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Review

A Systematic Literature Review on Data-Driven Residential and Industrial Energy Management Systems

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Abstract: The energy transition and the resulting expansion of renewable energy resources increasingly pose a challenge to the energy system due to their volatile and intermittent nature. In this context, energy management systems are central as they coordinate energy flows and optimize them toward economic, technical, ecological, and social objectives. While numerous scientific publications study the infrastructure, optimization, and implementation of residential energy management systems, only little research exists on industrial energy management systems. However, results are not easily transferable due to differences in complexity, dependency, and load curves. Therefore, we present a systematic literature review on state-of-the-art research for residential and industrial energy management systems to identify trends, challenges, and future research directions. More specifically, we analyze the energy system infrastructure, discuss data-driven monitoring and analysis, and review the decision-making process considering different objectives, scheduling algorithms, and implementations. Thus, based on our insights, we provide numerous recommendations for future research in residential and industrial energy management systems.

Keywords: energy management; renewable energy; demand response; optimization; artificial intelligence; scheduling; systematic literature review

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1. Introduction

1.1. Motivation

The energy crisis and climate change have enforced the transformation of the energy system within the last decades. While the increasing installation of renewable energy sources (RESs), such as photovoltaic (PV) and wind turbines (WTs), mitigates pollution, they also strain the electricity grid as they provide a volatile and uncertain electricity supply [1]. This challenge intensifies with rising electricity demand in the following decades [2] and increasing peak loads due to the simultaneous charging of electric vehicles (EVs). As a result, system complexity increases, power quality issues arise, and reliability, resiliency, and security are stressed [3]. Thus, the need for an energy management system (EMS) able to monitor, analyze, and optimize the supply and demand-side is essential. According to the International Electrotechnical Commission standard IEC 61970, an EMS is a computer system offering functionalities to effectively operate electrical generation and transmission while ensuring energy supply security at minimum cost [4].

1.2. Related Work

In the scientific literature, some reviews exist on residential and industrial EMSs, as shown in Table 1. However, the primary focus is on home and building EMSs, while only a few reviews address the industrial domain, focusing only on energy-intensive industries or strategic issues. Industrial EMSs specialize in large-scale facilities with high complexity and interdependencies, including features such as advanced data analytics, predictive maintenance, and real-time energy monitoring. Residential EMSs, on the other hand, are designed for homes and small buildings, focusing on user-friendly interactions, energy control, and the reduction of energy bills.

Table 1. Concept matrix of previous reviews for residential and industrial energy management systems.

General				Content	
Ref.	**Industrial**	**Residential**	**Year**	**Focus**	**Future Research**
[5]	✓		2022	Demand response (DR) in energy-intensive industries	Regulatory barriers, data communication/storing/processing, and lack of financial incentives
[6]	✓		2016	Strategic decision making	Long-term effects of various measures, non-energy-intensive industries
[7]		✓	2021	Autonomous systems using artificial intelligence	Real-time semantic feature selection approaches, unsupervised temporal energy pattern characterization, multi-agent systems, generalized automated DR
[8]		✓	2021	Coordinated home EMS: topologies, techniques	Cooperative learning, robust coordination, federated reinforcement learning (RL), uncertainties, blockchain technology, and privacy
[9]		✓	2021	Data-driven predictive control for demand-side management	Robust feature selection, benchmark dataset, data quality, transferrable and scalable data- models
[10]		✓	2020	Home EMS with appliances and scheduling	Grid reliability, load, and RES coordination, security, and privacy
[11]		✓	2021	Residential flexibility	Standardized representation of flexibility resources, quantifying energy flexibility
[12]		✓	2019	Home EMS with concepts, architecture, infrastructure	Appliance diversity, multi-objectives, consumption uncertainty, real-time interaction, continuous updating of feedback
[13]		✓	2018	Home EMS: DR, scheduling, optimization, and communication	Self-learning systems to minimize user involvement
[14]		✓	2020	Home EMS: concepts, configuration, and technologies	-
[15]		✓	2022	RL and model predictive control	Data efficiency, safety, generalization, and robust adaptability
[16]		✓	2021	Building load prediction	Algorithm development, feature selection, extraction, clustering, forecasting
[3]		✓	2020	EMS for smart grids considering user behavior	Greenhouse gas (GHG) emissions, DR participation, data security and privacy, customer awareness, outdated infrastructure, highly uncertain systems
[17]		✓	2022	Residential demand-side management, optimization	Include risk minimization in optimization, highly uncertain systems, standardized load classification, and other objectives, such as frequency/voltage stability
[18]		✓	2021	Multi-level EMS: architecture, objectives	Smart transformer, reactive power in EMS, an uncertainty factor of EVs
[19]		✓	2020	Microgrids: control methods	-
[20]		✓	2022	Microgrids: control and optimization methods	-

In the *industrial EMS domain*, Golmohamadi et al. [5] review industrial DR opportunities in energy-intensive industries, namely the cement manufacturing, aluminum smelting plants, and oil refinery industries. They classify the flexibility potentials of industrial processes and identify challenges, such as regulatory barriers, data communication, storage, and processing. A systematic review of industrial EMSs is provided by Schulze et al. [6], focusing on strategic planning, implementation, operation, controlling organization, culture, and conceptualization. They suggest that future research should focus on the long-term effects of various measures and non-energy-intensive industries.

In the *residential EMS domain*, Aguilar et al. [7] present a systematic review of smart building EMSs, emphasizing monitoring, analysis, and decision-making. Therefore, they group their research according to the “Autonomous Cycles of Data Analysis Tasks”. They conclude that future research needs to address real-time semantic feature selection approaches, unsupervised approaches for temporal energy pattern characterization, multi-agent systems, and a generalized automated DR. The framework, objectives, architecture, benefits, challenges, and different stakeholders of EMSs are reviewed by Rathor and Saxena [3]. They identify six challenges: handling GHG emissions, DR participation, data security and privacy, customer awareness and participation, outdated infrastructure, and highly uncertain systems. Zhang et al. [16] focus on data-driven model predictive control and RL-based control algorithms for building EMSs. Identified future challenges for model predictive control are design complexity, model dependency, and time-consuming computations, while research on RL could tackle data efficiency, safety, generalization, and robust adaptability problems. The literature on building EMSs, including scheduling objectives, physical and operational constraints, along with security issues, is surveyed by Leitao et al. [10]. Further, they provide a list of commonly managed household appliances and identify the remaining challenges of grid reliability, security, and privacy.

