A framework for enabling manufacturing flexibility and optimizing industrial demand response services

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Abstract. The energy industry is experiencing significant changes in terms of sustainability and competition, primarily driven by the introduction of renewable energy targets and emission limits. Demand response is a potential solution to reduce the critical peak; however, its implementation in industries can be challenging due to their production requirements. Technology enablers such as digital twin technology can enhance energy flexibility and optimize manufacturing and service processes. In this study, we aim to develop a framework that can help the manufacturing industry to optimise industrial demand response services and achieve a seamless interaction of different layers such as the physical, data infrastructure, digital twin, management, and aggregator. A systematic literature review and workshops were conducted to identify key technologies, decision areas and methods to enable both manufacturing and energy flexibility to reach demand response. Based on the results, an energy-flexible framework for manufacturing industries was developed.

Keywords: Digital Twin, Energy flexibility, Manufacturing flexibility, Demand response

1 Introduction

The EU Green Deal sets the EU on the path to a green transition which aims to reach climate neutrality by 2050 [1]. Along with the shortage of natural resources [2], this exerts pressure on the manufacturing industries, particularly on the high energy intensity industries like glass and steel, to reduce carbon emissions. This is because most of them still heavily depend on fossil fuel-based energy sources. For example, the industrial sector in Germany consumes 44% of the total electricity [3]. Therefore, greener energy transition efforts are increasingly necessary to reduce negative environmental impacts [4].

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In energy demand response, customers dynamically change their electricity consumption behaviour in response to time-of-use electricity price signals or real-time dispatching instructions to reduce critical-peak demand [5]. However, this approach can be challenging for industries like steel production, as it requires to heat up and maintain production at a high temperature. At present, the research on demand response mainly focuses on the traditional demand response in power systems, while the research in the analytical technique and evaluation method is not comprehensive enough and fail to consider from an industrial perspective [5].

Digital twin (DT) can provide ideas for solving the above problem through forming a one-to-one mapping between the physical and virtual layers and then optimizing manufacturing and service processes [6, 7]. The increasing application of Internet of Things (IoT) utilized in the manufacturing sector which generated a massive amount of data [8], which are useful for product lifecycle monitoring and maintenance, which are crucial tasks in manufacturing, aim to detect production exceptions and ensure normal task execution [9]. These technologies can enhance energy and production flexibility, but the actual implementation in the industries still faces problems and barriers like data integration [10] and the lack of industrial knowledge. A common challenge with the existing framework is inability to provide better decision support for industries when it comes to energy management. Therefore, there is a need for a holistic framework which can not only improve the decision-making process but a to reach the long-term goals of energy efficiency.

In this work, we aim to develop a framework which considered various key requirements and enabling technologies which can help the manufacturing industry to better implement them into their systems. In order to develop a feasible and adequate framework, we combine both systematic literature review to obtain a clearer overview of the current state of the art of energy systems and workshops with industry experts to provide actual industry practice to make our framework more robust. The following research questions will guide this study:

1. What are the key enabling technologies, decision areas, and methods for implementing industrial demand response in a manufacturing environment?
2. How can industrial demand response be applied and optimized in a manufacturing environment?

The structure of this paper is as follows: Section 2 presents a theoretical background of industrial demand response. The research methodology for the systematic literature review (SLR), workshops, and case study is outlined in Section 3. The results of the SLR are presented in Section 4, followed by the introduction of a novel framework in Section 5. Section 6 discusses the results and limitations of industrial demand response and concludes the paper in Section 7.

2 Industrial demand response

Flexibility on the demand side is an important resource to address the flexibility gap in the power grid caused by the rise of variable renewable energy sources [11]. Demand-side flexibility involves strategies aimed at adjusting end-user electricity consumption, typically achieved through energy efficiency measures and demand response programs. [11]. Demand response is defined as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time or incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [13].

Demand response strategies are gaining attention in power system operations as they can reduce peak load, defer infrastructure costs, enable active participation of consumers in grid operations, and enhance the efficiency, reliability, and safety of the power system. [14, 15].

