$ is a binary parameter equal to 1 if load l is allowed to be in active status and is 0 otherwise. We limit the number of usages a flexible load can have through Eq. (10). In it, $Usage_{l,min}$ and $Usage_{l,max}$ control the minimum and maximum number of times that flexible load l can be used during the optimization horizon respectively. Moreover, we impede the flexible load activation and deactivation at the same time using Eq. (11). Thus, these equations are:

$$Usage_{l,min} \leq \sum_{t \in T} y_{l,t} \leq Usage_{l,max} \forall\, l \in L \tag{10}$$

$$y_{l,t} + s_{l,t} \leq 1 \forall\, l \in L,\ t \in T. \tag{11}$$

The last constraint we consider for the activation and deactivation of flexible loads is to define the relationship between the binary variables and is as follows:

$$y_{l,t} \ - s_{l,t} \ = I_{l,t} - I_{l,t-1} \forall\, l \in L,\ t \in T \tag{12}$$

where $y_{l,t}$, $s_{l,t}$, and $I_{l,t}$ are binary variables used for starting time, ending time, and the status of the flexible load, respectively.

Storage model

We include storages into the optimization model using the following constraints. The first constraint is the energy storage balance given by Eq. (13). In this equation, ST is the set of the storages. It considers the stored energy in the storage at a given time t. Notably, $E_{e,t}$, $p_{e,t,ch}$, and $p_{e,t,dis}$ are variables for stored energy, charging rate, and discharging rate of the storage, respectively. $E_{e,loss}$ indicates the energy loss due to the energy exchange with the environment. Therefore, we have:

$$E_{e,t} = E_{e,t-1} + p_{e,t,ch} - p_{e,t,dis} - E_{e,loss} \qquad \forall\, e \in ST,\ t \in T. \tag{13}$$

Equation (14) represents the storage charging balance. In this equation, $p_{e,t,ch}$ represents the storage charging using the flexible loads connected to storage e, demonstrated as $l \in \gamma_e$. The loads connected to each storage charge them considering the conversion efficiency eff_l. Therefore, we have:

$$p_{e,t,ch} = \sum_{l \in \gamma_e} eff_l\, p_{l,t} \forall\, e \in ST,\ t \in T. \tag{14}$$

The third storage related constraint defines the drain times given by Eq. (15). In order to model the "drain", which is described in the EFDM, $p_{e,t,dis}$ should be equal to fixed parameter $p_{e,t,drain}$ at certain time slots. Moreover, the storage requires at certain times to charge up to the "target energy content" described in the EFDM. To do so, $E_{e,t}$ (energy content) should be equal to predefined values ($E_{e,t,target}$) at that certain time slots, as Eq. (16) collects. In Eqs. (15) and (16) the sets $T_{drain,e}$ and $T_{target,e}$ are the two constraints the optimization aims to satisfy. The former is the time to drain and the latter is the target energy content constraint. Therefore, these equations are:

$$p_{e,t,dis} = p_{e,t,drain} \forall\, e \in ST,\ \ t \in T_{drain,e} \tag{15}$$

$$E_{e,t} = E_{e,t,target} \forall\, e \in ST,\ \ t \in T_{target,e}\ . \tag{16}$$

Dependency

The inclusion of dependencies into the optimization model is not a trivial endeavour. Therefore we consider a set of five equations to introduce dependencies into the optimization model. These five equations (17), (18), (19), (20) (21) consider the effect of activating or deactivating one flexible load based on another flexible load creating based on the possible combinations of how they can interact. The following sets of load dependencies used in this model are:

- $D_{start-start-after}$: Activation of one load after activation of another.
- $D_{start-start-before}$: Activation of one load before activation of another.
- $D_{end-start-after}$: Activation of one load after deactivation of another.
- $D_{end-start-before}$: Activation of one load before deactivating another.
- $D_{exclusion}$: Restricts the activation of a load based on the activation of another load.

Pointedly, the first combination is as follows:

$$y_{l_i,t} \le \sum_{h=a}^{b} y_{l_j,t+h} \;\forall\, l_i \; and \; l_j \in D_{start-start-after} \;\; (i \neq j),\; t \in T \tag{17}$$

where it considers for the time steps from a to b that the optimization should activate the flexible load l_j after the activation of l_i. Differently, the second combination is Eq. (18). It is different from the previous equation as l_j must be now activated before the activation of the load l_i, formulated as follows:

$$y_{l_i,t} \le \sum_{h=a}^{b} y_{l_j,t-h} \;\forall\, l_i \; and \; l_j \in D_{start-start-before} \;\; (i \neq j),\; t \in T. \tag{18}$$

Another combination is to activate the load (l_j) after or before the deactivation of another load (l_i), represented as follows:

$$s_{l_i,t} \le \sum_{h=a}^{b} y_{l_j,t+h} \;\forall\, l_i \; and \; l_j \in D_{end-start-after} \;\; (i \neq j),\; t \in T \tag{19}$$

$$s_{l_i,t} \le \sum_{h=a}^{b} y_{l_j,t-h} \;\forall\, l_i \; and \; l_j \in D_{end-start-before} \;\; (i \neq j),\; t \in T. \tag{20}$$

The last combination for a dependency we consider is as follows:

$$\sum_{h=a}^{b} y_{l_j,t+h} \le (1 - y_{l_i,t})(b - a + 1) \;\; \forall\, l_i \; and \; l_j \in D_{exclusion} \;\; (i \neq j),\; t \in T \tag{21}$$

where a flexible load (l_i) prevents another flexible load's (l_j) activation. Thence, with these 5 equations creating a set of dependencies between two loads the model can consider interdependencies—two or more loads depend on each other and other loads—by creating a chain of loads which interdepend.

Grid constraint

The last constraint for our model can deal with the physical limitation of the grid connection point from industrial flexibilities. Therefore, we consider the physical grid constraint in the model through Eq. (22) to restrict the power exchange with the grid at the grid connection point. In the current version of the EFDM (Schott et al. 2019) the grid constraint is not included. Nevertheless, we consider this addition meaningful and propose to consider this adjustment in a future version of the EFDM. Thus, we have:

$$-P^{max}_{grid,t} \leq \sum_{l \,\in\, L_{Pos}} p_{l,t} - \sum_{l \,\in\, L_{Neg}} p_{l,t} \leq P^{max}_{grid,t} \forall\ t\ \in\ T. \quad (22)$$

Outputs

The optimization model with its objective function (Eq. 1) and the subjected constraints (Eqs. 2–22) calculates the optimal solution and provides two main outputs.

EFDM: flexible load measure

One output of the optimization model is describing a specific flexibility measure. In other words, it provides the optimal schedule for an industrial flexibility. A flexibility measure describes therefore no longer a flexibility potential. A flexibility measure contains a fixed load deviation (fixed power state for the intervals) with fixed periods (holding duration, modulation duration, activation/deactivation duration). The EFDM (Schott et al. 2019) enables in an standard manner to describe the flexibility measure using the so-called "flexible load measure" category, with its defined JSON Schema (van Stiphoudt et al. 2021).

Calculated profit

The second output of the optimization model is the maximized profit that industries could potentially achieve by marketing their flexibility load measures. For the calculation, the optimization in Eq. (1) considers the electricity prices passed as time series from the wholesale spot market (Day-Ahead, Intraday) or forecasted values in a specified validity time, Eq. (9), as well as the activation costs (ac_l) of a flexibility load measure. The calculated profit is the potential total amount given in Euros achievable by executing the calculated flexibility schedule. The optimization model calculates the profit per flexibility schedule.

Use cases and results

To demonstrate the capabilities of the proposed model, we investigate and evaluate the model under three different use cases. In the first use case, we evaluate the model using four simple, flexible loads in a simple context (i.e., without dependencies and storages). In the second use case, we evaluate the model using four flexible loads within an interdependent context (i.e., with dependencies and without storages). In the last use case, the complexity rises, and we evaluate the model using eight flexible loads in an interdependent and connected context, including storages (i.e., with dependencies and storages) to assess the full potential of the proposed model. However, our primary inputs, the EFDM is not a digital twin of a specific process. Still, we built them upon the learnings from several workshops and bilateral discussions with industrial partners from the paper and aluminum industry. We discussed several industrial processes they currently have, their structural features, the technical parameters, and the values they might include when describing their flexibility using the EFDM. However, our model contains synthetic data generated when describing the flexible loads since our industrial partners were unwilling to reveal actual production data and specific processes for publication.

Use case I—simple flexible loads

This first use case explores the capabilities of the optimization model when dealing with simple, flexible loads. We consider in this use case four different loads with neither dependencies among them nor a connection to a storage system. Therefore, the optimization model implements:

- Optimization function: given by Eq. (1).
- Main constraints: subject to Eqs. (2)–(12).

We collect in Table 3 an overview of the four flexible loads and their characteristics included in their EFDM description. The electricity prices considered, input for the optimization (24 h horizon), corresponds to the EPEX Day-ahead auction DE-LU on the 08/08/2020 (Bundesnetzagentur 2022).

All considered flexible loads have the same type, 'decrease.' In other words, the flexibility they offer is to decrease their power consumption. For example, load $L1$ can operate in between two power states (P_{max} and P_{min}). Three out of four loads do not face any restrictions concerning their validity (when the optimization cannot activate them). However, the optimization model can only activate load $L3$ between 18:00 and 24:00. Similarly, almost all loads have no activation costs, except $L4$, which in this case it costs 130 € every time it gets activated. Each load has a different holding duration. For instance, load $L2$ can remain activated for a minimum of 1 h and a maximum of 2 h. Only $L2$ needs a period of 3h between activations regarding their regeneration time. Finally, the optimization can decide not to activate any of the loads. Contrary, if the optimization uses the loads, it is restricted by the usage number. For instance, the optimization can use $L1$ up to three times or $L4$ one time.

We collect the optimization results in Fig. 4. In it, the flexible load $L1$ is a 'decrease' type; it should decrease its power consumption when the prices are high. Indeed, Fig. 4 corroborates this operation as $L1$ decreases its power between 01:00–04:00, 17:00–20:00, and 21:00–24:00, also within the limits of the validity time and the usage number to achieve a higher profit (reduction of power when the electricity price is high).

Similarly, the optimization activates flexible load $L2$ twice, in the beginning, between 01:00 and 03:00, and almost at the end, between 19:00 and 21:00. Although the activation between hours 18 and 24 could result in a higher profit (price is higher than hours 1–3), the 3-h regeneration time prevents it.

Table 3 Load's characteristics considered in use case I

key figure	Units	L1	L2	L3	L4
Load deviation type	–	Decrease	Decrease	Decrease	Decrease
Power state	MW	[0, 1]	[2, 2]	[3, 4]	[0.5,1.5]
Validity restriction	Time	None	None	18–24	None
Activation cost	€	0	0	0	130
Holding duration	h	[1, 3]	[1, 2]	[1, 1]	[2, 2]
Regeneration time	h	0	3	0	0
Usage Number	–	[0, 3]	[0, 2]	[0, 1]	[0, 1]

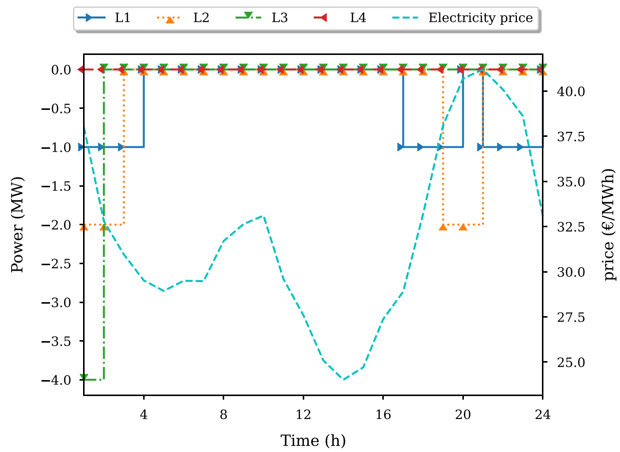


Fig. 4 Optimal scheduling for flexible loads in case I

The optimization reduces the power of flexible load $L3$ by 4 MW only once during the entire optimization horizon. It makes the maximum profit based on the electricity market prices and the validity of this load, restricting its usage between 18:00 and 24:00. This restriction prevents the optimization from decreasing the power consumption when the electricity prices are the highest (19:00–23:00).

Concerning the last flexible load, the optimization does not activate (reduce the power of) $L4$ since it has an activation cost, and it will decrease the total profit.

Finally, the model needed 0.180 s to converge in this use case to optimize these four flexible loads.