Mahapatra et al. [12] focus on concepts, technical background, architecture, and infrastructure of home EMSs, suggesting that future challenges require productive feedback, offering context to provide actionable suggestions, motivating consumers, regular updating, and decreasing the system's costs. The review on home EMSs presented by Zafar et al. [14] refers to the main concepts, configurations, enabling technologies, and popular communication technologies for DR applications. Shareef et al. [13] review DR programs, scheduling techniques, communication protocols, and optimization techniques for home EMSs, concluding that the trend is towards cooperating and self-learning artificial intelligence techniques to reduce user involvement. Panda et al. [17] present a literature review on residential demand-side management. They outline future research directions, such as highly uncertain systems, standardized load classification, and other objectives such as frequency or voltage stability. Hussain et al. [18] review different EMSs at the home, aggregator, and network levels, considering objective functions, constraints, optimization algorithms, communication protocols, and the impact of EVs. Smart transformers, reactive power in EMSs, and EV uncertainty factors are challenges for future research. Coordinated home EMSs are reviewed by Aliabadi et al. [8], including topologies and techniques. Identified research gaps are cooperative learning, robust coordination, federated RL, uncertainties, blockchain technology, and privacy.

Other reviews within the residential EMS domain only consider specific elements of modern EMSs. Li et al. [11] focus on the characterization and quantification of energy flexibility, metrics, methods, and applications. Future research directions are standardized energy flexibility representation and quantification of flexibility potentials. Zhang et al. [15] review the application of machine learning techniques in building load prediction, concluding that algorithm development, followed by data-supporting methods such as feature selection, extraction, clustering, and weather forecasting, are increasingly relevant. A review of data-driven predictive control for demand-side management is presented by Kathirgamanathan et al. [9]. Identified challenges are a methodology for robust feature selection, finding a benchmark dataset, the influence of data quality, and how to make data-driven models transferrable and scalable. Salehi et al. [20] review the control strategies in the microgrid, single- and multi-objective optimization methods, and Pareto-optimal solutions. Elmouatamid et al. [19] focus on control approaches for microgrid EMS, including centralized, decentralized, and hierarchical management structures.

1.3. Paper Contributions and Organization

Based on the previously analyzed reviews, multiple publications cover residential EMSs and their infrastructure, architecture, flexibility, demand-side management, mathematical optimization, control structure, and data-based predictions. However, only a few reviews deal with industrial EMSs, referring to selected industries or specific EMS components. Research from residential EMSs is not easily transferable to industrial use cases as it differs significantly in size, complexity, and dependency of the individual process steps. For example, a suitable optimization algorithm in the residential domain does not necessarily satisfy the increased safety, reliability, or optimality requirements in the industrial context. Consequently, this paper presents a holistic review of industrial EMSs and a comparison of residential and industrial EMSs to identify differences, similarities, and synergies. To our knowledge, we are the first to review residential and industrial EMSs comprehensively. Therefore, the main contributions of this paper are as follows:

- First, to provide a comprehensive overview of state-of-the-art industrial EMSs compared to the residential domain. Here we focus on the EMS's infrastructure, data-driven monitoring and analysis, and decision-making.
- Second, to propose a practical guide about the differences between residential and industrial EMSs.
- Finally, to present a detailed discussion about trends and future research directions.

We organize the remaining work as follows. We formulate the review methodology in Section 2. In Section 3, we present the literature review, considering the infrastructure of the EMS, followed by the data-driven analysis, monitoring, and decision-making. In Section 4, we discuss future research directions regarding residential and industrial EMS, and in Section 5, we provide a conclusion of our work.

2. Methods

This review follows the approach of Webster and Watson [21] to increase transparency and replicability and to prevent researcher bias [22]. To thoroughly comprehend the research area, we initially explore different search terms (STs) and databases, namely ScienceDirect, Web of Science, and Scopus. Based on thematic relevance and publication coverage, we chose ScienceDirect as an adequate database. Later, we include selected publications from other databases by conducting a forward and backward search, where we analyze cited articles. We determine the following final ST:

ST = (“energy management system”) AND (residential OR home OR building OR industry OR industrial OR microgrid).

We then search the database using the ST in the title, abstract, and keywords. To ensure scientific standards, we restrict the search to academic studies published in peer-reviewed journals and limit our search to publications from the last five years, as research on this topic is highly dynamic. As shown in Figure 1, we pre-select 78 articles from the initial 114 publications based on their title. Moreover, given the general criteria of the English language, full-text availability, and matching research discipline, the thematic relevance of the article is critical. Here, we sort publications according to the following criteria: (i) lack of thematic reference to EMSs, (ii) lack of reference to residential or industrial use, and (iii) lack of reference to simulation or implementation of the EMSs.

Figure 1. Selection procedure for the literature base.

After analyzing the abstract and full text, 42 publications remain. Next, we conducted a forward- and backward search and select 51 publications for our final literature base. Finally, we analyze the publications regarding the three categories: (i) design of the energy management infrastructure, (ii) data-driven analysis and monitoring, and (iii) decision-making. The categorization is non-exclusive, i.e., each article can be assigned several categories.

3. Review of Residential and Industrial Energy Management Systems

To further analyze the state-of-the-art research in residential and industrial EMSs, we first outline the design of the EMS infrastructure. Here we focus on energy demand, supply, storage, and advanced metering infrastructure (AMI). Secondly, we address data-driven analysis and monitoring, including data generation and processing. Thirdly, we analyze the decision-making, considering multiple optimization objectives, scheduling algorithms, implementation, and software tools used. The results are presented in Table 2. Within the concept matrix, we distinguish between the EMS categories home (H), building (B), microgrid (M), and industrial (I). Further, we outline if the EMS can actively shift the energy consumption of some devices (flexible loads), integrate RESs, or ESSs, and whether the publications provide a detailed description of the applied sensors and communication protocols. While the monitoring section highlights the usage of openly available datasets and data preprocessing algorithms, the analysis section shows whether the EMS includes energy demand forecasting or clustering algorithms to perform non-intrusive load monitoring or error detection. Finally, we distinguish whether the EMS can simultaneously consider multiple objectives and outline the scheduling technique used to optimize the energy flow.

Table 2. Concept matrix in the literature of residential and industrial energy management systems.