As the industrial sector holds a significant portion of the cost-effective demand response potential [16], industrial Demand Response stands out as a highly promising solution for unlocking the potential of demand-side flexibility [17]. Successful implementation examples have been documented across various industrial sectors. However, barriers such as regulations, information and technology infrastructure requirements, production disruption risks, limited knowledge, and social acceptance still hinder the adoption of demand response programs and strategies in industries [18–20].

Different resources are currently available to support the effective implementation of industrial demand response, such as tools for defining energy-aware scheduling and planning of manufacturing systems, as well as aggregators and the use of DT [21–26]. Flexibility market regulations are also evolving rapidly to facilitate demand response adoption. However, additional research is necessary to overcome the remaining challenges [18] and can provide valuable insights into the implementation and outcomes of various industrial demand response programs.

3 Methods

To develop a manufacturing and energy flexible framework for industrial demand response, a two-step research methodology is proposed. Firstly, a systematic literature review will be conducted to investigate the current state-of-the-art at the intersection of manufacturing, energy, and digitalization. This will assist in creating an initial version of the framework. Secondly, inputs from industrial experts will be gathered through workshops to refine the framework and make it more applicable to an industrial setting.

3.1 Systematic literature review

The goal of a systematic literature review is to facilitate theory development, align existing research, and discover areas where additional research is needed [27]. The systematic literature review was conducted using Scopus and Web of Science to provide wide coverage of published literature. The reporting of this review was guided by PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-analysis extension for Scoping Reviews) [28]. To identify relevant literature, the search was performed on “Title, abstract and keywords” with Terms listed in Table 1.

Table 1. Keywords used in the SLR

Manufacturing	Energy	Digitalization
Production	Aggregator	Digital twin
Manufacturing	Demand response	Cloud computing
Industry	Smart grid	Digitalization

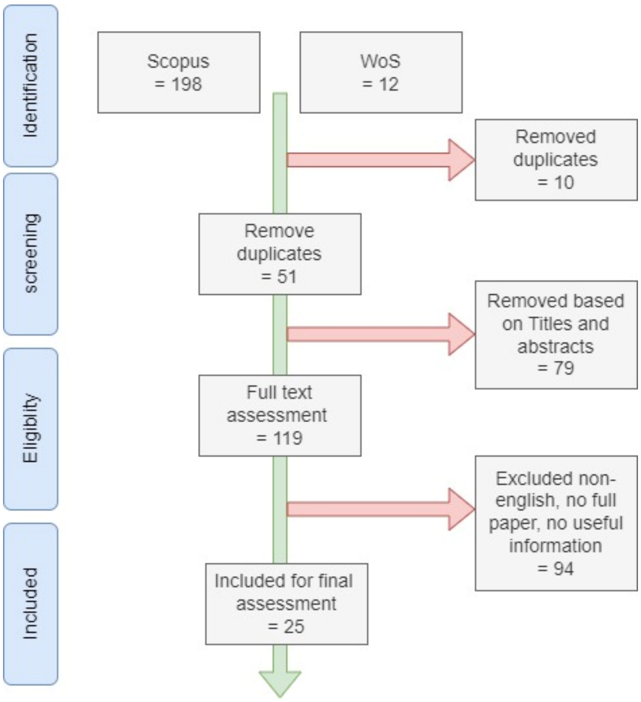

Fig. 1. Systematic literature review process flow.

In our search, we focused on peer-reviewed articles and conference proceedings to provide a wider overview of current digital tools used to achieve industrial demand response of energy systems. Only publications in English were considered. No-full paper and posters are excluded in our search. A total of 25 articles were included in the final review. The SLR process flow is summarized in Fig. 1 and the results are presented in section 4.