Use case II—flexible loads with dependencies

This second use case explores the capabilities of the optimization model when dealing more complex definition of flexible loads, as we consider dependencies between loads. In this use case, we consider a new four different loads without including a connection into a storage system. For this use case, the optimization model considers and implements the following:

- Optimization function: given by Eq. (1).
- Main constraints: subject to Eqs. (2)–(12).
- Dependencies constraints : subject to Eq. (17) for the $D_{start-start-after}$ dependency and Eq. (19) for the $D_{end-start-after}$ dependency.

Similar to the previous use case, we offer in Table 4 an overview of the four flexible loads and their characteristics included in their EFDM description. Additionally, we describe the dependency between loads in Table 5. As in the previous use case, we consider the same date, simulation horizon (24 h), and source for the electricity prices, the EPEX Day-ahead auction in the area of DE-LU on the 08/08/2020 (Bundesnetzagentur 2022).

In this second use case, there is a mix of load types. Three loads ($L2$, $L3$, $L4$) are decrease type, while $L1$ is increase type. In other words, the flexible load $L1$ can increase

Table 4 Load's characteristics considered in use case II

key figure	Units	L1	L2	L3	L4
Load deviation type	–	Increase	Decrease	Decrease	Decrease
Power state	MW	[0.5, 1]	[2, 2]	[3, 4]	[0.5, 1.5]
Validity restrictions	Time	None	None	None	None
Activation costs	€	0	0	0	0
Holding duration	h	[1, 3]	[1, 2]	[1, 1]	[2, 2]
Regeneration time	h	0	0	0	0
Usage Number	–	[0, 3]	[0, 2]	[0, 1]	[0, 2]

Table 5 Characteristics of dependencies in use case II

Trigger load	Dependent load	Dependency type
L2	L1	L1 must start 1–3 h after the activation of L2
L3	L4	L4 must start 2 h after deactivation of L3

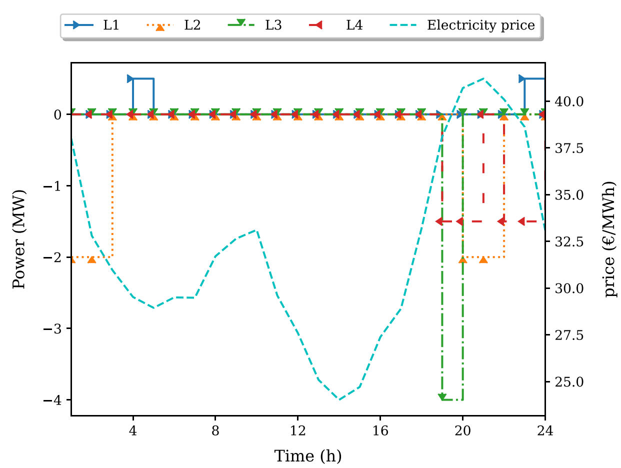


Fig. 5 Optimal scheduling for flexible loads in use case II

its power consumption contrary to the other loads. All loads in this use case have continuous power states, meaning they can only decrease or increase their power consumption by the values collected in Table 4. None of the loads have any activation costs or regeneration time. However, all loads face limitations imposed by the holding duration and the usage number. The former requires $L1$ to remain a minimum of one and a maximum of 3 h in each activation period. The latter limits the optimization to use a maximum of three times $L1$.

We collect the results of the optimization in Fig. 5.

The results provided by the optimization follow the imposed restrictions. On the one hand, the first dependency ($D_{start-start-after}$) in Table 5 forces $L1$ activation between 1 and 3 h after the activation of $L2$. In other case the optimization activates $L2$ between 01:00 and 03:00 while $L1$ between 05:00 and 06:00. However, the $L1$ and $L2$ dependency prevents $L1$ from increasing its power consumption during the lowest electricity price

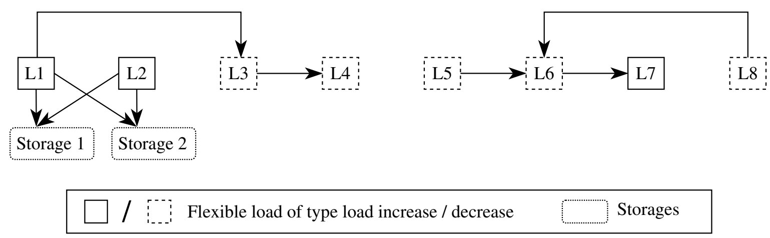


Fig. 6 Relationship between flexible loads and storages in use case III

Table 6 Characteristics of the loads' key figures of use case III based on the description of the EFDM

key figure	Units	L1	L2	L3	L4	L5	L6	L7	L8
Load deviation type	–	Increase	Increase	Decrease	Decrease	Decrease	Decrease	Increase	Decrease
Power state	MW	[1,2]	[2,2]	[1,2]	[0.5,1.5]	[2.2,2.7]	[1.8,3.2]	[1.2,2.2]	[1.3,1.7]
Validity restrictions	Time	None	None	None	None	None	None	None	None
Activation costs	€	0	0	0	0	0	0	0	0
Holding duration	h	[1,3]	[1,2]	[1,3]	[2,3]	[1,2]	[1,1]	[1,1]	[1,2]
Regeneration time	h	0	0	0	0	0	0	0	0
Usage Number	–	[0,5]	[0,4]	[0,2]	[0,3]	[0,1]	[0,2]	[0,2]	[0,3]

period (13:00–15:00). The optimization considers the same logic for the second activation of $L2$ at 20:00 given the constraint of $L2$; the optimization can only activate it twice. On the other hand, the second dependency forces the optimization to use $L4$ after 2 h of deactivating $L3$. The optimization activates $L3$ by decreasing 4 MW the power and decreasing, 2 h later, by 1.5 MW the power consumption of $L3$. However, since $L4$ can have two activations, the optimization between 19:00 and 21:00 decreases by 1.5 MW the power of $L4$. For this use case, the optimization model needed 0.112 s.

Use case III—flexible loads with dependencies and storages

This last use case explores an even more complex case than the previous ones. In this use case, the optimization faces eight flexible loads with several dependencies. Additionally, this use case includes two storages systems. We depict this complex relationship in Fig. 6.

For this complex use case, the optimization implements:

- Optimization function: given by Eq. (1).
- Main constraints: subject to Eqs. (2)–(12).
- Dependencies constraints: subject to Eq. (17) for the $D_{start-start-after}$ dependency and Eq. (19) for the $D_{end-start-after}$ dependency.
- Storage constraints: subject to Eqs. (13)–(16).

As previous use cases, we collect in Table 6 all flexible loads' characteristics contained in the EFDM description. Additionally, we collect in Table 7 the description of the dependencies constraints the loads have, whereas in Table 8 we collect the description of the two storages present in the use case. Both storages have 10 MWh capacity, modeled with 0 energy loss and specified drain time and quantity. Storage 1 should be drained between

Table 7 Characteristics of dependencies in use case III

Trigger load	Dependent load	Dependency type
L1	L3	L3 must start 2 h after the activation of L1
L3	L4	L4 must start 3 h after the deactivation of L3
L5	L6	L6 must start 3 h after the activation of L5
L6	L7	L7 must start 3 h after the activation of L6
L8	L6	L6 must start 3 h after the deactivation of L8

Table 8 Characteristics of storages in use case III

Storage	Max capacity [MWh]	Energy loss [MW/h] $E_{e,loss}$	Drain time [hour] $T_{drain,e}$	Drain quantity [MW] $p_{e,t,drain}$	Connected to
Storage 1	10	0	[19,21]	1	L1, L2
			[36,38]	1.2	
Storage 2	10	0	[15,17]	1.5	L1, L2
			[43,45]	1.1	

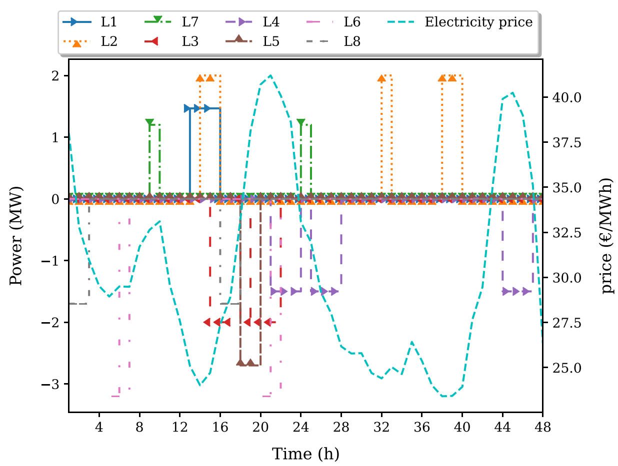


Fig. 7 Optimal scheduling for flexible loads in use case III

hours 19–21 and 36–38 with the power equal to 1 and 1.2 MW, respectively. Likewise, Storage 2 should be drained between hours 15 and 17 with 1.5 MW and during hours 43–45 with the amount of 1.1 MW. Both flexible loads, $L1$ and $L2$ connect to each storage system and have conversion efficiency (eff_l) equal to 1. Following the previous two use cases, the electricity prices input for the optimization considered corresponding to the EPEX Day-ahead auction DE-LU. In this case, the simulation horizon considers 48 h, therefore, the prices are for 08/08/2020, and 09/08/2020 (Bundesnetzagentur 2022).

We depict the optimization results in Figs. 7 and 8. The former presents the optimal load schedule for all loads. The latter presents the scheduling for the storage systems. The loads $L1$ and $L2$ must charge the storage systems to provide the energy demand required by the industrial process during the drain times. Therefore, it uses $L1$ and $L2$

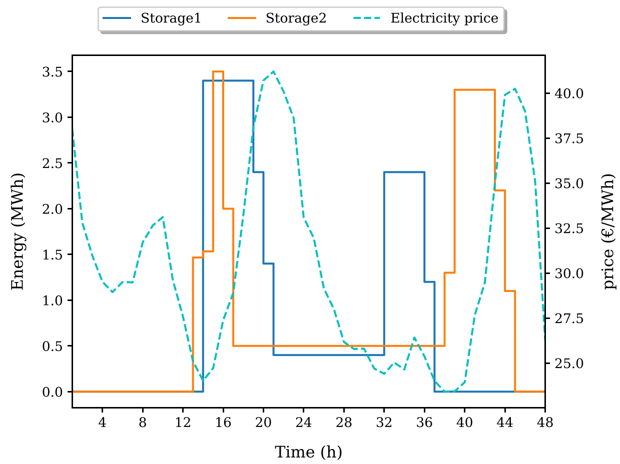


Fig. 8 Optimal scheduling for storages in use case III

several times during the optimization horizon (48 h) in the low-price hours accordingly between hours 12:00–26:00 and 32:00–40:00 (see Fig. 8). From our results (see Fig. 7), we can observe that optimization can deal with difficult constraints. For instance, $L1$, $L2$, and $L7$ increase their power consumption when prices are low without exciding the number of times the optimization can activate them. Nevertheless, these complex constraints provoke the activation of some flexible loads when the electricity price is not at its highest. For instance, the optimization activates $L6$ at hour 06:00, not the highest price hour, because it depends on $L8$.

Overall, all these complexities impact the optimization model, which requires a total of 3.3 s to converge.

Discussion

We tested the model in three synthetic use cases developed from discussions with aluminum and paper industries, where we exposed the optimization model against an increasing complexity in the industrial process description. We acknowledge the limitations of our evaluation, especially by not considering an existing industrial process due to the unavailability of data and not comparing our results to the benchmark of an exact process modeling.

Nevertheless, the model we propose performs as intended. We demonstrate the model's capability to offer a solution when facing complex EFDM descriptions. Examples of complex EFDM description are continuous power states, regeneration time, energy and material storage modeling, activation/deactivation ramping, different modulation numbers, holding durations, dependencies between flexible loads, and even connections to storage systems. The model's ability to handle EFDM descriptions has implications.

First, the optimization model does not require information on material flow nor information about the baseline power consumption of the industry, which industrial companies are not usually willing to share due to competitiveness. Thus, industrial companies can describe their processes without disclosing sensitive data and minimizing the necessary information. However, certain information still is required for the description using the EFDM, but not intrusive. On the one hand, the optimization using the EFDM might yield a worse result than the exact modeling of a specific industrial process. However, it might depend on the level of detail expressed in the flexibility description using the EFDM. On the other hand, the model is generic and serves its purpose for any industrial process described using the EFDM. Consequently, the model is replicable. In other words, different companies can use the model for their industrial processes and would require only one model instead of many multiple specific models for each industrial process.

Second, the optimization model can handle different time steps (e.g., 1 h and 15 min) and horizons such as day-ahead and intraday markets, opening a potential marketing opportunity for industrial companies. However, the model might face constraints (i.e., computation time and resources needed) when calculating the optimal solution with many loads, dependencies, and storage systems.