General			Demand and Supply				AMI		Monitoring		Analysis		Objectives		Scheduling			
Ref.	*Year*	*Category*	*Non-Flexible Load*	*Flexible Load*	*RES*	*ESS*	*Sensors*	*Communication*	*Data Available*	*Preprocessing*	*Forecasting*	*Clustering*	*Single Objectives*	*Multi-Objectives*	*Rule-Based*	*Math. Modeling*	*Metaheuristic*	*Game Theory*
[23]	′21	H	✓	✓										✓				
[1]	′20	H		✓	✓	✓							✓			✓		
[2]	′19	H		✓					✓				✓				✓	
[24]	′21	H	✓	✓		✓			✓				✓			✓		
[25]	′19	H	✓	✓	✓	✓			(✓)					✓			✓	
[26]	′21	H		✓	✓	✓			(✓)					✓		✓		
[27]	′21	H	✓	✓	✓	✓			(✓)	✓	✓		✓			✓		
[28]	′22	H	✓	✓	✓	✓				✓	✓		✓					
[29]	′21	H			✓								✓					
[30]	′20	H	✓	✓	✓	✓				✓				✓		✓		
[31]	′20	H	✓		✓	✓					✓		✓		✓			
[32]	′21	H	✓	✓	✓	✓							✓	✓			✓	
[33]	′21	H	✓	✓	✓	✓								✓		✓		
[34]	′18	H	✓				✓	✓						✓		✓		
[35]	′18	H	✓	✓	✓	✓					✓			✓		✓		
[36]	′21	H	✓	✓	✓	✓	✓	✓			✓			✓	✓		✓	
[37]	′20	H					✓	✓					✓		✓			
[38]	′22	H	✓	✓	✓	✓								✓			✓	
[39]	′22	H	✓	✓	✓	✓			(✓)				✓				✓	
[40]	′19	H	✓	✓	✓	✓							✓				✓	
[41]	′21	H	✓		✓	✓					✓		✓		✓			
[42]	′20	H	✓		✓	✓			✓					✓			✓	
[43]	′20	B	✓	✓	✓	✓								✓			✓	
[44]	′22	B		✓			✓	✓			✓							
[45]	′18	B	✓	✓	✓						✓					✓		
[46]	′18	B	✓	✓		✓			✓		✓		✓		✓			
[47]	′19	B	✓						✓	✓	✓							
[48]	′21	B	✓	✓					(✓)				✓		✓			
[49]	′22	B	✓						(✓)	✓	✓							
[50]	′18	B	✓				✓		(✓)									
[51]	′19	B	✓				✓	✓	(✓)									
[52]	′21	B	✓		✓	✓			(✓)		✓		✓			✓		
[53]	′20	M	✓	✓	✓	✓							✓			✓		
[54]	′20	M	✓	✓	✓								✓				✓	
[55]	′18	M	✓	✓	✓	✓								✓			✓	
[56]	′18	M	✓		✓	✓			(✓)		✓		✓		✓			
[57]	′18	M		✓									✓			✓		
[58]	′22	I			✓	✓												
[59]	′19	I	✓	✓	✓	✓							✓			✓		
[60]	′20	I	✓	✓					✓	✓		✓	✓			✓		
[61]	′22	I	✓		✓	✓							✓		✓	✓	✓	
[62]	′22	I	✓			✓							✓			✓		
[63]	′21	I	✓		✓	✓					✓		✓				✓	
[64]	′21	I	✓	✓		✓								✓		✓		
[65]	′21	I	✓	✓	✓	✓								✓		✓		
[66]	′21	I	✓		✓	✓				✓	✓		✓			✓		
[67]	′20	I	✓	✓									✓					✓
[68]	′19	I	✓		✓	✓							✓			✓		
[69]	′20	I	✓	✓	✓								✓				✓	
[70]	′20	I	✓	✓									✓				✓	
[71]	′19	I	✓	✓	✓								✓			✓		

3.1. *Design of the Energy Management System Infrastructure*

Today's energy systems have significantly increased in complexity and ambiguity [3]. As shown in Figure 2, an EMS coordinates heterogenous loads, volatile RESs, and energy storage systems (ESSs) by applying AMI, modern communication standards, and external information systems. The following sections present a detailed review of these components within the *residential* and *industrial* domains. In particular, we address DR, flexible and non-flexible loads classification, and RESs, including PV, WTs, and heat pumps. Further, we consider ESSs, such as batteries and EVs, sector coupling, and AMI, including smart meters, sensors, and wireless and wired communication protocols.

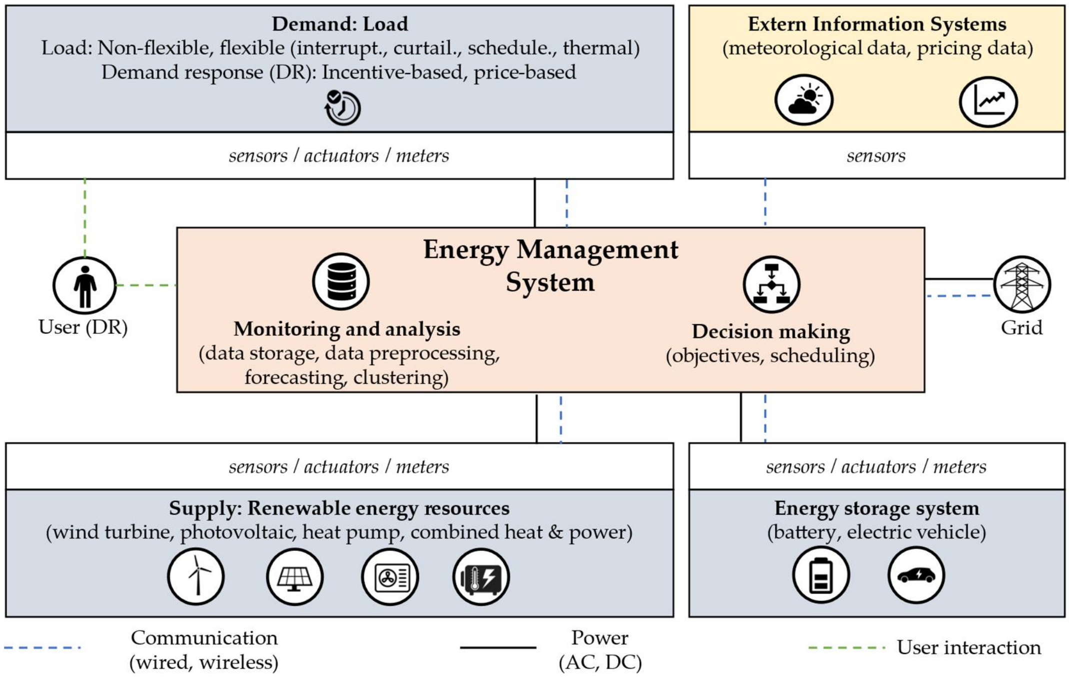

Figure 2. A modular design of an energy management system infrastructure.