3.2 Workshops

To enhance the systematic literature review and address its limitations, several workshops were conducted. These workshops involved participants from both academia and industry, with diverse roles including researchers, consultants, IT experts, production leaders, and engineers. During the initial workshop, the results of the literature review were presented and discussed among the experts. Based on these discussions, the main layers and connections of the manufacturing and energy flexible framework for industrial demand response were determined. The participants were then divided into smaller focus groups to delve deeper into the main functions, activities, and decisions required at each layer. A total of five workshops, including one for the main structure and one for each layer, were conducted to develop an industrial-ready framework for demand response based on the literature review. The final framework is presented in section 5.

4 Literature review results

The following section presents an overview of key enabling technologies and applied decision areas that are utilized to enable and operate demand response. A summary of the collected papers is provided in Table 2.

Table 2. Summary of the collected papers

Author	Key enabling technology	Decision areas	Methods
[29]	WiMAX communication technology is the most preferred	Communication	ZigBee, Multi-criteria decision making
[30]	Highlighted operational data generated during the building life cycle are essential for realizing the energy-efficient operation	Data processing and information sharing	Data-driven deep learning, physical model-driven
[31]	Traditional equipment efficiency correction models only consider the historical load factors and variations in the environmental factors	Energy load prediction and visualization	Digital twin models, visualization models, polynomial regression, back propagation neural network
[32]	Framework using blockchain as an addition of a security layer	Cybersecurity	Copula model
[33]	Reinforced Learning algorithms select the optimum battery planning measures based on forecasts of wind power and photovoltaic availability.	Data visualization, forecasting	Multi-criteria decisions via an individual user
[34]	Deep learning layout that uses generative adversarial networks (GAN) to forecast the hourly power generation	Forecasting	Reinforced learning
[35]	Machine learning algorithms for forecasting, storage optimisation, energy management systems, power stability and quality, security, and energy transactions.	Optimising energy scheduling	Machine learning
[36]	Integrated digital twin and big data provides key technologies for data acquisition (such as sensor, Bluetooth, and WIFI for data communication) in energy-intensive production environments	Data processing and integration, prediction	Data mining algorithm, Big data analyses

[37]	The importance of the transformation from a traditional centralized energy system to a decentralized one using IoT, smart grid, blockchain, fog computing	Decentralized energy system	Decentralized decision making
[38]	AI has been applied for network provision, forecasting (weather and energy demand), routing, maintenance and security, and network quality management.	Forecasting	ANN, fuzzy logic, SVMS and genetic algorithms
[39]	Energy systems are no longer passive and uni-directional but active and bi-directional with end-users taking active roles in the operation and management of the energy system	Energy demand based on user behaviour	Distributed Energy optimization method
[40]	Developed a novel approach to identify critical branches to strengthen and shield the smart-grid power system threats	Cybersecurity	Markov Decision Process Model
[41]	Developed uncertainty modelling approaches for optimization problems under uncertainty for circumventing the impact of ambiguous parameters	Operation and technical uncertainties in the energy grid	Deterministic model
[42]	The architecture can be used to reproduce any functional plant with minimal cost and which is scalable	Communication	Cybersecurity testing, research, and education
[43]	Proposed a unified Hypervision scheme based on structured decision-making concepts, providing operators with proactive, collaborative, and effective decision support	Data management, security	Human-centered design approaches
[44]	Proposed an energy behaviour simulation in equipment digital twin model.	Energy demand management	Data-driven hybrid Petri-net, Gaussian kernel extreme learning machine
[45]	Highlighted digital technologies can make modern power systems more effective, reliable, secure, and cost-effective	Energy demand management	Markov model and clustering algorithms, SVM-based technique
[46]	Concluded AI-initiated learning processes by using digital twins as training environments can enhance buildings' adaptability	Energy demand management	Building-integrated AI, reinforcement learning
[47]	The proposed DT-based method can reduce the operating cost of IES by 63.5%, compared to the existing forecast-based scheduling methods.	Scheduling, forecasting	Deep neural network, multi-vector energy system
[48]	Investigated how blockchain and IoT together can improve existing smart grid	Energy management and load control	Energy load control