Third, even though this paper concentrated on testing the model for industrial flexibility, the applications of the proposed optimization model can go beyond the industrial sector. For instance, if electric vehicles and residential buildings use the EFDM to describe their flexibility, they could use the model.

Conclusions

We presented an optimization model to generate an optimal load schedule based on electricity prices and a generic data model for flexibility description, the EFDM. The model provides the schedule also using the EFDM description, simplifying the communication, technical, and economic issues specific use-case-oriented optimization models face. We evaluated the model under several use cases to demonstrate its capabilities when facing simple or complex industrial flexibility descriptions considering electricity prices from a day-ahead market. The model handled all the complexities, although the computation time and complexity grow as the optimization needs to consider more flexible loads and dependencies between loads and storage systems. Therefore, the model might face some limitations against a significant number of variables or when misused (i.e., used for whole industrial process scheduling). Future research could tackle some inefficiencies (computation time) and other limitations we acknowledge (comparison of the results with an exact optimization model). Nevertheless, the proposed optimization model could help industries market their flexibility. The model could enable any demand-user, such as residential or electric vehicle charging management operators, to use the generic optimization model if they describe their flexibility using the EFDM.

Acknowledgements

Supported by PayPal and the Luxembourg National Research Fund FNR (P17/IS/13342933/PayPal-FNR/Chair in DFS/Gilbert Fridgen).

About this supplement

This article has been published as part of Energy Informatics Volume 5 Supplement 1, 2022: Proceedings of the 11th DACH+ Conference on Energy Informatics. The full contents of the supplement are available online at https://energyinformatics.springeropen.com/articles/supplements/volume-5-supplement-1.

Author contributions

All authors contributed to the conception of the research. RB, MS and SPM contributed to the design of the work. RB, CvS and SPM drafted the first version of the paper. MS and GF supervised the research conception, provided feedback and participated in the paper revision. All authors read and approved the final manuscript.

Funding

Financial support from the Kopernikus-Project "SynErgie" by the Federal Ministry of Education and Research of Germany (BMBF) and the project supervision by the project management organization Projektträger Jülich (PtJ).

Availibility of data and materials
Not applicable.

Declarations

Competing interests
The authors declare that they have no competing interests.

Published: 7 September 2022

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Publisher's Note

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3.3. Research Paper 3 – *Energy flexibility scheduling optimization considering aggregated and non-aggregated industrial electrical loads*

Energy Proceedings
Vol 29, 2022
ISSN 2004-2965

Energy flexibility scheduling optimization considering aggregated and non-aggregated industrial electrical loads#

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ABSTRACT

In the modern energy sector, energy flexibility is highly essential. Participation in demand response programs is open to different power customers, with the greatest potential for some high-consumption industrial firms. This paper proposes a novel optimization model to maximize the profit obtained by marketing energy flexibility in a generic manner which is applicable for different industries. Two particular strengths of this model are its inclusion of dependencies between loads and load aggregation. We investigate the model's performance in two use cases: one with dependent loads and another with aggregated loads. Results demonstrate that the proposed model can achieve its objectives in different use cases, giving exceptional usage for industrial flexibility cases.

Keywords: industrial flexibility optimization, aggregated loads flexibility, generic flexibility data format

NONMENCLATURE

Indices and Sets	
F	Set for Load
M_f	Set for measures of load *f*
T	Set for time
f	Index for loads
m	Index for measures
t	Index for time
$D_{start-start-after}$/ $D_{start-start-before}$	Set for dependencies that one load should start after/before the start of another one
$D_{exclusion\_after}$/ $D_{exclusion\_before}$	Set for dependencies that one load should not start after/before the start of another one
Parameters	
$e_{f,m,i}$	Power for measure *m* of load *f* at step *i*
$\lvert e_{f,m} \rvert$	Time length of measure *m* of load *f*
DT_f	Regeneration time of load *f*
p_t	Electricity price at time *t*
c_f	Load activation constant cost
$validity_{f,t}$	Times that load *f* can start
$Usage_{f,min}$	Minimum permissible number of usages for load *f*
$Usage_{f,max}$	Maximum permissible number of usages for load *f*
Variables	
$x_{f,t}$	Load activation binary variable equal two 1 if load *f* is activated at *t* and 0 otherwise
$y_{f,m,t}$	Measure activation binary variable equal two 1 if measure *m* of load *f* is activated at *t* and 0 otherwise
Abbreviations	
EFDM	Energy Flexibility Data Model
inf	Infinity

1. INTRODUCTION

The rising electrification of the industrial sector impacts the electricity grid [1]. A common issue is grid congestion, which is solvable via network and infrastructure expansion. We can also mitigate congestion and other challenges by using energy flexibility on the demand side and active consumer engagement in balancing and wholesale markets [2]. Industries utilize a substantial quantity of energy in general and electricity in particular [3]. As a result, the industrial sector offers enormous potential for capturing existing energy flexibility and using it to solve such issues. Industries who desire to offer their energy flexibility face obstacles due to the complexity of energy markets. The difficulty results from the variety of options and substantial price fluctuation in markets. These hinder the evaluation of revenue potentials and the decision to invest in energy flexibility. Decision making tools are significantly important for tackling this issue [4].

This study proposes a novel optimization model that determines when and in what quantity industry can offer flexibility in electricity markets and maximize profit. The decision-making process for energy flexibility marketing can employ the optimization model. For the description of energy flexibilities and associated parameters, the optimization model employs a generic data model [5].

Compared to other optimization models in this domain, our model is novel in its allowance for dependencies between flexible loads. In many industries, there is a link between different machines which creates dependency between the operation of machines. Prior research, for example [6] and [7], often do not consider machine dependencies. Others, such as [8] and [9], use the material flow of an industrial process (e.g. in chemical plants) to create dependencies. However, this approach limits the model's generalizability. The proposed model in this paper directly takes machine dependencies into account and creates a generic model.

A second contribution of this model is the use of complex aggregated loads for flexibility. There are many opportunities for aggregators with industrial loads to combine different loads into complex aggregated loads and optimize flexibility [10]. The novel mathematical formulation here can optimize flexibility for both aggregated and non-aggregated loads.

2. OPTIMISATION MODEL

2.1 Inputs and Outputs

The optimization model requires two inputs. The first input is the electricity market price. The second input is information about the industrial company's prospective energy flexibility. We used the energy flexibility data model (EFDM) [5] to describe the energy flexibility. The EFDM defines three classes to describe energy flexibility potential: flexible loads, storages, and dependencies.

Following this data model's specification allows for a more generic modeling of energy flexibility. As indicated in Fig. 1, we consider flexible loads and dependencies as possible inputs of the EFDM in this paper.

The output of the optimization model consists also of two parts. The first output indicates the calculated schedule and the flexible load measures with their parameters, such as power deviation amount or activation time. The second output is the potential profit from offering and selling the energy flexibility based on the results of the optimization model and the calculated schedule.

Industrial companies can describe their flexibilities based on the EFDM [5]. The EFDM uses key figures (represented in *Table 1*) to describe key characteristics of loads. Moreover, it can describe the relationships between different loads using the dependency concept, which demonstrates the necessity of activation (or deactivation) of one load after (before) another load.

To use the inputs from the EFDM for the optimization model, we transform the inputs such that they can be used in the model. Key figures such as validity, usage number, and holding duration can be imported directly from the EFDM for the optimization. One of the important concepts in the optimization model is the measure. The measure describes specific characteristics that one load can have based on the key figures of the EFDM for that specific load. The next

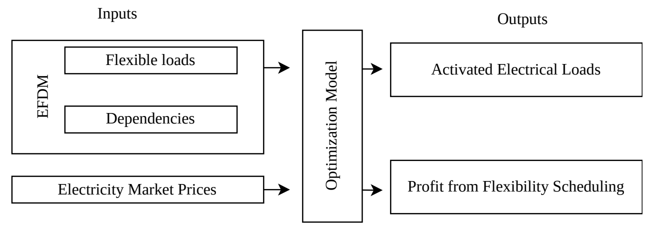

Fig. 1 - Inputs and outputs of the optimization model

Table 1 - Key figures of the EFDM used for optimization

Key figures	*Description*
Power state	Load deviations from normal operation point
Holding duration	The length of the operation for load per usage
Usage number	The total permissible number of usages for each load during optimization period
Validity	The interval that using flexible load is allowed for energy flexibility purposes
Activation gradient	The rate power changes during activation
Deactivation gradient	The rate power changes during deactivation
Regeneration duration	The time length that a load should not be activated after its deactivation
Costs	The cost of using flexible load, excluding the costs of electricity

Table 2 - Example for one load

Load	*Power state*	*Holding duration*	*Activation gradient*	*Deactivation gradient*
L1	*1 MW*	*[2,3] hours*	*inf*	*inf*

Table 3 - Possible measures of flexible load L1 prepared for optimization model

Measures of L1	$\lvert e_{f,m} \rvert$	$e_{f,m,i}$
Measure1	*2*	$e_{1,1,1} = 1,\ e_{1,1,2} = 1$
Measure2	*3*	$e_{1,2,1} = 1,\ e_{1,2,2} = 1,$ $e_{1,2,3} = 1$

example clarifies how to transform information in the EFDM for one load in a format that the optimization model can use.

Based on the information in Table 2, there are two options for *L1* to participate in the market. *L1* can be activated, and then remains active for 2 hours (measure 1) or 3 hours (measure 2), and then be deactivated as presented in Table 3.

2.2 Mathematical Model

The objective function of this paper is to maximize the profit gained by offering energy flexibility to the market:

$$max \sum_{f \in F} \sum_{m \in M_f} \sum_{t \in T} y_{f,m,t} \left(-c_f + \sum_{i=1}^{\lvert e_{f,m} \rvert} e_{f,m,i} * p_{t+i-1} \right). \quad (1)$$

In the objective function, the binary variable $y_{f,m,t}$ indicates if the optimization activates measure *m* of load *f* at time *t*. If so, we multiply this binary variable by the net profit gained by market participation. Equation (2) restricts the number of activations of each load. Equation (3) relates the activation time of each measure and each load. Each load can have several measures. Regarding equation (3), the optimization allows the activation of at most one measure of each load at each time. To restrict the periods that we can use each load for energy flexibility, we have proposed equation (4). Therefore, these equations are

$$Usage_{f,min} \leq \sum_{t \in T} x_{f,t} \leq Usage_{f,max} \quad \forall\ f \in F\ , \quad (2)$$

$$x_{f,t} = \sum_{m \in M_f} y_{f,m,t} \quad \forall\ f \in F\ , \forall\ t \in T\ , \quad (3)$$

and

$$x_{f,t} \leq validity_{f,t} \quad \forall\ f \in F\ , t \in T. \quad (4)$$

After activation of each measure, the optimization forces the deactivation of the flexible load before the end of optimization period (*T)* considering regeneration time (DT_f) and the length of that measure ($\lvert e_{f,m} \rvert$):

$$y_{f,m,t} \times \left(t + \lvert e_{f,m} \rvert + DT_f - 1 \right) \leq T \quad \forall\ f \in F\ , \forall\ m \in M_f\ , \forall\ t \in T\ . \quad (5)$$

After its deactivation and during the regeneration time, the optimization does not allow the activation of flexible load. Therefore, after the activation of one measure ($y_{f,m,t}$) of flexible load *f*, the optimization cannot activate that flexible load again until $\lvert e_{f,m} \rvert$ time steps and regeneration time DT_f have passed. As presented in equation (6), if measure *m* of load *f* activates at *t*, load *f* cannot start until this measure is deactivated after $\lvert e_{f,m} \rvert$ time steps and regeneration time (DT_f) of load f has passed:

$$\sum_{h=2}^{\lvert e_{f,m} \rvert + DT_f} x_{f,t+h-1} \leq \left(1 - y_{f,m,t}\right) \times (\lvert e_{f,m} \rvert + DT_f - 1) \quad \forall\ f \in F\ , \forall\ m \in M_f\ , \forall\ t \in T. \quad (6)$$

We consider dependencies between different loads using 4 equations. First, the activation of one load may force the activation of another load; we formulate this dependency in equations (7) and (8). Equation (7) describes that load *j* should start *a* to *b* time steps after the activation of load *i.* If load f_i is activated at *t*, $x_{f_i,t}$ will be equal to 1. Therefore, $x_{f_j,t}$ must be equal to 1 from *a* to *b* time steps after *t*. The same approach can describe equation (8), where the activation of load *i* necessitates the activation of load *j* in the previous time steps. These equations are

$$x_{f_i,t} \leq \sum_{h=a}^{b} x_{f_j,t+h} \quad \forall\ f_i \ and\ f_j \in D_{start-start-after} \quad (i \neq j), t\ \in T \quad (7)$$

and

$$x_{f_i,t} \leq \sum_{h=a}^{b} x_{f_j,t-h} \quad \forall\ f_i \ and\ f_j \in D_{start-start-before} \quad (i \neq j), t\ \in T\ . \quad (8)$$

Second, we formulate the exclusion of one load due to the activation of another load in equations (9) and (10). These equations formulate the exclusion of load *i* from *a* to *b* steps after or before the activation of load *j* , respectively. Here, if load f_i is activated at *t,* $x_{f_i,t}$ will be equal to 1, and all $x_{f_j,t}$ must be zero from *a* to *b* time steps after *t*. Likewise, equation (10) excludes one load before the activation of another. Thus, these equations are

$$\sum_{h=a}^{b} x_{f_j,t+h} \leq (1 - x_{f_i,t}) \times (b - a + 1) \quad \forall\ f_i \ and\ f_j \in D_{exclusion\_after} \quad (i \neq j), t\ \in T \quad (9)$$

and

$$\sum_{h=a}^{b} x_{f_j,t-h} \leq (1 - x_{f_i,t}) \times (b - a + 1) \ \forall\ f_i \ and\ f_j \in D_{exclusion\_before} \quad (i \neq j), t\ \in T\ . \quad (10)$$

3. *CASE STUDY AND RESULTS*

We demonstrate the capabilities of the proposed model in two cases. In the first case, we consider several flexible loads and dependencies. In the second case, we use aggregated loads and assess the model's ability to optimally schedule them. For all cases, we use synthetic data of flexible loads as input. For electricity prices, we use EPEX Day-ahead auction results from the market region Germany-Luxembourg.