3.1.1. Energy Demand, Supply, and Storage

With the rising installation of RESs, flexibility is increasingly essential to balance energy demand and supply. To enhance residential and industrial flexibility potentials, advanced EMSs apply different DR techniques, integrate ESSs, and exploit flexible loads. While energy savings due to increased user awareness or energy-efficient technologies [10] are the prerequisite for a modern energy system, an EMS can also shift the operation of flexible appliances to times of local energy generation and off-peak tariffs [72]. To further exploit this demand-shifting potential, the literature distinguishes between non-flexible and flexible loads [24,33,36]. While the scheduling of flexible loads does not reduce the user comfort level significantly [36], non-flexible loads must be started immediately [36] and cannot be interrupted, adjusted, or curtailed [27]. It is worth mentioning that flexible loads can be further categorized as curtailable, schedulable, interruptible, and thermal loads [27]. However, depending on the publication, deviating formulations for flexible and non-flexible loads exist, such as (non-)delayable [23], (non-)schedulable [43], fixed/unfixed [40], (non-)critical [24], (non-)deferrable [55], (un-)controllable [27], or essential loads [30].

In *residential* EMSs, several appliances are integrated into the energy system and classified regarding flexibility, as shown in Table 3. In a nutshell, load flexibility can be applied by automating flexible device control, exploiting the user's indifference to minor temperature changes, considering the user's behavior, and using existing electrical storage on the device level. While all authors consider washing machines, dishwashers, and dryers as flexible, the classification between flexible and non-flexible loads is unclear for other applications. Apaydin-Özkan et al. [23] suggest that the customer manually operate the air conditioner, thus classifying it as non-flexible. In contrast, Rochd et al. [36] propose a model that automatically regulates an air conditioner within a temperature band. Here, flexibility is gained through automated control and allowed temperature variations that do not affect users' comfort. Similar reasoning applies to other thermal loads, such as refrigerators. Integrating the user's behavior can increase flexibility for applications such as toasters, microwaves, vacuum cleaners, or kitchen appliances. Here, Ahmad et al. [53] propose a human interaction factor, which determines the users' willingness to interact with that appliance and to delay its use for each appliance. Tantawy et al. [38] differentiate between non-active, semi-active, and fully-active users willing to postpone certain activities. Another option to increase flexibility is exploiting integrated battery storage in appliances such as laptops to delay charging in critical periods. Other devices, such as the TV, are uniformly classified as non-flexible, which would directly decrease users' comfort.

Table 3. Flexible and non-flexible residential loads analyzed in the literature.

Load	Ref. Non-Flexible	Ref. Flexible
Washing machine		[1,23,24,26,28,30,32,33,36,38,40,43,53,55]
Dishwasher		[1,23,24,26,28,30,32,33,36,38,40,43,53]
Dryer		[1,23,24,26,28,32,33,36,38,40,43,53]
Refrigerator	[23,30,32,33,36,38,40]	[24,28,43,55]
Laptop and PC	[24,27,36]	[26,30,32,33,38,40,43,55]
Air conditioner	[23,38]	[24,26,27,30,33,34,36,39,46]
Lights	[23,24,30,32,33,36,38,40,55]	[40,43,55]
Microwave	[23,27,36,38]	[26,27,30,32,33,40]
Vacuum cleaner	[23,27,30,32]	[1,26,33,38,40]
Oven	[23,27]	[24,26,30,32,33,40,43]
EV		[26,32,33,38,40,53,55]
TV	[23,24,27,30,32,33,43]	
Water/pool pump		[23,38,43,55]
Water heater		[23,30,38,55]

On the *industrial demand-side*, loads differ significantly in heterogeneity, interdependency, and size. In addition to automating flexible device control, including the user's indifference to minor temperature changes, EMSs can exploit further load flexibility by sector coupling, hydrogen production, and material buffers. While Lu et al. [66] differentiate between critical, shiftable, and controllable loads in a steel powder manufacturing system, Klyapovskiy et al. [65] increase flexibility by using a potential electricity surplus for hydrogen production. Choobineh and Mohaghehghi [73] distinguish between direct load control, where the utility directly shuts down the load remotely, and indirect load control, where the customer receives an optional request from the utility. Both Cirera et al. [60] and Wang et al. [71] increase flexibility by exploiting the users' indifference to minor temperature changes, considering the modification of a refrigerator within desired temperature bounds [60] and heating, ventilation, and air conditioneing [71]. In addition, material buffers are integrated [66,67] to increase industrial flexibility.

Beyond introducing various flexibility potentials in residential and industrial EMSs, another issue involves encouraging the users to apply their flexibility in a system-stabilizing way. For this purpose, DR programs are introduced, through which users can benefit from a grid-stabilizing behavior. These DR programs can be classified into the following categories: (i) incentive-based DR, such as direct load control, interruptible rates, emergency DR programs, and demand bidding programs [10], and (ii) pricing-based DR, namely real-time pricing, critical peak pricing, time-of-use pricing, or hourly pricing [55].

Considering the renewable electricity generation technologies, *residential and industrial EMSs* support PV and WTs. While PV can help mitigate global warming and reduce electricity costs [43], the electricity output mainly depends on solar irradiance, the array area, the solar cell array efficiency, and outdoor temperature [74]. Thereby, weather conditions, time of day, or local shading can strongly affect PV generation and thus increase volatility and uncertainty. Similar to PV, WTs are a promising RES, highly dependent on the average wind velocity and air density [55].

To mitigate the volatility, ESSs-like batteries or EVs can effectively balance the volatility of renewable generation [75]. While in unidirectional charging, the electricity flows from the grid to the EV, in bidirectional charging, EVs supply the grid, buildings, or industrial sites with electricity [14].

EVs could act as mobile ESSs, charging in low tariff hours and discharging in peak hours to the electricity grid, assuming bidirectional charging capabilities [43]. EVs have lower installation and maintenance costs per kWh than ESSs, providing extra financial benefits [32]. Modern EMSs not only consider electricity generation but also include heat supply via heat pumps [35] and combined cooling, heating, and power (CCHP) plants to increase energy efficiency by recovering heat for room cooling and water heating [43].

3.1.2. Advanced Metering Infrastructure

Based on the energy demand, supply, and storage, an EMS must implement an infrastructure for communication and data collection among the different components to integrate flexible loads, DR programs, RESs, and ESSs. An AMI allows bidirectional energy and information exchange between the EMS, smart meters [56], and sensors using wired and wireless communication technologies. Thus, enabling data logging, remote application monitoring, data security, and displaying electricity prices to facilitate users' participation in the electricity market [17]. Smart meters are intended to send user consumption information to the utility, receive price information, and control commands through the customer gateway [56]. They are used in many industrial and residential cases [38,47,50,70].