	ecosystem toward facilitation of better monitoring services.		
[49]	Presented new empirical evidence to validate data-driven twin technologies as novel ways of implementing consumer-oriented demand-side management	Energy demand management	DNN, ordinary differential equation, linear autoregression, Linear regression, Naïve model, predictive analytics model
[50]	Highlighted that government should invest in the development of AI	Energy demand management	Various AI models
[51]	Proposed the use of the Open Automated Demand Response standard protocol in combination with a Decentralized Permissioned Market Place based on Blockchain	Contracting and Services	Simulation modelling
[52]	Formulated a lumped model for forecasting the rate at which electricity is consumed with inadequate real-time energy data	Forecasting	Lumped model for forecasting
[53]	Propose an IoT-based privacy protection strategy via edge computing, data prediction strategy	Cybersecurity and prediction	Numerical simulations, edge computing system

From the collected papers, smart grid systems with communication technology have been highlighted as a key enabler for industrial demand response which can provide stable, efficient, scalable, and cleaner electrical energy system [29, 37, 48, 53, 54]. Abdulsalam et al., [29] concluded that iMax is the most suitable for advancing metering in smart grids, followed by Zigbee; while Power Line Communication is the least suitable. Smart grids can generate different types of data, from energy generation to consumption, and can move from silo systems to integrated networks for data analysis to improve operational efficiency [30]. Moreover, the DT depends on communication technologies to efficiently manage devices in the system [41].

With the adoption of different data communication tools, cybersecurity of the energy system must be considered to prevent any malicious activities such as hacking. Lei et al., [40] proposed a chain of defence concept using reinforcement learning framework to empower the system operator to incorporate existing cyber protections and strategy in a more dynamic, adaptive, and flexible ways to enhance cyber-resilience. Chen et al., [53] proposed a privacy protection strategy via edge computing, data prediction strategy, and pre-processing to overcome the drawbacks of the current cloud computing system. Blockchain can also be adopted in the energy system as an additional security layer. The data-storage structure of blockchain enables energy tracing and prevents data tampering [32, 55]. This is because any form of data tampering can alter the data analysis for forecasting.

Forecasting and predicting are the main decision areas in the demand response to improve energy efficiency by flattening the daily energy demand level [56]. By constructing digital twins of an integrated energy system, the manufacturing industry can benefit from its capabilities to improve coordination among various energy converters, hence enhancing energy efficiency, cost savings and carbon emission reduction [47]. For example, Ye et al., [31] demonstrate that digital twin forecasts of the renewal energy and load of both wind and solar energy were closely matched to the actual values. [47] trained a deep neural network to make statistical cost-saving scheduling by historical forecasting errors and day-ahead forecasts, and the proposed methods can reduce operating costs by 65%.

Forecasting the demand for energy usage is critical for better energy management where the industry can better coordinate with the production schedule [35]. In our search, most of the collected work only focuses on the energy perspective. Tomat et al., [57] highlighted that user behaviour can have a critical impact on demand response effectiveness. Lee and Yim [58] concluded that having a clear understanding of on-demand behaviour can enable an efficient operation of energy supply. Similarly, for the manufacturing sector, a better integration of production scheduling and planning management with energy management is important to enable optimizing industrial demand response services. For example, steel production requires a high amount of energy, often fossil fuel to bring the heat up to and must continue even though the cost of energy has gone up during operation.

From the literature review, the published frameworks identified mainly focus on the interaction between the smart grid and aggregator layers or have a strong energy demand management focus in industrial cases. However, a holistic integration of the methods and technology integration is still missing [38] .

5 Framework for industrial demand response services

To enable demand response services, consistent and seamless interaction between the physical, data infrastructure, DT, management, and aggregator layers is essential. Through the use of an SLR and workshops with experts, the crucial activities and communication structure required for industrial demand response services have been identified and integrated into a framework.