The first case uses data from 1 day (07/10/2020) and the second case uses data from 1 week (05/10/2020 – 11/10/2020) [11]. We used Gurobi solver [11] with a Intel i7-9750H processor and 32 GB RAM for the simulations using the Python programming language. The simulation time was less than one second for all cases.

3.1 Case I

In Case I, we consider four different flexible loads with different characteristics such as holding duration, power state, activation/deactivation gradient, number of usages, validity period, and activation cost (Table 4). The load deviation type indicates if the flexible load will decrease (*load decrease* type) or increase (*load increase* type) during the energy flexibility provision. Moreover, the loads have dependencies between each other as presented in Table 5.

Fig. 2 illustrates the results of Case I. The first flexible load *L1* decreases its power consumption between 17:00-22:00. Although this period is not the highest price period, it gets activated because the model considers the validity restriction of *L1* which prevents its activation between 8:00-13:00 during the highest price period. Moreover, the optimization selects the 3-hours period as holding duration for *L1* to obtain the highest possible profit. The second flexible load of the *decrease* type reduces its power consumption three times, as per its maximum usage number. The optimization does not use *L2* during the period between 10:00-12:00. Rather, the optimization selects 11:00-13:00 for activating *L2* to satisfy a 1-hour regeneration period of *L2*. Due to the dependency between *L1* and *L3*, the optimization activates *L3* three hours after the activation of *L1* to satisfy the dependency between them.

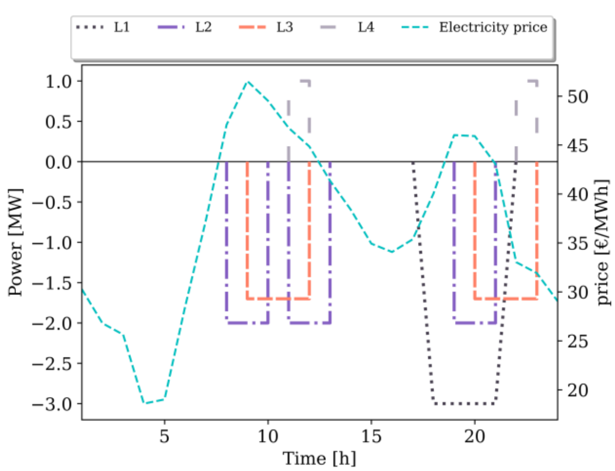

Fig. 2 - Results of Case I

Table 4 - Characteristics of flexible loads considered in Cases I

Key Figure	*Units*	*L1*	*L2*	*L3*	*L4*
Load deviation type	-	decrease	decrease	decrease	increase
Power state	MW	[3,3]	[2,2]	[1.7, 1.7]	[1,1]
Activation gradient	MW/h	3	inf	inf	inf
Deactivation-gradient	MW/h	3	inf	inf	inf
Validity restriction	time	1-12	-	-	-
Activation cost	Euro	0	0	0	0
Holding duration	h	[1,3]	[1,2]	[2,3]	[1,3]
Regeneration time	h	0	1	2	0
Usage Number	-	[0,1]	[0,3]	[0,2]	[0,2]

Table 5 - Dependencies between loads in Case I

Trigger load	*Dependent load*	*Dependency type*
L1	L3	L3 must start 3 hours after the activation of L1
L3	L4	L4 must start 1 to 2 hours after the activation of L3

L3 uses another activation during the peak price hours to gain more profit. Furthermore, the optimization activates *L4* of load type *increase* twice although increasing power reduces the profit while the electricity price is positive. The existing dependency between *L3* and *L4* necessitates the activation of *L4* 1-2 hours after *L3*. Thus, the optimization requires the consideration of high-price periods for *L3* and low-price periods of *L4*. Thus, *L4* is active 2 hours after *L3* to match low-price periods.

3.2 Case II

In this case, we evaluate the functionality of our model for aggregated loads. We assume here that *L1* and *L2* result from the aggregation of other flexible loads, and both are the load *decrease* type. The proposed model can use these aggregated loads for energy flexibility optimization purposes. *L1* and *L2* are aggregated flexibilities used as inputs to the model, as depicted in Fig. 3. The minimum usage number of both flexible loads is 0. The maximum usage number of the flexible loads *L1* and *L2* are 6 and 10, respectively.

Fig. 4 illustrates the results of Case II. The activation of both aggregated loads *L1* and *L2* are coinciding with the high price hours, in order to maximize the profit gained. In each activation of *L1*, aggregated load *L1* decreases by 1 MW. After one hour, it decreases by 2.5 MW and remains unchanged for 1 hour. Then it decreases by 2 MW for an hour and deactivates afterwards. The same logic explains the power changes for *L2* in each activation. The optimization activates *L1* and *L2* respectively 10 and 6 times, which are the highest possible usage numbers for these aggregated loads.

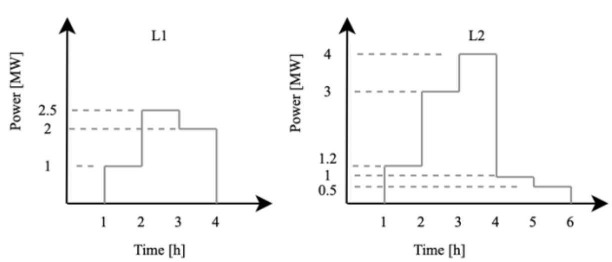

Fig. 3 - Aggregated flexibilities used as input for Case II

4. DISCUSSIONS

We tested our model for two different cases to demonstrate the capabilities of the model in calculating a schedule for energy flexibilities. The proposed model had the intended performance. The evaluations indicated the ability of the model to capture the potential flexibilities for simple and complex EFDMs. The proposed model can consider different power states for loads, regeneration time, activation/deactivation gradients, various holding durations, and between-load dependencies for both aggregated and non-aggregated electrical loads, which is neglected in other models. Using aggregated loads can reduce the computational burden significantly, since the number of binary variables in the problem decreases when using aggregated loads.

The concept of measure used here adds potential to this model. Since only one measure of each load is allowed for activation at each time, we can define various measures for aggregated loads, and the optimization will choose the most profitable one based on electricity prices. For instance, *L1* in Fig. 5 has three different measures (red, blue, and grey lines) and *L1* can follow only one of the measures in each activation period.

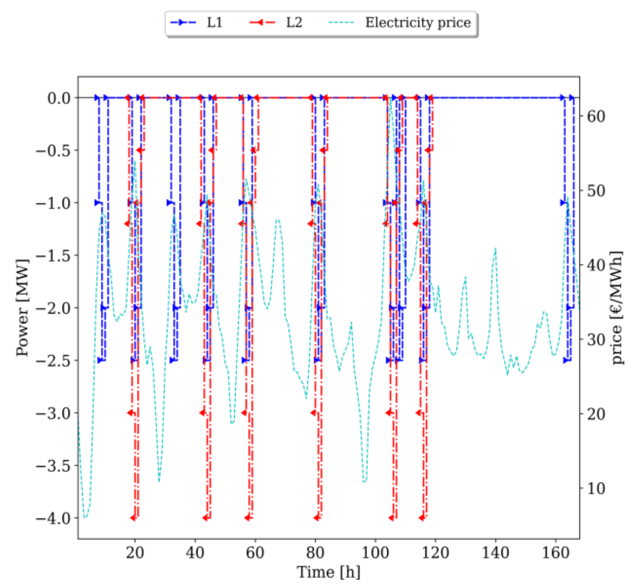

Fig. 4 - Results of Case II

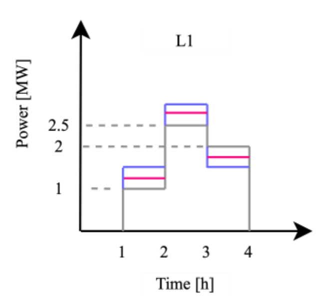

Fig. 5 - Different measures of aggregated load L1

The proposed model also does not require the information about baseline power consumption or material flow in industrial processes for the optimization. This is particularly valuable since some industries avoid sharing this information.

Although we proposed the model for the industrial sector in this paper, it is applicable for other energy sector users such as electric vehicles and residential buildings, due to the generic format of the required data as input.

This model and the evaluated cases have some limitations. We acknowledge especially that due to the unavailability of real data, our cases relied on synthetic data instead. Moreover, the calculation time of the problem increases as the optimization periods and number of loads increase.

5. CONCLUSIONS

In this study, we proposed an optimization model based on a generic data format to calculate the optimal energy flexibility scheduling for industrial loads. We evaluated the model in different simple and complex use cases including aggregated and non-aggregated loads, and results indicated the model's capability to handle different cases and maximize profit from energy flexibility provision. In future research, we will consider adding energy storage systems to the model for flexibility purposes. We will also consider using heuristic methods to reduce the calculation time.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the financial support of the Kopernikus-Project "SynErgie" by the Federal Ministry of Education and Research of Germany (BMBF) and the project supervision by the project management organization Projektträger Jülich (PtJ). Supported by the Luxembourg National Research Fund (FNR) and PayPal, PEARL grant reference P17/IS/13342933/PayPal-FNR/Chair in DFS/ Gilbert Fridgen.

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3.4. Research Paper 4 – *Impact of minimum energy requirement on electric vehicle charging costs on spot markets*

Impact of minimum energy requirement on electric vehicle charging costs on spot markets

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***Abstract*—Simultaneous charging of electric vehicles (EVs) increases the peak demand and might lead to higher electricity prices. This could increase EV charging costs and make EVs unattractive. Smart charging utilizes the flexibility provided by EVs and adapts charging behavior in response to the electricity market price signals. However, some studies indicate users' reluctance to participate in smart charging programs, as they perceive the risk of their vehicle not being charged sufficiently at required times. As a countermeasure, several researchers use the concept of minimum state of charge (SOC_{min}). It is the percentage of the battery up to which the EV is charged uncontrollably at full power right after it is connected to the charger. Depending on the users' SOC_{min} requirement, there might be an impact on EV flexibility and subsequently on EV charging costs. We developed a novel flexibility algorithm which quantifies EV flexibility in terms of both energy and power as a function of time. To calculate the EV charging costs, we developed a two-stage scenario-based stochastic optimization model. Optimization utilizes flexibility input and minimizes charging costs while participating in both day-ahead and intraday markets. We found that in most cases where EVs provide some flexibility, there was no significant increase in charging costs. However, we observed a 50% increase in costs when EVs do not provide flexibility. Therefore, EVs possess high flexibility potential. This flexibility can be provided almost without any loss of user comfort for high monetary gains.**

***Index Terms*—Electric vehicles, Flexibility, Electricity markets**

I. Introduction

During the last couple of years due to its environmentally positive effects, we have seen a rapid increase in electric vehicle (EV) penetration. This trend is expected to continue in the coming years [1]. However, the introduction of EVs brings new challenges to the existing power system. When EVs charge simultaneously, it could lead to an increase in peak power demand. This could subsequently lead to significant increase in wholesale market prices [2]. Furthermore, existing power grid capacities should be increased to prevent the grid from overloading and voltage issues [3]. All these factors would increase the costs of electricity procurement, which is reflected in the user's bill, making EVs unattractive.