In addition to smart meters, *residential EMSs* use various sensors to measure indoor and outdoor temperature, relative humidity [45,50], occupancy detection [34], meteorological data [36], and thermal comfort [45]. Shareef et al. [37] measure room temperature and humidity with the DHT22 (STMicroelectronics, Shanghai, China) sensing module and light intensity within the room with the TEMT 6000 (Vishay Americas, Greenwich, CT, USA) light sensing module. They validate the readings by a comparison with the measurements of a commercial ST-1309 LUX (ATP Instrumentation, Ashby-de-la-Zouch, UK) meter. To monitor the internal temperature of a refrigerator and the water temperature in a water heater, they apply the waterproof DS18B20 (Maxim Integrated, San Jose, CA, USA) temperature sensor. The room's occupancy status is identified with a passive infrared motion detection sensor and an SEN 1059 (DF Robot, Shanghai, China) CO_2 sensor, which utilizes an inverse relationship between CO_2 concentration and voltage [37]. Mataloto et al. [51] measure temperature/humidity with a DHT22 (STMicroelectronics, Shanghai, China) sensor, light with a photoresistor sensor, motion with a passive infrared sensor, and air quality with an MQ-135 (Zhengzhou Winsen Electronics Technology, Zhengzhou, China) sensor suitable for detecting smoke, carbon dioxide, and other gases. By comparing the measurements with a highly sensitive IR temperature thermometer, they excluded the temperature/humidity sensor "DHT11" (Guangzhou Aosong Electronics, Guangzhou, China) due to unreliable outputs and low quality.

Advanced *industrial EMSs* are equipped with sensors to measure physical and electrical quantities, including voltages, power flows, and environmental conditions such as temperature, humidity, or vibration [73], frequencies, and heat flows [60]. Cirera et al. [60] operate a refrigeration system, employing the pressure sensors WIKA S20 (WIKA Alexander Wiegand SE, Klingenberg, Germany), the temperature sensors WIKA T15.H (WIKA Alexander Wiegand SE, Klingenberg, Germany), or valve positioning reeds, and integrate the controllers 319-3 (Siemens, Munich, Germany) and S7-200 (Siemens, Munich, Germany) to communicate with a relational MySQL database.

Wired and wireless communication technologies are essential to enable communication between heterogenous components, such as sensors and meters. Table 4 shows the different communication technologies for EMSs. In *residential EMSs*, wired communication can involve a variety of technologies, such as power line communication (PLC) for home area networks and fiber optic-based communication for wide area networks [17]. Based on wireless communication, Rochd et al. [36] implement Zigbee and Wi-Fi communication in their home, while Shareef et al. [37] use Zigbee to communicate between the appliance monitoring and controlling circuitries. Mataloto et al. [51] base their EMS on three wireless communications protocols, long range wide Area network (LoRaWAN), Wi-Fi, and infrared. LoRaWAN is especially suited for buildings due to the penetrability of walls compared with others, such as Wi-Fi, Bluetooth, ZigBee, or Z-Wave. While Charoen et al. [44] connect their devices via Wi-Fi, Tantawy et al. [38] link all smart home appliances, RESs, and ESS over a home area network, considering ZigBee, Z-Wave, and Wi-Fi as communication technologies.

In *industrial EMSs*, the reviewed literature provides no detailed overview of communication protocols. However, it is worth mentioning that the same communication technologies can be considered.

Table 4. Wireless and wired communication protocols for energy management [3,14,17,76–79].

	Technology	Data Rate	Coverage Range
Wired	Narrowband PLC	Up to 300 Mbps	Up to 1500 m
	Broadband PLC	Up to 500 Kbps	Up to 3 km
	Ethernet	Up to 100 Gbps	Up to 100 m
	Fiber optics	Up to 100 Gbps	Up to 100 km
	Modbus	Up to 20 Mbps	Up to 1200 m
Wireless	GSM	Up to 14.4 kbps	Up to 10 km
	GPRS	Up to 170 Kbps	Up to 10 km
	WiMAX	Up to 75 Mbps	Up to 50 km
	Z-wave	Up to 250 Kbps	Up to 30 m, unlimited with mesh
	ZigBee	Up to 250 kbps	Up to 100 m
	Wi-Fi	Up to 900 Mbps	Up to 100 m
	Bluetooth	Up to 721 Kbps	Up to 100 m
	Cellular (LTE)	Up to 100 Mbps	Up to 100 km
	LoRaWAN	Up to 50 Kbps	Up to 40 km
	Infrared	Up to 4 Mbps	Up to 30 m

3.2. Data-Driven Analysis and Monitoring

Building up on the AMI, data are a crucial component of EMSs. The following chapter firstly addresses data-driven monitoring, considering different types of data and preprocessing, and secondly presents the data-driven analysis, including advanced forecasting and classification techniques. Moreover, with machine learning-based forecasting techniques and clustering for data analysis, the focus increasingly turns to data quality, time resolution, features, and granularity.

3.2.1. Monitoring

Data-driven EMSs store and monitor high volumes of data to improve decision-making. While large historical datasets assist in detecting seasonal deviations, monitoring real-time data enables the control of the various EMS components. In this context, real-time refers to data logging every second, while many EMSs only provide a lower logging frequency of 15 min up to one hour.

As shown in Figure 3, the data collected in the literature can be divided into six categories: (i) demand-side data, (ii) supply-side data, (iii) user data, (iv) environmental data, (v) meteorological data, and (vi) pricing data.