Throughout the workshops with experts from the aggregator, energy, digitalization, and manufacturing sides, all agreed that the current frameworks in literature lack providing a comprehensive framework that allows for implementation in industrial companies and for layers to be connected and communicated from the physical to the aggregator layer. The SLR results (section 4) emphasize the importance of smart grid systems in enabling industrial demand response, which can help create a stable, efficient, scalable, and cleaner electrical energy system. As a result, this framework focuses specifically on the key activities relevant to aggregators and industrial manufacturing companies. Both the literature and expert group have recognized the general DT framework as suitable for representing the entire communication line with critical activities for industrial demand response services. This framework is visualized in Fig. 2 and described in the following.

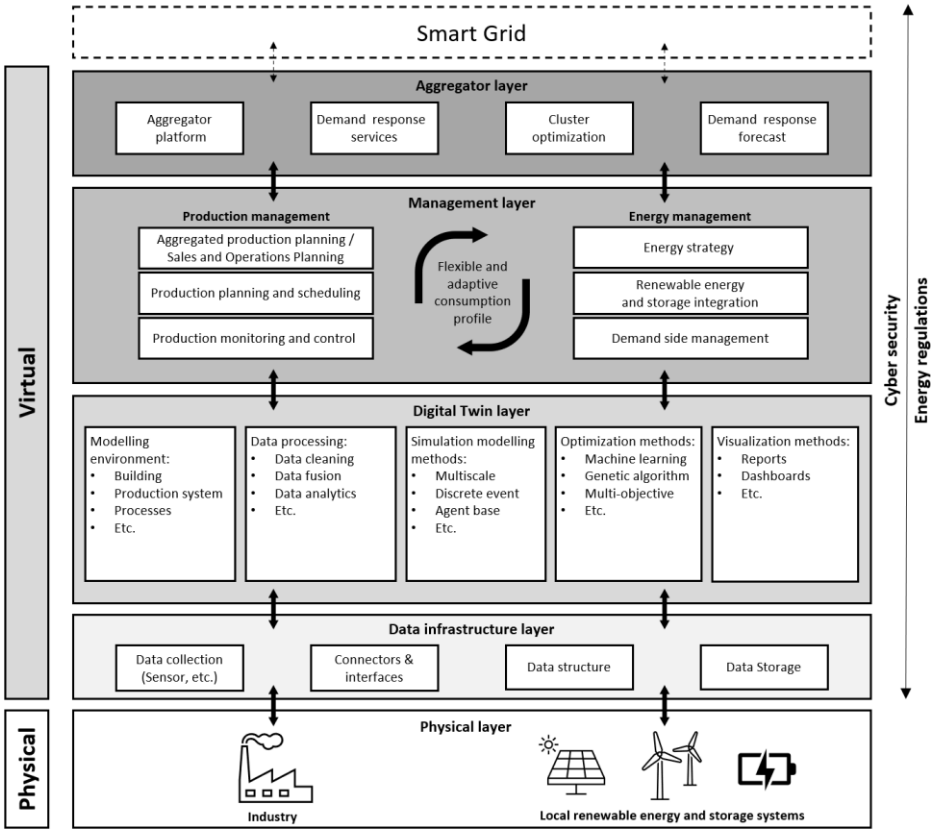

Fig. 2. Framework for industrial demand response services

Manufacturing companies can find interruptions or significant reductions in production difficult to manage. To provide demand response capabilities that are attractive, it is advantageous to have local renewable energy and storage systems. These systems can be highly effective in allowing production to continue while simultaneously providing demand services to reduce energy peaks in the grid. However, these systems must be properly managed to interact with production and the aggregator at the right time. Therefore, it is essential to establish an end-to-end data infrastructure. Data plays a critical role in identifying high-energy consumers in production and understanding energy reduction capabilities. Appropriate sensors and meters need to be selected and applied to identify high-energy consumers in manufacturing, and machine data needs to be extracted.

In the digital layer, which includes the data infrastructure layer, it is important to define data collection, interfaces, data structure, and data storage to ensure consistency, interoperability, and system robustness. The data must be processed (e.g., data cleaning, fusion, etc.) to enable data-driven simulation and optimizations. In the DT layer, various DTs need to be established and interact to reflect both manufacturing and energy flow processes. Their detailed representation allows for simulating and optimizing complex manufacturing processes, with a focus on energy factors, to provide a baseline and different scenarios for energy consumption profiles. The results of simulation and optimization must be presented and visualized for decision-making, which occurs in the management layer.