This caveat could be addressed by using demand response (DR) programs [4]. DR refers to the alteration of user demand in response to signals coming from the power system. In that notion, the charging behavior of EVs can be used as flexibility service where charging adapts to the power system conditions and to the user mobility requirements. This is commonly termed as smart charging. The electricity prices are usually lower during the off-peak periods. Therefore, charging EVs at lower prices would simultaneously reduce the procurement costs of energy suppliers and reduce the peak demand.

Several studies have developed optimization models for smart charging of EVs with the objective to maximize the revenue of EV aggregator while participating in electricity markets [5], [6]. To consider uncertainties of electricity market prices and vehicle availability, [7]–[9] proposed two-stage stochastic optimization models with objective to maximize the revenue of EV aggregators. These studies optimally scheduled EV charging while considering price uncertainty in electricity markets and different travel patterns for EVs. However, all the above studies assumed that users would participate in smart charging programs and thus provide full flexibility throughout the charging session.

There are some studies that indicate users' reluctance to participate in smart charging programs [10], [11]. This is because users perceive certain risks in smart charging programs, including fear of losing control and not being charged sufficiently at the required times. As a countermeasure, several researchers and practitioners use the concept of SOC_{min} [12]–[14]. SOC_{min} is the percentage of the battery up to which the EV will be charged in an uncontrolled manner at full power right after it is connected to the charger. SOC_{min} plays a large role in the acceptance of smart charging and counteracting range anxiety [15]. [15] evaluated the charging costs incurred for smart charging with this additional user requirement, i.e. SOC_{min}, while participating in the German day-ahead electricity market. We extend their work by considering several cases with different possible SOC_{min} values and we evaluate EV flexibility for each of the cases. Additionally, we evaluate monetary value of EV flexibility when participating in both day-ahead and intraday markets. In our paper, we strive to answer the following research questions:

- RQ1: How does the SOC_{min} requirement impact the EVs flexibility potential?
- RQ2: What is the monetary value of EV flexibility depending on SOC_{min} when participating in wholesale electricity spot markets?

To answer RQ 1, we propose a novel flexibility algorithm to quantify flexibility. We quantify EV flexibility in terms of both energy and power as a function of time. This will tell us the amount of power that can be varied in each timestep whilst maintaining the required energy level to satisfy user requirements. To evaluate the flexibility algorithm, we use synthetic mobility dataset based on German mobility behavior. We then use this flexibility as an input to our optimization model to simulate EV charging.

To answer RQ 2, we developed a two-stage scenario-based stochastic optimization model with the objective to minimize the charging costs while participating in both day-ahead and intraday markets. To consider the uncertainty in the intraday market, we modelled different prices scenarios. We used German day-ahead and intraday electricity market data to evaluate our optimization model.

II. Mathematical framework

In this section, we present the mathematical formulation used for flexibility algorithm and optimization model used to optimize the EV charging behavior.

A. Flexibility algorithm

The flexibility provided by an EV varies for each charging session based on the user charging requirements. These requirements include $E^{arrival}$, the energy level of the EV battery at the time of arrival ($t^{arrival}$). $E^{departure}$, the energy that should be transferred to EV by the time of departure ($t^{departure}$). $E^{minimum}$, the energy that should be transferred to satisfy the SOC_{min} requirement. The maximum charging power of EV is $P^{EV,max}$. As we only consider unidirectional charging, we can only use $E^{departure}$ for flexibility provision.

We only consider the part of EV battery capacity which offers flexibility, $E^{departure}$, and model the flexibility metrics - energy and power metrics accordingly. The energy metrics are minimum energy level (E_t^{min}) and maximum energy level (E_t^{max}). The minimum energy level represents the minimum cumulative energy that must be transferred to the EV at time t to satisfy the user's energy requirements. As we assume a linear charging of the EV, we calculate E_t^{min} by using Equation (1), where charging power at time t is P_t. The charging process to determine E_t^{min} is divided into three phases within its plugin duration (Equation (2)). The first phase is between $t^{arrival}$ and time taken for the minimum energy transfer, which is t^{min}. The second phase is between t^{min} and $t^{critical}$, where $t^{critical}$ is the time after which the P_t should be maximum to satisfy the user's energy requirement. The third phase is the time between $t^{critical}$ and $t^{departure}$. Hence, the P_t in the first phase, second phase, and third phase are $P^{EV,max}$, 0, and $P^{EV,max}$ respectively.

$$E_t^{min} = E_{t-1}^{min} + P_t \times \Delta t \tag{1}$$

$$P_t = \begin{cases} P^{EV,max} & t^{arrival} < t \leq t^{min} \\ 0 & t^{min} < t \leq t^{critical} \\ P^{EV,max} & t^{critical} < t \leq t^{departure} \end{cases} \tag{2}$$

The maximum energy level (E_t^{max}) represents the maximum cumulative energy that can be transferred to the EV at time t. As we assume a linear charging of EV, the maximum energy level at time t , E_t^{max} is calculated by Equation (3). The charging process to determine E_t^{min} is divided into two phases (Equation (4)). The first phase is between $t^{arrival}$ and $t^{instant}$. $t^{instant}$ is the time it takes to transfer $E^{departure}$ when charged at full power. The second phase is between $t^{instant}$ and $t^{departure}$ where there is no energy transfer. Hence, the charging power in first phase and second phase is $P^{EV,max}$ and 0 respectively.

$$E_t^{max} = E_{t-1}^{max} + P_t \times \Delta t \tag{3}$$

$$P_t = \begin{cases} P^{EV,max} & t^{arrival} < t \leq t^{inst} \\ 0 & t^{inst} < t \leq t^{departure} \end{cases} \tag{4}$$

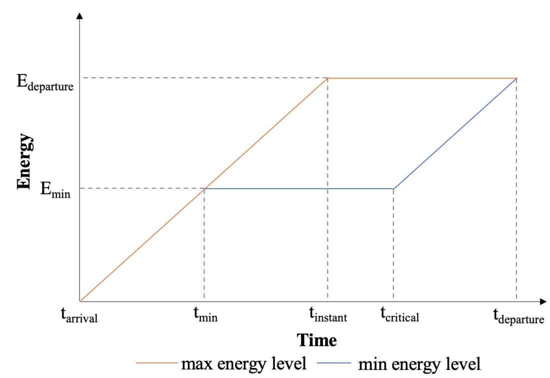

Fig. 1. Representing EV flexibility in energy vs. time graph.

The minimum and maximum energy levels can be represented in the energy vs. time graph as illustrated in Figure 1 above. From the Figure 1 it is quite evident that EV does not provide any flexibility until t^{min}. The power flexibility metrics are minimum power (P_t^{min}) and maximum power (P_t^{max}) at time t. The (P_t^{min}) when there is no flexibility, that is until t^{min}, is equal to $P^{EV,max}$. When EV offers flexibility, from t^{min} to $t^{departure}$, (P_t^{min}) is equal to 0. The maximum power (P_t^{max}) during the whole plugin duration is equal to $P^{EV,max}$.

The flexibility provided by an EV during its plugin duration is quantified by using energy (E_t^{min}, E_t^{max}) and power parameters (P_t^{min}, P_t^{max}). These parameters will convey the amount of power with which EV can be charged while maintaining upper and lower limits of cumulative energy transfer.

In our study, we calculate the individual flexibilities of each EV separately and then aggregate them (i.e, summation of the flexibility metrics of individual EV) to obtain the aggregated flexibility of all EVs. We represent the corresponding aggregated energy and power flexibility metrics as $E_t^{min,agg}$, $E_t^{max,agg}$ and $P_t^{min,agg}$, $P_t^{max,agg}$. Thus, it represents a virtual battery with minimum and maximum power and energy levels.

B. Optimization model

This section presents the mathematical model to minimze the energy provider's costs incurred for EV charging. We developed a two-stage scenario-based stochastic optimization model considering the price uncertainty of the intraday market. To consider intraday price uncertainty, we generate scenarios for intraday electricity prices first and employ them as optimization input afterwards.

We consider the uncertainty of intraday prices by utilizing probability density function (PDF) to create scenarios based on historical data and to model probabilistic nature of intraday market behavior. We employ normal PDF to generate scenarios for intraday prices as illustrated in Equation (5) below [16].

$$PDF(x) = \ 1/(\delta\sqrt{2\pi})\ exp(-(x-\mu)^2/(2\delta^2\ )). \quad (5)$$

using normal PDF, we generate different scenarios for intraday price. The value for each scenario and its corresponding probability are calculated using Equations (6) and (7) respectively:

$$\chi_{x,\ n_x} = \frac{1}{\rho_{x,\ n_x}} \times \left(\int_{x_{start,\ n_x}}^{x_{end,\ n_x}} x.PDF\,(x)\,dx \right), \quad n_x = 1, 2,\ \ldots,\ N_x \quad (6)$$

$$\rho_{x,\ n_x} = \int_{x_{start,\ n_x}}^{x_{end,\ n_x}} PDF\,(x)\,dx \quad , \qquad n_x = 1, 2,\ \ldots,\ N_x. \quad (7)$$

where $\chi_{x,\ n_x}$, $\rho_{x,\ n_x}$, and n_x are value, probability, and number of intervals for the scenario x,respectively. In this paper, we consider 7 intervals illustrating 7 scenarios for intraday prices of each time period.

The objective function in this paper is to minimize the costs of energy provider using our two-stage scenario-based stochastic optimization method. One prominent feature of two-stage stochastic optimization is the division of decisions in two stages. The energy provider takes some decisions in the first stage, and compensates any unfulfilled resource allocation in the second stage of the optimization. The objective function used in our paper is illustrated in Equation (8):

$$\sum_{t\in T} (P_t^{DA} \times c_t^{DA}\ )\Delta t + \sum_{w\in W}\sum_{t\in T} \rho_w \times (P_{t,w}^{RT} \times c_{t,w}^{RT}\ )\Delta t. \quad (8)$$

The objective function is divided into two parts. The first part is the total cost of energy provider in day-ahead market in the optimization period T, and the second part is expected cost of the energy provider in intraday market under various scenarios, W. The energy provider purchases the required power from the day-ahead market in the first stage, and compensates the rest of the required power based on the occurring scenario in the second stage. We use the generated scenarios from the previous section as input for the stochastic optimization. P_t^{DA} and c_t^{DA} are power purchased from the day-ahead and day-ahead price, respectively at time t. ρ_w is the probability of occurrence of each scenario w. Moreover, $P_{t,w}^{RT}$ and $c_{t,w}^{RT}$ are variable and parameter illustrating the purchased power from intraday market and intraday market prices at time t for scenario w.

In the scenario-based stochastic optimization used in this paper, P_t^{DA} is the same for all the scenarios. Therefore, the power balance between day-ahead and intraday is attained by using the Equation (9) below:

$$P_t^{DA} + P_{t,w}^{RT} = \quad P_{t,w}^{agg} \qquad \forall\ t \in T, w \in W. \quad (9)$$

$P_{t,w}^{agg}$ is the variable for aggregated charging power of EVs, which is restricted by the connected vehicles to the grid, illustrated in the Equation (10):

$$P_t^{min,agg} \ \le P_{t,w}^{agg} \ \le\ P_t^{max,agg} \quad \forall\ t \in T, w \in W. \quad (10)$$

$P_t^{min,agg}$ and $P_t^{max,agg}$ are inputs from the flexibility algorithm from previous section and are restricting the allowed charging power for EVs.

In this paper, we assume that all the EVs connected to the grid create a large virtual battery. This virtual battery can describe the characteristics of the connected vehicles while giving a proper understanding for mathematical modeling of EVs. By aggregating the effect of all connected EVs in $E_{t,w}^{agg}$ variable, Equation (11) can depict the virtual battery energy balance:

$$E_{t,w}^{agg} = E_{t-1,w}^{agg} + P_{t,w}^{agg} \times \Delta t - E_t^{cars,disconnected} \quad \forall\ t \in T, w \in W. \quad (11)$$

In this regard, $E_{t,w}^{agg}$ is the variable illustrating the energy capacity of virtual battery which is affected by $E_{t-1,w}^{agg}$, $P_{t,w}^{agg}$, and $E_t^{cars,disconnected}$ which are energy capacity of virtual battery in prior time step, aggregated charging power of EVs at current time step t for scenario w, and the energy capacity related to EVs which left their chargers at current time step t, respectively. $E_t^{cars,disconnected}$ resulted from the flexibility calculations and is the same for all scenarios. Moreover, $E_{t,w}^{agg}$ is restricted by the aggregated energy metrics of connected EVs as illustrated in the following Equation (12):

$$E_t^{min,agg} \le\ E_{t,w}^{agg} \le\ E_t^{max,agg} \quad \forall\ t \in T, w \in W \quad (12)$$

where $E_t^{min,agg}$ and $E_t^{max,agg}$ are minimum and maximum energy levels of connected EVs, respectively.