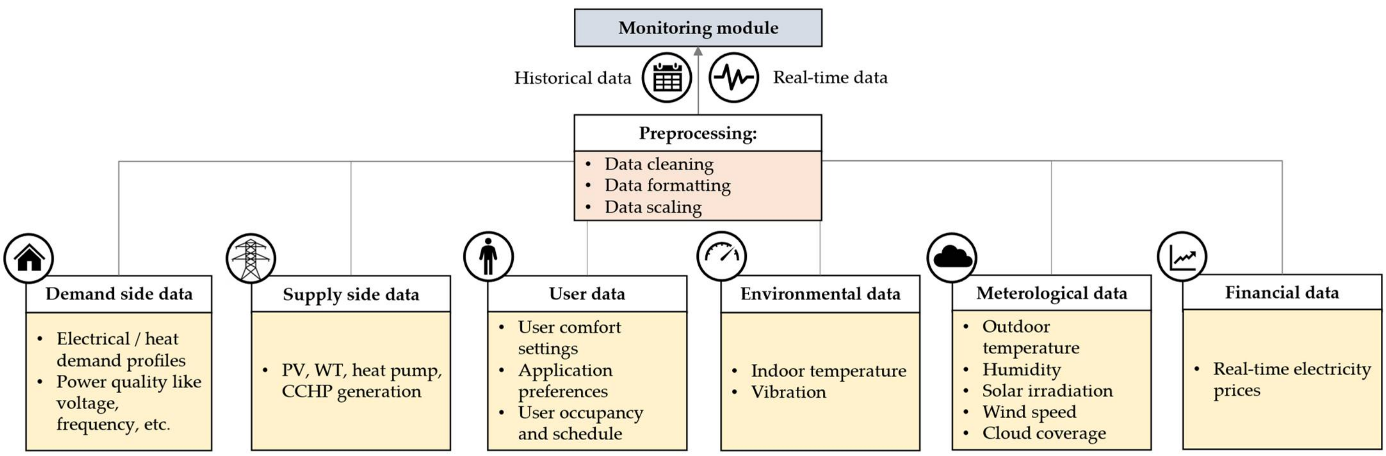

Figure 3. Real-time and historical data for energy management systems.

Regarding demand-side data, residential EMSs consider electric load profiles of individual appliances [53] or monitor the whole building load [51]. In contrast, industrial EMSs focus more on the interdependencies between the different appliances and machines, as the complexity of industrial production processes is higher in residential applications [73]. For supply-side data, residential EMSs monitor the electricity grid, PV [24,27,28,30,36], WTs [27,28], CCHPs [43], diesel generators [54], and heat pumps [2]. In addition, industrial EMSs include hydrogen production [65]. While *residential EMSs* include occupancy detection [25,34], presence detectors [50], and indoor temperature [50] for environmental data, industrial EMSs also consider pressure sensors [60], temperature sensors [60], humidity and vibration [73]. Only residential EMSs consider user data, namely consumers' preferences and priorities for various applications [53], consumers' comfort levels [23,43,50], and consumers' location [50]. Meteorological data includes outdoor temperature [46,50], solar irradiance [33,69], wind speed [61], and general weather conditions [69]. Most publications in residential and industrial EMSs use financial data, namely electricity prices.

In addition to real-time data, historical datasets can help pre-calibrate algorithms and provide reference values. The number of openly available historical datasets in the literature is increasing, as shown in Table 5. It is worth mentioning that most of the datasets are based on a time resolution from 15 min up to one hour, which makes it challenging to analyze the voltage/frequency stability, harmonic distortion, or the technical implementation of EMSs. While various datasets for residential loads exist, industrial datasets are very limited. Here the existing datasets are aggregated to protect private and sensible data [80], making it impossible to analyze the data on a small-scale level and to assess the power quality.

Table 5. Open available historical datasets for energy management systems.

Ref.	Category	Description
[81]	Res. load	Synthetic building operation dataset at 10 min resolution
[82]	Res. load	Dataset for US residential/commercial buildings at 15 min resolution
[83]	Res. load	Residential load profiles of a kindergarten school for three years
[84]	Res. load	Hourly application load profiles of 3053 energy meters from 1636 buildings
[85]	Res. load	Power consumption of one household with a one minute sampling rate over four years
[86]	Res. load	Individual household electric power consumption
[87]	Res. load	HVAC system-attack detection, building (3-floor, 12-zone)
[88]	Res. load	Dataset for NILM: two year, one min resolution of electricity, water, natural gas
[89]	Ind. load	Hourly electricity load profiles of paper-producing/food-processing industries
[90]	Ind. load	Steel industry energy consumption dataset
[80]	Ind. load	EMSx: benchmark set with 70 industrial historical photovoltaic/load scenarios
[91]	EV	EV charging, Norway, two years: user ID, plugin, plug out, charged kWh, duration
[92]	EV	Lithium-ion battery aging dataset based on electric vehicle real-driving profiles
[93]	Wind	Meteorological/power/forecast data from computer model for 2007–2013
[94]	Wind	Offshore wind resource data in the US at 5 min resolution
[95]	Solar	Metadata and performance data from experimental PV generation sites
[24]	Solar	Temperature, irradiation
[96]	Heat pump	Heat pump generation
[97]	Technical	Baseline report of cost/performance data for electricity generation/ storage

Apart from the data collected, preprocessing is essential to improve the data quality for residential and industrial EMSs. Among the analyzed publications, only a few address data quality and specify the preprocessing methods used. The techniques most commonly used are data cleaning, formatting, and scaling. Data cleaning involves removing outliers, filling in missing values [66], and noise detection [15]. For example, Kim et al. [47] removed 25,979 missing values by applying the sliding window algorithm to use multivariate time series data as input. To tackle value ranges of different data points, the min-max scaling approach and the sine-cosine scaling technique exist for scaling [49,66]. Luo et al. [49] normalize meteorological data such as temperature, wind velocity, or solar radiation into a range of [0–1] by applying min-max scaling. Further, they apply sine-cosine scaling to convert cyclical measures into corresponding sine and cosine values. For example, with categorical or original hour variables, there would be a 23 h difference between 23:00 and 0:00 instead of the actual one-hour difference. Meanwhile, day and month are converted into binary variables using a one-hot encoding approach.

Yet, a detailed analysis quantifying the effect of the applied preprocessing techniques on the forecasting and optimization performance is missing. Since data cleaning and formatting provide the basic requirements regarding data quality, benchmarking the influence of min-max scaling and sine-cosine scaling on the analysis performance would be interesting.

3.2.2. Analysis

While forecasts predict the uncertain behavior of RESs, clustering algorithms can identify patterns and trends in energy data, thus supporting robust EMSs. Therefore, in this section, we differentiate between different forecasting techniques and present different use cases for clustering. In the literature, two forecasting procedures exist: (i) machine learning-based modeling and (ii) mathematical and statistical modeling, as shown in Figure 4. Further, forecasts can predict uncertain outcomes regarding demand, supply, EVs, and user and financial applications.