The management layer focuses on establishing a manufacturing and energy system for flexible and adaptive consumption profiles. Decision-making in this layer ranges from strategic to operational levels. Production needs to identify its manufacturing flexibility in times of production scheduling, while energy needs to integrate renewable energy and storage systems and drive effective demand-side management. The aggregator agent that provides demand response services connects many different manufacturing companies, usually through a platform. The aggregator agent performs forecasting of energy demands and supplies to identify potential energy gaps and provide flexibility to the grid. By communicating with manufacturing companies and exchanging possible consumption profiles, the aggregator can optimize the cluster and provide incentives back to the manufacturing companies to encourage them to provide energy flexibility to the grid.

6 Discussion

The introduced framework aims for a consistent and seamless interaction between the physical, data infrastructure, DT, management, and aggregator layers. This is essential for all types of manufacturing industries, particularly high energy intensive industry, to enable a more flexible demand response. The central part of the framework for industrial demand response is the identification, optimization, and adaption of energy consumption profiles of manufacturing processes. The data-driven models with real-time and historical production data enable the identification of different energy consumption down to the product, machine, and process levels. This allows moving away from aggregated energy consumption data and supports the reduction of complexity in the interplay between manufacturing processes and energy consumption. The interplay between manufacturing and energy management and the aggregator agent is crucial to develop schedules that meet demand and orders and, on the other hand, improve energy consumption to reduce energy prices and CO_2 emissions. Real-time communication with manufacturers and aggregator needs to enable cluster optimization and allow the manufacturer to change their manufacturing schedules in time.

The energy industry is going through significant changes in terms of sustainability and competition, with the introduction of renewable energy targets and emission limits. One potential solution to balance the power supply during periods of over- and undersupply from high levels of uncertain, renewable generation is through demand response. The framework can help balance fluctuating power supply, but it requires accurate control and market frameworks to optimize the use of this geographically distributed resource. Moreover, it can support the replacement of the traditional model of large and centralized generators operating within a monopoly with vertically integrated systems that enable competitive marketplaces. However, the development of complex models of electrical demand is necessary at both the component and system levels to accurately represent the highly diverse, dynamic, and uncertain nature of demand, as well as the complexities of end-user interaction with the system.

The presented framework serves as a useful guideline for industries seeking to improve the flexibility of their industrial demand response. However, it is important to note that the framework has limitations. While it primarily focuses on production scheduling and energy strategy, it is important to consider deeper level components such as changes in the human workforce, disruption of the supply chain, and geopolitical factors to build a more robust and resilient energy system for the industry. Furthermore, the framework has only been tested in the steel industry and large-scale companies. To implement this framework successfully, a high level of digital infrastructure, particularly the data infrastructure layer, is required. The availability and accessibility of different types of data are crucial for the digital twin process to simulate and optimize a process or production system, which requires sensors to be installed at desired locations. Therefore, while larger manufacturing firms may find this framework more readily applicable due to their greater resources, SMEs may face more challenges in its implementation.

7 Conclusion

This study aimed to address the current limitations and enhance the understanding of the interplay between manufacturing and energy industries and reduce the complexity for demand response. The developed framework creates an end-to-end communication and data sharing between the management of the manufacturing sites and the aggregator providing demand response services. Data-driven models and simulations based on DT can help manufacturing industry to identify a variety of possible energy consumption profiles for different manufacturing schedules to meet demand and orders. This framework can service a guideline for manufacturing sector to cope with the changes in the energy sector but the level of digital infrastructure the manufacturer can be the main limitation of the for a successful implantation.

Future research should focus on expanding the framework and identifying additional key decision areas and decision-making methods. Furthermore, it should be tested in various industries beyond steel and small and medium enterprises, and their feedback should be used to improve the framework.

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