III. Testing and validation

A. Datasets

We use existing synthetic mobility data to derive the required inputs for calculating the EV flexibilities [17]. We consider mobility data of 1000 EVs with battery capacity of 75 kWh and max charging power of 7.4 kW. For the SOC_{min} values, we generate different cases where all the EV users chose a specific SOC_{min} value in each case. The cases are illustrated in Table I below. We analyze only the home charging case, with following assumptions 1. all vehicles will predominantly charge at home, and 2. all vehicles are always plugged in while parked at home. 3. all vehicles are charged until 100% SOC is reached or max SOC that can be reached within parking duration.

Please note that our model results hold, even if users decide to charge their battery only up to, e.g., 80% of their capacity to avoid battery degradation. In that case, 100% SOC would just correspond to 80% of the battery capacity. However, for reasons of simplicity, we will not make this distinction in the following.

TABLE I
EV CASES BASED ON SOC_{MIN} REQUIREMENT

Case	Description
0% SOC_{min}	All vehicles offer full flexibility
x% SOC_{min}	All vehicles have SOC minimum requirement of x%
100% SOC_{min}	All vehicles offer zero flexibility (uncontrolled charging)

We used German wholesale electricity market price data to calculate procurement costs. For day-ahead prices, we use historical data for January 2020 [18]. We generate scenarios individually for one day and compile intraday price scenarios for the whole month. In Figure 2, we illustrate the average electricity prices of German day-ahead and intraday market of a typical representative day of January.

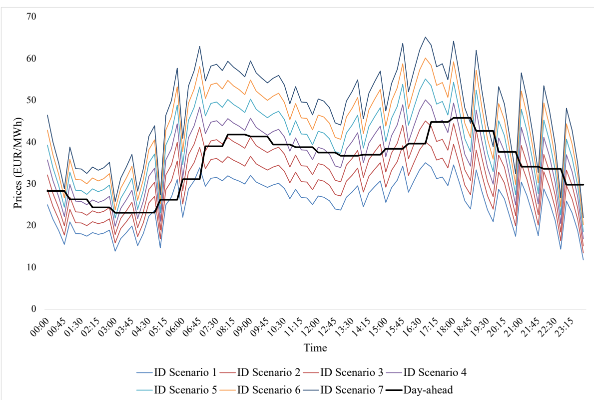

Fig. 2. Average day-ahead and intraday scnearios electricity prices.

B. Results

We calculate EV flexibilities for all the SOC_{min} cases for one month using the flexibility algorithm described in Section II-A. EV flexibilities are timeseries of energy ($E_t^{min,agg}$ and $E_t^{max,agg}$) and power ($P_t^{min,agg}$ and $P_t^{max,agg}$) flexibility metrics. Used timeseries data are for the range of one month and resolution of 15 minutes.

We model the EV as virtual battery, albeit only with the possibility of charging. Therefore, the energy metrics - $E_t^{min,agg}$ and $E_t^{max,agg}$, can be interpreted as minimum and maximum energy level of the virtual battery at time t. The power metrics - $P_t^{min,agg}$ and $P_t^{max,agg}$, can be interpreted as minimum and maximum charging capacity of the virtual battery.

Figure 3 illustrates the average power metrics for a typical day in month of January. As depicted in Figure 3, the maximum power curve for all the cases is the same. This is because maximum power is simply the sum of maximum charging power of all EVs connected to the charger. The value of $P_t^{max,agg}$ is maximum between midnight and 06:00, which is basically when the most EVs are connected to the charger. The $P_t^{min,agg}$ is zero when all EVs offer full flexibility at time t. Therefore, in the 0% SOC_{min} case the minimum power curve is always zero. In other SOC_{min} cases, EVs do not offer full flexibility until their SOC_{min} requirement is satisfied. Therefore, there are very few instances where $P_t^{min,agg}$ value is little over zero. This is because for most EVs, the $SOC_{arrival}$ is already greater than or equal to the SOC_{min} values. For EVs, whose $SOC_{arrival}$ value is already less than their SOC_{min} values; the power required to satisfy their SOC_{min} requirement is not significant. Therefore, the variation in minimum power curves for all SOC_{min} cases is not very significant.

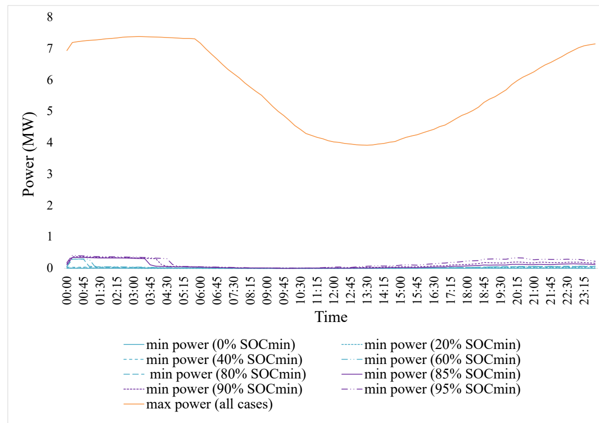

Fig. 3. Power metrics.

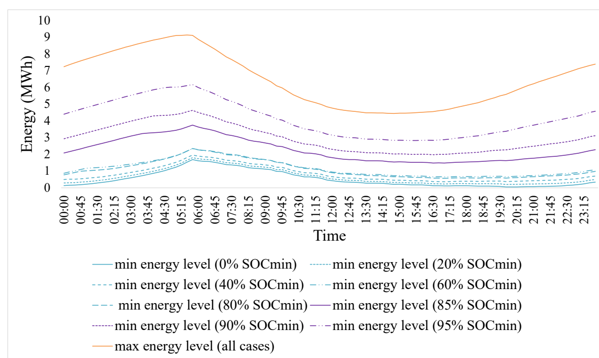

Fig. 4. Energy metrics.

Figure 4 illustrates the average energy metrics of a typical day in January. The maximum energy curve is the same for all cases as it just gives the sum of maximum allowable energy level of the EVs connected to the charger. The minimum energy level gives the cumulative energy that must be transferred at each time interval to satisfy the user requirements. Therefore, as the value of SOC_{min} increases, the value of the minimum energy level curve also increases. The difference between minimum and maximum energy gives the operational energy capacity of the virtual battery. As power metrics are almost similar for all cases, a higher operational energy capacity represents greater flexibility. Therefore, we can see a reduction in flexibility as the value of SOC_{min} increases.

We will illustrate how we optimally scheduled the electric vehicle charging using the modelled flexibilities. In Figures 5 and 6, we can observe the power procured from day-ahead and intraday market for EV charging on a random day (y axis scales are different in two figures, values in y-axis of Figure 5 are lower). The objective of energy provider is to minimize the overall costs. Therefore, the energy provider prefers to procure the power when the prices are low. Due to lower prices in the intraday market, most of the power is purchased from intraday market. In this regard, as illustrated in figure 6, most of the power for charging EVs is procured at 00:45, 04:00, 20:45, and 21:45, when the prices are lowest. Moreover, at times such as 02:00 and 04:00 some part of the required power can be provided from the day-ahead market, where the prices are lower in the day-ahead market.

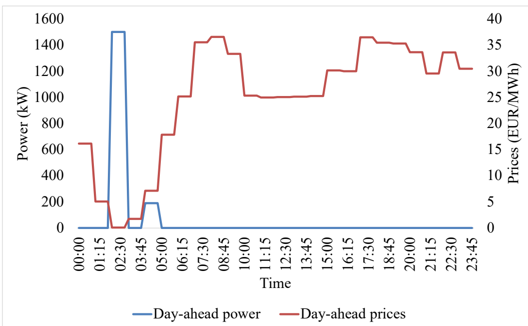

Fig. 5. Aggregated power procured for EV charging on a random day from day-ahead market

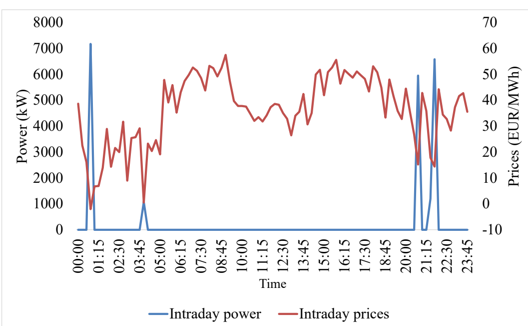

Fig. 6. Aggregated power procured for EV charging on a random day from intraday market

The total energy consumed to charge the EVs is 200 MWh for one month. From Figure 7, we can observe that the majority of the energy is procured from the intraday market for all SOC_{min} cases. However, as the flexibility decreases, the share of energy procured from the day-ahead market increases. It is evident that the intraday market prices are quite volatile as depicted in Figure 2. Prices can be extremely high or extremely low compared to the day-ahead market. As flexibility decreases, the probability of purchasing energy at lower prices decreases. This results in a slight increase in share of energy procured from the day-ahead market.

We illustrate the corresponding costs incurred to procure the required energy from the electricity markets for all SOC_{min} cases in Figure 8. We can observe that as the flexibility decreases, the costs increase. The charging costs until 80% SOC_{min} are almost similar. The charging costs starts to increase from 85% SOC_{min} case. However, the difference in

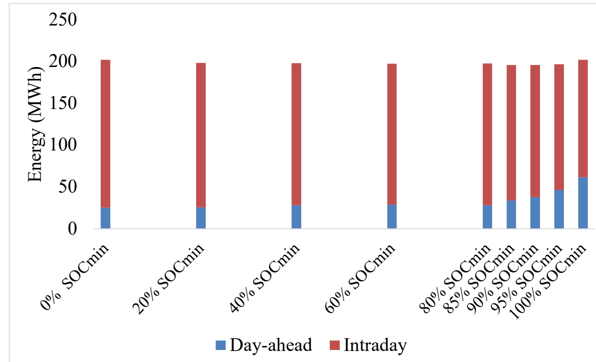

Fig. 7. Energy procured for EV charging

costs between the cases where the EVs offer flexibility and no flexibility is quite considerable. Costs increased by almost 50% for the 100% SOC_{min} case even when compared to the 95% SOC_{min} case.

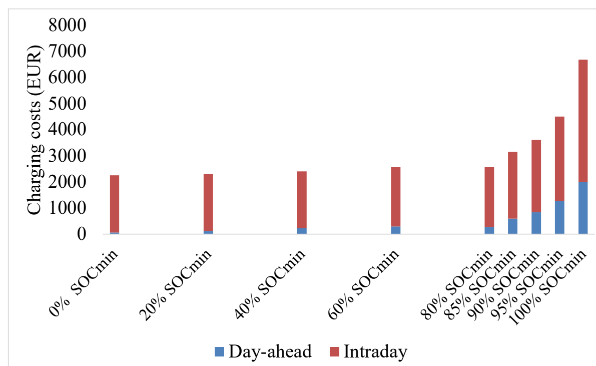

Fig. 8. EV charging costs

IV. Discussion

We found that as the SOC_{min} value increases, the flexibility decreases. However, the reduction in flexibility was considerable only for the cases where SOC_{min} value was greater than 80% compared to 0% SOC_{min} case. This is because for most EVs, the battery percentage rarely drops below 80% due to their mobility patterns, given available charging options. The same holds true for charging costs where the costs were almost similar until the 80% SOC_{min} case and increased only for the cases where the SOC_{min} was above 85%. However, even compared to the case of 95% SOC_{min}, the charging costs for the case where EVs do not offer flexibility were 50% higher. This further ascertains the importance of flexibility for the energy providers.

For EV users, it makes little difference whether their EV is charged instantaneously every day to a SOC_{min} of 80% or 100%. Even for an emergency at night (e.g., to the nearby hospital), a SOC_{min} of 80% would be sufficient for most. However, people are used to fill the tank of conventional cars immediately to their full capacity; thus, full charging of EVs is rather standard [19]. This standard needs to be changed as it is quite evident that it might not affect user comfort to a relevant amount.

There are some limitations in our paper that we would like to address in our future research. We assumed that all vehicles have the same specifications and undergo the linear charging process without efficiency losses. In reality, vehicle specifications will be different and the charging process is not linear. In principle, all EVs do not charge every day, but only a couple of times a week, depending on the user. We assumed that we know the user mobility patterns and corresponding requirements. However, these limitations will not have a major influence on the final outcome, i.e., high monetary value for the flexibility of EVs. In future research, we will consider more stochastic user scenarios and evaluate their impact on EV flexibility and charging costs.