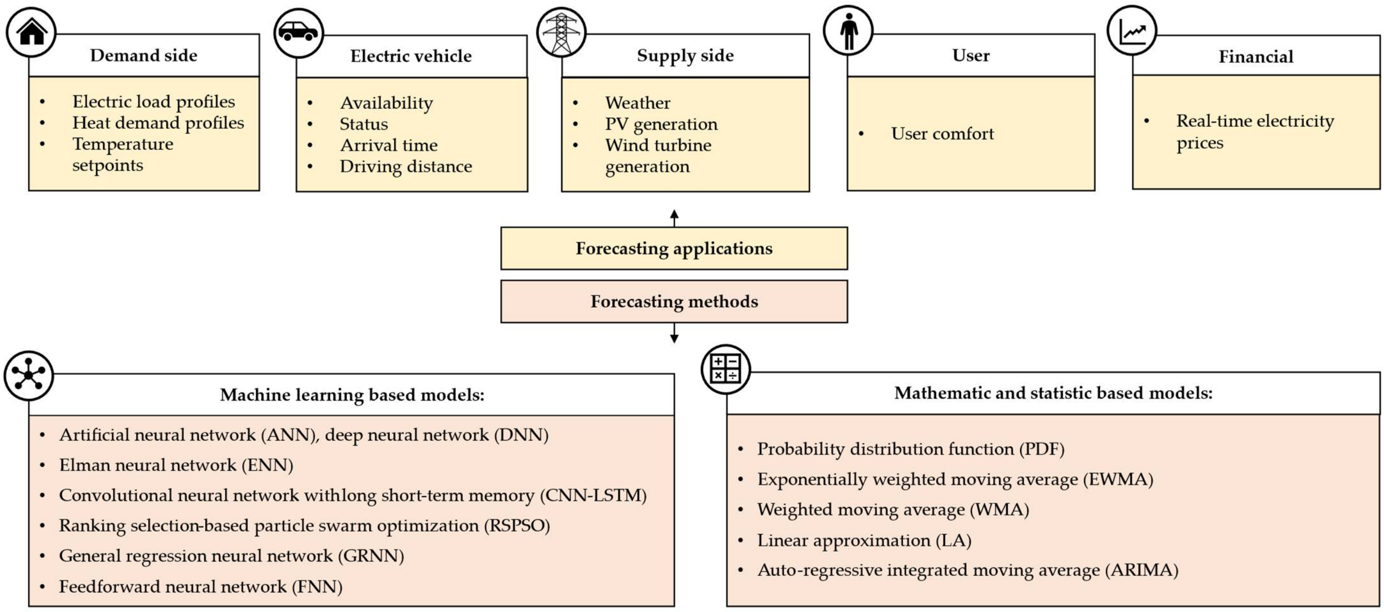

Figure 4. Forecasting algorithms and applications for energy management systems.

Various prediction algorithms exist in the *residential* EMS literature for machine learning-based forecasting methods. Charoen et al. [44] predict the temperature setpoint of an air-conditioning system by applying an artificial neural network (ANN) with three fully connected layers while considering the features: outdoor temperature, outdoor humidity, and weather conditions. In contrast to most ANNs, which are primarily trained offline with historical datasets to obtain fixed weights and biases, Youssef et al. [56] use an adaptive online training technique. They introduce a feed-forward ANN, using the Levenberg–Marquardt back-propagation algorithm, comparing the load for each subsequent hour with the forecasted value and backpropagating the error to fine-tune the weights and biases. In addition, Rafique et al. [52] use a feed-forward ANN with back-propagation learning to predict the household load and solar PV generation. Luo and Oyedele [49] present a self-adaptive and robust deep-learning model powered by ranking selection-based particle swarm optimization to predict electricity load in buildings with moving horizons.

Further, they test four typical activation functions: sigmoid, hyperbolic tangent, rectified linear unit, and exponential linear unit. Two forecasting models for real-time prices, PV and WT generation, are proposed by Koltsaklis et al., combining unsupervised and supervised machine learning algorithms [27] and a general regression neural network (GRNN) [28]. While the unsupervised machine learning part corresponds to K-medoid clustering, the supervised part refers to the Elman neural network (ENN). Kim et al. [47] present a convolutional neural network with a long short-term memory (CNN-LSTM) that can effectively extract spatial and temporal features to predict housing energy consumption. While CNN removes noise and considers the correlation between multivariate variables, LSTM models temporal information and maps time series into separable spaces to generate predictions.

For *industrial* EMSs, Lu et al. [66] propose a deep learning-based forecasting model for renewable generation and electricity prices to overcome uncertainties while considering prediction errors. They use a hybrid CNN-LSTM model with multivariate time series data as input and multistep single time series data as output. Gao et al. [63] apply a generative adversarial network (GAN) to predict PV generation, while for load power prediction, simple averaging (SA) is used.

Only *residential* EMSs use mathematical and statistical-based forecasting models. Rafique et al. [52] predict EV availability, travel distance, and range by applying probability distribution functions to historical time series data. Ma and Li [31] apply the exponentially weighted moving average (EWMA) model to predict the energy consumption of a room and to adapt to seasonal changes. A combination of the weighted moving average (WMA) and linear approximation is used by Varzaneh et al. [41] to predict the next day's electricity demand. Koltsaklis et al. [27] evaluate the performance of their ENN by comparing it to an auto-regressive integrated moving average (ARIMA) model.

In addition to forecasting, clustering is a vital feature of advanced EMSs. In the literature, clustering is used for (i) non-intrusive load monitoring (NILM) and (ii) attack detection. While intrusive load monitoring involves installing sensors on each appliance, NILM measures appliances' aggregated power consumption profiles and returns individual consumption profiles. Therefore, NILM is both time and cost-effective [98].

For *residential* EMSs, Keramati et al. [98] use NILM to disaggregate the total power consumption of a household into individual consumption of the appliances. To tackle the challenge of differentiating devices consuming nearly equal power, they incorporate the water consumption patterns of machines to separate otherwise-indistinguishable appliances. Elnour et al. [99] present an analysis of a heating, ventilation, and air conditioning (HVAC) system's security analysis using the Isolation Forest (IF) approach for attack detection.

In *industrial* EMSs, Cirera et al. [60] propose a data-driven methodology that improves the refrigeration systems' efficiency on the load side. They validate the NILM approach with a MATLAB simulation.

3.3. Decision-Making

After analyzing the different energy systems' infrastructure, data monitoring module, forecasting, and clustering techniques, this chapter further investigates decision-making. Therefore, we present the objectives used in the literature, examine the scheduling algorithms, and summarize the differences in realization and software tools used.

3.3.1. Objectives

Modern energy systems can control energy demand, supply, and storage, considering various, possibly contradictory, objectives. As shown in Table 6, in the literature, four objectives exist: economical, technical, environmental, and social.