V. Conclusion

In our paper, we evaluate the impact of the minimum SOC requirement on EV flexibility potential and charging costs. We developed a flexibility algorithm to quantify flexibility using energy and power metrics as a function of time. We then calculated the flexibility for each case and use it as input to the optimization model to simulate EV charging. To evaluate the monetary value of flexibility, we developed scenario-based stochastic optimization model with the objective of minimizing EV charging costs while participating in both the day-ahead and intraday markets. We modelled 7 different intraday prices scenarios to consider the uncertainty in the intraday market.

In summary, EVs possess high flexibility that can be provided without almost any loss of comfort (80% of the SOC is sufficient for almost all daily driving needs) for high monetary gains (160% reduction in charging costs). Therefore, it is vital that EV users provide this kind of flexibility. Energy providers could motivate users to provide flexibility by incentivizing them. These incentives can be financed by revenues generated from the flexibility of EV users.

Acknowledgment

The authors gratefully acknowledge the financial support of Fondation Enovos under the aegis of the Fondation de Luxembourg in the research project INDUCTIVE. Supported by PayPal and the Luxembourg National Research Fund FNR, Luxembourg (P17/IS/13342933/PayPal-FNR/Chair in DFS/Gilbert Fridgen).

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3.5. Research Paper 5 – *Robust Noisy PMU Data Recovery in Transient Conditions through Self-Attention Neural Networks*

Noisy PMU Data Recovery in Transient Conditions through Self-Attention Neural Networks

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***Abstract*—This paper utilizes the self-attention-based Imputation method to effectively manage missing data in Phasor Measurement Units (PMUs) during transient power system disturbances. By employing self-attention neural networks, this method adeptly processes multivariate noisy datasets. This method significantly enhances the accuracy and operational reliability of the grid performance during disturbances under three different missing data patterns and various missing data ratios. We conducted a comprehensive comparative analysis with other imputation methods using the IEEE 39-bus New England system. As inputs for the imputation, we employed voltage magnitudes and angles. Results demonstrate the superiority of this method in maintaining data integrity and ensuring system stability. In comparative testing, this method reduced Mean Absolute Error (MAE) by approximately 5% to 50% across different cases compared to the best result from other methods in most scenarios, although it underperformed slightly in highly sparse data conditions with a missing ratio of 0.9. The method demonstrated robustness through its high imputation accuracy and fast performance, confirming that it is well-suited for real-time applications in smart grid monitoring, thanks to its ability to process data in parallel.**

***Index Terms*—PMU, self-attention, data imputation, real-time monitoring, missing data, deep neural networks**

I. Introduction

Phasor measurement units (PMUs) are instrumental in modern power systems, providing high-resolution, time-synchronized measurements of electrical quantities like voltage and current phasors [1]. These devices enhance the operational integrity and situational awareness within power grids by capturing real-time data essential for system monitoring, control, and decision-making. However, PMUs frequently encounter data loss issues during critical transient events—such as faults or system disturbances—due to hardware malfunctions, communication failures, and synchronization errors.

Missing data in PMUs during transient power system events presents significant challenges for grid reliability and operational safety [2]. Transient events, such as faults or rapid load changes, require immediate and accurate data to ensure effective response strategies. However, PMUs can fail to capture critical data due to hardware malfunctions, GPS-time synchronization issues, and data transmission delays [3]. Such data losses degrade the performance of synchrophasor-based applications, especially those involving real-time feedback control, where even minimal latency can lead to erroneous decision-making and potentially severe consequences like blackouts or brownouts [4].

Data imputation in power systems has two main method classes; the first includes conventional state estimation (SE)-based approaches and the second is data-driven approaches [5]. SE methods heavily depend on accurate network parameters and topology, where errors in power network models can influence their effectiveness [6]. The second method utilizes data-driven techniques that do not require power system parameters for data imputation. Data-driven approaches primarily utilize matrix completion and conventional machine learning methods for imputation purposes. A significant limitation of these methods is their inability to handle high-order spatiotemporal data [7]. Other machine learning techniques like multiple imputation by chained equations (MICE) [8] are mostly employed for complex scenarios. The integration of singular value decomposition (SVD) [9] and matrix factorization methods address missing data by capturing underlying temporal and spatial dependencies in PMU data, crucial for maintaining grid stability.

Within the literature, different authors proposed various innovative data-driven approaches to address the challenge of missing PMU data correction in smart grids under noisy and complex conditions. Different methods such as convolutional neural networks (CNNs) [5], generative adversarial networks (GANs) [1], gated recurrent unit (GRU) [10], and Graph Convolutional Networks (GCNs) [2] are proposed to refine PMU data correction and noise filtration. However, they have several shortcomings. The application of GANs, while promising, might face challenges in practical noisy settings as it fails to explicitly model and mitigate inherent measurement noise during the correction process [11]. The GRU-based approach's exclusion of spatial correlation metrics can impede its ability to effectively utilize hidden spatiotemporal relationships, crucial for accurate PMU data recovery [12]. Lastly, the use of unweighted graph models in deep learning integration may restrict the full capture of intricate spatial correlations between network nodes, limiting the effectiveness of the data recovery and system state prediction processes [13].

The primary objective of this paper is to introduce an imputation method to address missing data in PMUs during transient power system events based on the self-attention (SA) mechanism, which is extensively utilized in other domains such as large language models (LLMs) and image generation [14]. This approach leverages the capabilities of SA models to process high-dimensional, noisy data swiftly and accurately, making it ideal for real-time applications in spatiotemporal multivariant datasets. SA mechanisms facilitate parallel computation, allowing for simultaneous processing of all elements in the input sequence, significantly enhancing speed and efficiency [15]. Our contributions include demonstrating superior speed and accuracy over existing methods on simulated PMU datasets, validating robustness in real-world noisy conditions, investigating the effectiveness under different missing data ratios and patterns, and ensuring easy integration with current power system infrastructures. Therefore, this approach enhances operational reliability and situational awareness in modern power grids.

The paper is structured as follows. Section II outlines the proposed approach. Section III explains the dataset, evaluation metrics, missing patterns, benchmark models, and results. Finally, section IV concludes the paper.

II. Methodology

Our approach consists of two key components: (1) a joint-optimization training strategy for imputation and reconstruction; (2) the SA-based imputation for time series model. In this paper, we detail the joint-optimization training approach. Additionally, the authors in [16] discussed the SA-based imputation model for the time series extensively. We employed a joint-optimization training strategy designed to effectively impute and reconstruct multivariate time series data with missing entries illustrated in Fig. 1. This methodology integrates two principal tasks: Masked Imputation Task (MIT) and Observed Reconstruction Task (ORT). These tasks leverage a SA mechanism, facilitating robust learning from datasets that contain incomplete observations.

We define a multivariate time series as a dataset X with T time steps and D dimensions formalized as $X = \{x_1, x_2, \dots, x_T\} \in \mathbb{R}^{T\times D}$, where each time step $x_t = \{x_t^1, x_t^2, \dots, x_t^D\} \in \mathbb{R}^{1\times D}$. Not all dimensions are fully observed, leading to potential missing values. Thus, x_t^d denotes the variable of the d-th dimension at the t-th step in X. The presence of data in each dimension at each time step is indicated by a missing mask vector M, defined as

$$M_t^d = \begin{cases} 1 & \text{if } x_t^d \text{ is observed,} \\ 0 & \text{if } x_t^d \text{ is missing.} \end{cases} \tag{1}$$

The MIT is designed to enable the model to predict missing values effectively. During training, a fraction of the observed values are randomly masked—simulating missing data. These artificially masked points are known only during training to guide the learning process. Following the artificial masking process, the modified input time series is represented as $\hat{X}$ accompanied by its corresponding missing mask vector $\hat{M}$. The vector $\hat{X}$ and missing mask vector $\hat{M}$ are then concatenated and used as imputation model input. The resulting time series, which includes both reconstructions and imputations, is represented as $\tilde{X}$. To differentiate between values that are artificially missing and those originally missing, we introduce an indicating mask vector I. The mathematical definitions for $\hat{M}$ and I are provided to clarify these distinctions illustrated in (2) and (3), respectively.

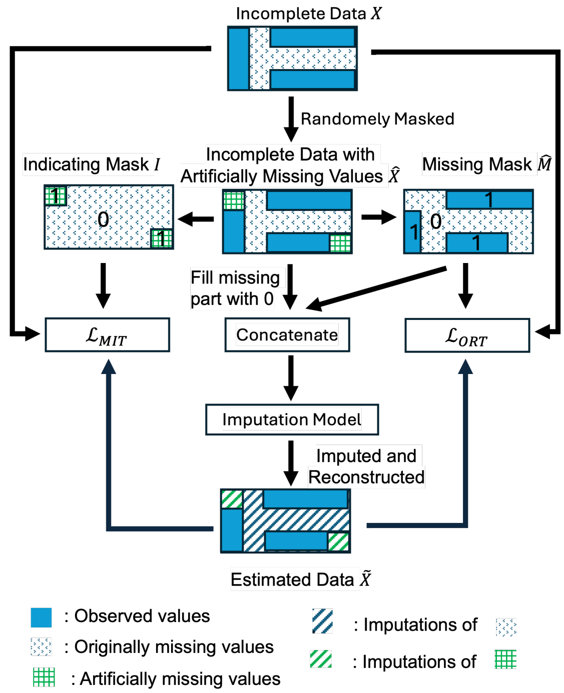

Fig. 1. Joint-optimization training approach.

$$\hat{M}_t^d = \begin{cases} 1 & \text{if } \hat{X}_t^d \text{ is observed,} \\ 0 & \text{if } \hat{X}_t^d \text{ is missing.} \end{cases} \tag{2}$$

$$I_t^d = \begin{cases} 1 & \text{if } \hat{X}_t^d \text{ is artificially masked,} \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

The imputation loss is quantified using the Mean Absolute Error (MAE) between the predicted and actual values:

$$\ell_{\text{MAE}}(\text{estimation}, \text{target}, \text{mask}) = \frac{1}{\sum_{d=1}^{D}\sum_{t=1}^{T} \text{mask}_t^d} \times \sum_{d=1}^{D}\sum_{t=1}^{T} \left(\left| \text{estimation}_t^d - \text{target}_t^d \right| \odot \text{mask}_t^d \right) \tag{4}$$

Where $\odot$ is the element-wise product. The MIT loss calculation is as follows:

$$\mathcal{L}_{\text{MIT}} = \ell_{\text{MAE}}(\tilde{X}, X, I). \tag{5}$$

The ORT focuses on reconstructing the observed components of the time series as accurately as possible. This task ensures that the model's output aligns closely with the actual observed data. The reconstruction error is calculated as:

$$\mathcal{L}_{\text{ORT}} = \ell_{\text{MAE}}(\tilde{X}, X, \hat{M}). \tag{6}$$

The training process involves minimizing a combined loss function that incorporates both MIT and ORT, ensuring comprehensive learning:

$$\mathcal{L} = \mathcal{L}_{\text{ORT}} + \lambda \mathcal{L}_{\text{MIT}} \tag{7}$$

Here, λ is a tuning parameter that balances the contributions of the imputation and reconstruction tasks to the total model training loss. We fixed it at 1. The model iteratively learns to impute missing values while refining its ability to reconstruct observed data accurately.

III. EXPERIMENTAL EVALUATIONS

In this section, we first describe the data generation process. Then, we explain the evaluation metrics used for validation. Next, we discuss the missing patterns used in this paper. Following this, we describe the benchmark models used for comparing the capabilities of the proposed method. Finally, we present the results, detailing the performance of our method in various scenarios. We executed the simulations on a high-performance computing environment that comprises two Intel Xeon Gold processors, each featuring 14 cores operating at 2.60 GHz. The system is further augmented by dual NVIDIA Tesla V100-SXM2 GPUs, each equipped with 32 GB of dedicated memory.

A. Dataset

In this paper, we evaluate the model using the New England 39-bus network, a benchmark also referred to as the IEEE 39-bus or the 10-machine New England power system, which is prevalently cited in dynamic systems literature. To address a variety of typical operating conditions and contingencies, we generated 4800 transient samples through time-domain simulations. We simulated three-phase faults at inter-area corridors using both Python and MATLAB, with a resollution of a 1/120-second sampling rate. Based on the methodology outlined in [17], 15 PMU locations were strategically selected. We incorporated the voltage and phase data from each PMU, crucial for the model's inputs, along with artificially introduced noise while maintaining a signal-to-noise ratio (SNR) of 40 dB. The fault initiation occurs at the first second into the simulation and extends randomly for a duration ranging from 0.1 to 0.3 seconds. We split data randomly into train, test, and validation sets in proportions of 70%, 15%, and 15% , respectively. This division ensures that the model is trained extensively, validated accurately, and tested comprehensively to evaluate its performance across various unseen scenarios.

B. Evaluation Metrics

For the evaluation of our imputation methods, we use three key metrics: Mean Absolute Error (MAE), , Mean Squared Error (MSE), and Root Mean Square Error (RMSE). These metrics are essential for assessing the accuracy of the imputation, providing a comprehensive view of performance across different scenarios.

The definitions and calculations for these metrics are as follows:

$$\begin{aligned}\text{MAE}(\text{estimation}, \text{target}, \text{mask}) &= \frac{1}{\sum_{d=1}^{D}\sum_{t=1}^{T}\text{mask}_t^d} \times \\ &\sum_{d=1}^{D}\sum_{t=1}^{T}\left(\left|\text{estimation}_t^d - \text{target}_t^d\right| \odot \text{mask}_t^d\right)\end{aligned} \tag{8}$$

$$\begin{aligned}\text{MSE}(\text{estimation}, \text{target}, \text{mask}) &= \frac{1}{\sum_{d=1}^{D}\sum_{t=1}^{T}\text{mask}_t^d} \times \\ &\sum_{d=1}^{D}\sum_{t=1}^{T}\left(\left(\text{estimation}_t^d - \text{target}_t^d\right) \odot \text{mask}_t^d\right)^2\end{aligned} \tag{9}$$

$$\begin{aligned}&\text{RMSE}(\text{estimation}, \text{target}, \text{mask}) = \\ &\sqrt{\text{MSE}(\text{estimation}, \text{target}, \text{mask})}\end{aligned} \tag{10}$$

These metrics compare the imputed values (estimation) against the true data values (target), factoring in the areas of missing data through the use of a mask (mask). The mask ensures that the evaluation focuses only on the imputed portions of the data, allowing for a fair assessment of imputation accuracy.

C. Modeling Missing Data Patterns

We investigate three distinct patterns of data loss to model real-world missing data scenarios in power grids, as illustrated in Fig. 2. Each pattern reflects different common issues that can occur in data capture:

- Pattern 1: Data loss occurs randomly across all buses and at all times, suggesting anomalies in data capture like sensor malfunctions or transmission disruptions.
- Pattern 2: Data points are missing for extended periods at randomly chosen buses, similar to power grid issues, often due to maintenance or equipment failures.
- Pattern 3: At random moments, data from all buses are absent, typically because of GPS signal failures or network congestion, affecting the entire data collection system simultaneously.

D. Benchmark Methods

Benchmarking different imputation methods is crucial in assessing their effectiveness and adaptability to various missing data patterns encountered in real-world datasets. By comparing a range of approaches, we can identify the most appropriate techniques based on the specific characteristics and challenges of the data, as follows:

- LOCF (Last Observation Carried Forward): This method quickly fills missing entries with the last available value, suitable for minimal change scenarios but potentially biased.
- MICE: MICE iteratively uses regression models to estimate multiple plausible values for each missing point, enhancing robustness in statistical analysis.

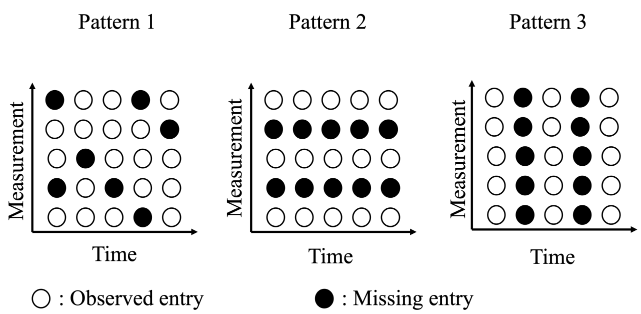

Fig. 2. Illustration of three missing data patterns used in the analysis.

- SoftImpute: This approach leverages soft thresholding of SVD to fill in missing data, optimizing for matrices presumed to be low-rank, ideal for structured sparse data.
- Iterative SVD: It employs truncated SVD in a repetitive manner to approximate missing entries, capturing underlying data structure well in nearly low-rank matrices.

Each method offers unique advantages depending on the data's characteristics and the nature of the missingness.

E. Results

In this section, we naluze the results to demonstrate the effectiveness of the SA-based method across various missing data scenarios within PMU datasets. Table I highlights the superior accuracy of the proposed method in imputing missing PMU data, where it consistently achieves the lowest MAE across all tested ratios. Notably, at a missing ratio of 0.1, this method records an MAE of 0.0171, significantly outperforming the next best method, SoftImpute, which shows an MAE of 0.058. This trend of dominance persists as the missing ratios increase, though the margin of superiority narrows at higher ratios.

Reflecting on accuracy in terms of average squared differences, the SA-based method's superiority is further evidenced by a MSE of 0.0022 at a 0.1 missing ratio, which is substantially lower than that of other methods. This suggests that this method not only provides more accurate predictions but also exhibits less variance in its predictions. Additionally, with a RMSE of 0.0467 at the same missing ratio, this method significantly outperforms competing methods, showcasing its effectiveness in minimizing the average squared differences between predicted and actual values. However, the superiority reduces by increasing the missing ratio rate.

Fig. 3 offers a visual demonstration of the SA-based method's accuracy by comparing the imputed voltage magnitudes to the actual values from PMUs during simulations with a 0.7 missing ratio for pattern 1. It clearly illustrates the close alignment between the imputed and actual values, indicating that the this method effectively captures the true dynamics of the system, even with significant data missing. This visual representation further highlights the precision of the proposed method in reconstructing accurate and reliable voltage profiles, crucial for maintaining grid stability.

TABLE I
EVALUATION OF IMPUTATION METHODS FOR PATTERN 1

Missing ratio	0.1	0.3	0.5	0.7	0.9
MAE					
LOCF	0.0969	0.1399	0.1849	0.275	0.5249
MICE	0.114	0.138	0.147	0.164	**0.2208**
SoftImpute	0.058	0.0717	0.0760	0.088	0.3856
Iterative SVD	0.1618	0.1703	0.1712	0.176	0.2255
Self-attention	**0.0171**	**0.0349**	**0.0428**	**0.0808**	0.2933
RMSE					
LOCF	0.3024	0.3861	0.4499	0.568	0.8589
MICE	0.273	0.289	0.3131	0.335	0.4383
SoftImpute	0.156	0.1627	0.1800	0.220	0.6459
Iterative SVD	0.313	0.313	0.3212	0.334	**0.4297**
Self-attention	**0.0467**	**0.0746**	**0.0931**	**0.2041**	0.5747
MSE					
LOCF	0.0914	0.1491	0.2024	0.323	0.7377
MICE	0.074	0.0835	0.0980	0.112	0.1921
SoftImpute	0.0244	0.0265	0.0324	0.048	0.4172
Iterative SVD	0.0985	0.0983	0.1031	0.111	**0.1846**
Self-attention	**0.0022**	**0.0056**	**0.0087**	**0.0416**	0.3303

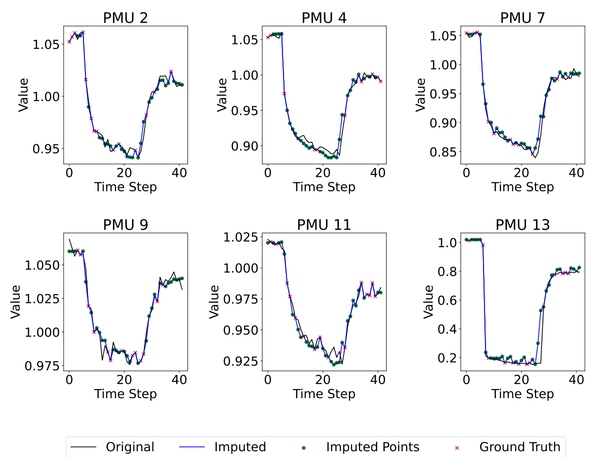

Fig. 3. Voltage magnitude of selected PMUs in 0.7 missing ratio and missing pattern 1 for SA method.

Fig. 4 provides a series of plots comparing the performance (MAE, RMSE, MSE) of different imputation methods across three different missing data patterns. The plots reveal that the SA-based method consistently results in lower error metrics across all patterns, emphasizing its robustness and adaptability to different types of data missingness. Moreover, different imputation methods exhibit varying performances based on the missing data pattern. For instance, while the error rates for MICE remain relatively stable across different missing ratios in Pattern 1, they increase as the missing rate rises in Pattern 2. This variation underscores the impact of missing ratio and patterns on the effectiveness of each method.

Table II emphasizes the computational efficiency of the SA-based method, crucial for real-time applications. This method processes data at a remarkably fast rate of 0.00001968 seconds per sample, faster than more traditional methods like MICE and SoftImpute, underscoring its suitability for high-speed data

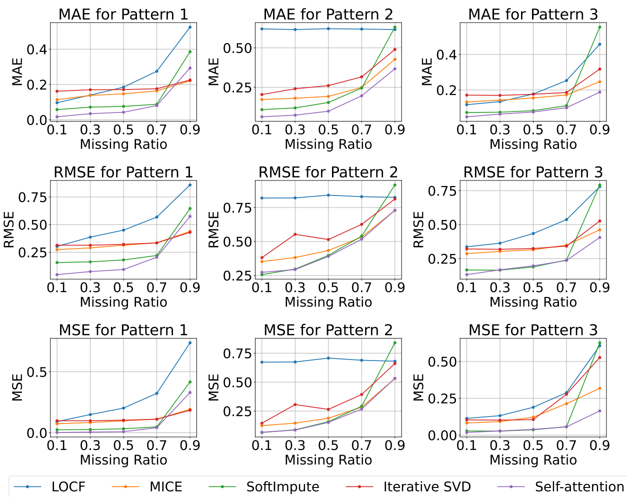

Fig. 4. Evaluation of method under various missing ratios and patterns.

TABLE II
IMPUTATION TIME PER SAMPLE

Method	SA	LOCF	MICE	Soft Impute	Iterative SVD
Time(s)	0.000019	0.000016	0.036360	0.0356	0.0085

processing in dynamic environments.

Overall, the SA-based Imputation Technique outperforms other methods in most cases across different patterns, according to the detailed performance metrics and comparisons shown in the figures. This robust performance, combined with swift computation times, significantly enhances the accuracy and efficiency of PMU data recovery, reinforcing its potential for integration into power grid operations to improve reliability and responsiveness.

IV. Conclusions

In this paper, we introduced a self-attention-based imputation technique that significantly enhances the accuracy of PMU data across different missing data patterns and rates during power system disturbances. Our comprehensive testing on the IEEE 39-bus system demonstrates the technique's superiority in handling various scenarios—ranging from sparse to dense missing data conditions—with consistently lower Mean Absolute Error rates. Particularly effective in noisy environments, our approach adeptly navigates the challenges posed by three distinct missing data patterns, showcasing its robustness and adaptability. This method's rapid processing and seamless integration with existing power system infrastructures mark it as a transformative solution for maintaining grid stability and operational reliability in modern power grids.

Acknowledgment

This research was funded in part by the Luxembourg National Research Fund (FNR) and PayPal, PEARL grant reference 13342933/Gilbert Fridgen. For the purpose of open access, and in fulfillment of the obligations arising from the grant agreement, the author has applied a Creative Commons Attribution 4.0 International (CC BY 4.0) license to any Author Accepted Manuscript version arising from this submission.

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3.6. Research Paper 6 – *Federated Learning for Energy Systems*

Federated Learning for Energy Systems

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Abstract: This chapter, Federated Learning for Energy Systems, addresses the role of emerging smart technologies in modern power systems, which have resulted in the generation of substantial data by stakeholders such as system operators, energy suppliers, and end-users. This data surge presents both opportunities and challenges, particularly in terms of privacy and data accessibility. Federated Learning (FL), an innovative approach in Artificial Intelligence, is highlighted as a key solution. FL enables the collaborative training of models across distributed datasets without sharing raw data, thereby addressing privacy concerns while complying with regulatory frameworks.

The chapter explores the fundamentals of Federated Learning, originally introduced to mitigate data silos and privacy issues associated with centralized machine learning architectures. It elaborates on the two main FL architectures—centralized and decentralized—highlighting the trade-offs between privacy, scalability, and reliability. Applications of FL within the energy sector are also discussed, including renewable generation forecasting, load prediction, and anomaly detection in smart grids. Each application demonstrates how FL can improve efficiency and security while enabling stakeholders to use data collaboratively.

Additionally, the chapter focuses on the application of FL for short-term load forecasting (STLF), which is crucial for operational efficiency in energy systems. By utilizing distributed smart meter data, FL enhances forecasting capabilities while addressing privacy concerns. Various neural network architectures, such as LSTM and transformer-based models, are also reviewed in the context of FL-based STLF, demonstrating improvements in accuracy and privacy preservation.

Moreover, the full text of this publication is accessible in the book titled *AI for Energy* by IEEE/Wiley.

Keywords: Applications, Energy System, Federated Learning, Load Forecasting