Economic objectives minimize different cost functions. While residential EMSs focus primarily on electricity costs, industrial EMSs also consider operational and total costs. It is worth mentioning that the underlying formula of the objective functions can differ slightly, based on the modeling technique. Regarding technical objectives, residential EMSs mainly minimize the peak-to-average ratio, while industrial EMSs minimize asset degradation [73]. Only residential EMSs consider social objectives: the user's discomfort and waiting time. Here, the user's comfort can be considered by minimizing the difference between a reference temperature and the actual room temperature [35]. When considering environmental goals, residential and industrial EMSs minimize emissions, namely CO_2, NO_x, and SO_x [43]. In addition to these objectives, Javadi et al. [26] also address uncertainty by considering the probability of different scenarios [26], and Ali et al. [43] add conditional value at risk to the objective function to overcome the risk of lost load.

Table 6. Objectives for residential and industrial energy management systems.

Objective	Ref. Residential	Ref. Industrial
Economical objectives		
Min electricity/ energy cost	[1,2,23,25–28,30–34,36–41,43,46,52,53,55–57]	[63,66,69–71]
Min total fuel cost	[24]	
Min generation cost	[54]	
Min operational cost		[59,62,65,73]
Min total cost		[58,61,64]
Max profit		[64]
Technical objectives		
Min peak average ratio	[23,26,30,32,38,40,55]	
Min battery degradation	[52]	
Min asset degradation		[73]
Max grid support	[35]	
Min power losses		
Ecological objectives		
Min emissions	[43]	[73]
Min electricity consumption	[25,48]	
Max H_2 production		[65]
Min grid energy use	[29,35]	
Social objectives		
Min discomfort	[23,26,32–36,40]	
Min waiting time	[38,40,55]	

In addition to comparing different objective categories, another differentiation criterion is whether the objective has a single- or multi-objective function. In the literature, some residential and industrial EMSs address the complexity of modern energy systems by considering multiple objectives from different objective categories. In residential EMSs, the following objectives are combined: (i) energy costs and emissions [43], (ii) energy cost and discomfort [33,34,36], (iii) energy cost, peak-to-average ratio, and discomfort [23,26,32], (iv) energy cost, peak-to-average-ratio, the user's waiting time [38,55], and (v) self-consumption, discomfort, and grid support [35]. Industrial EMSs minimize operational costs, emissions, and asset degradation simultaneously [73] and combine the objectives of operating costs and green hydrogen production [65].

In the literature reviewed, the weighted sum method [2,32,34,42,68] and lexicographic goal programming [26,73] exist to solve a multi-objective optimization problem. While the multi-sum method transforms the optimization problem into a single-objective optimization problem by assigning weights to the individual objectives, extended lexicographic goal programming uses priority ordering amongst the different objectives.

3.3.2. Optimization Techniques

Based on the predefined objective function, EMSs schedule energy demand, supply, and storage by applying various optimization techniques. As shown in Figure 5, five categories of optimization techniques exist: (i) rule-based optimization, (ii) mathematical optimization, (iii) metaheuristic optimization, (iv) RL, and (v) game theory approach.

Rule-based algorithms coordinate and prioritize the energy system according to a predefined set of rules. While the logical structure makes the decision-making comprehensible, these algorithms are challenging to extend [36]. Only residential EMSs apply rule-based optimization techniques in the literature reviewed. While Shareef et al. [37] define if/then statements to manage household appliances, considering user preferences, day-ahead electricity prices, and room occupancy, Rochd et al. [36] manage energy sharing among power sources to fulfill the demand optimally. The rule-based algorithm of Varzaneh et al. [41] enables PV integration for off-peak demand shifting, including an ESS. MATLAB software is used to simulate and implement the algorithms [36,37,41], and the considered time resolution differs from real-time [37], over 10 min intervals [36] to hourly intervals [41]. It is worth mentioning that all publications that apply rule-based algorithms not only simulate the EMS but implement it technically [36,37,41,56].

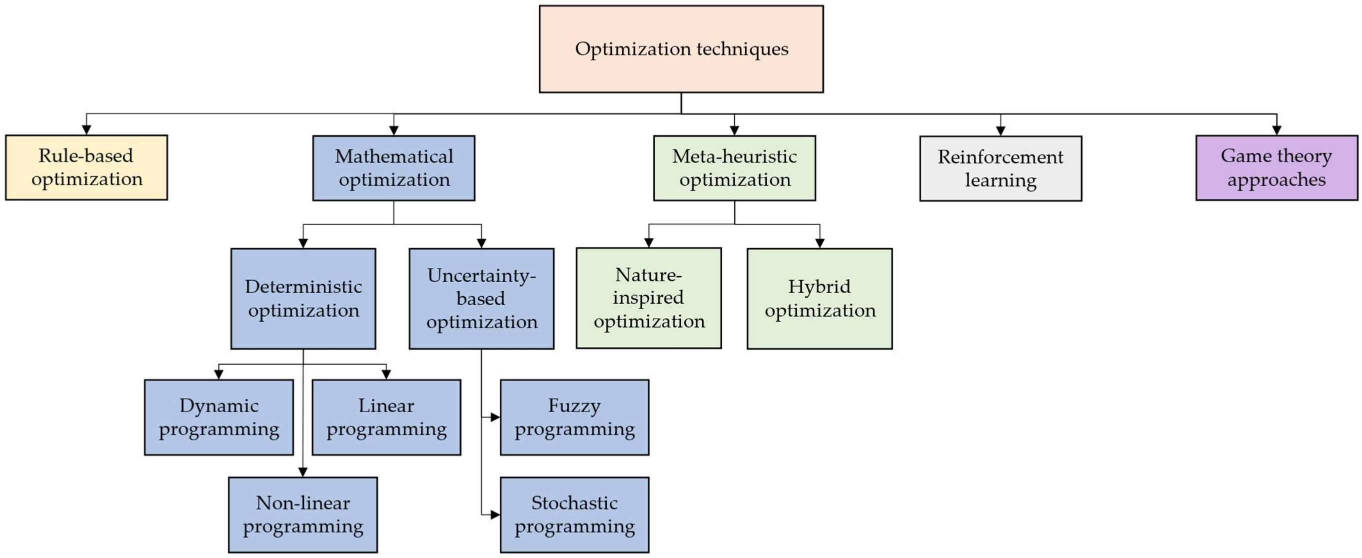

Figure 5. Classification of optimization techniques for energy management systems.

Mathematical optimization algorithms model the energy system by formulating an objective function and various constraints. Here, a distinction can be made between (i) deterministic methods, such as linear programming, non-linear programming, and dynamic programming, and (ii) uncertainty-based methods, such as stochastic programming and fuzzy programming. While deterministic methods do not consider uncertainties about future events, such as PV generation or electricity demand, uncertainty-based methods reflect these uncertainties directly in modeling.

- **Linear programming** (LP) expresses the objective function and constraints in linear and deterministic relationships. It is often used due to its relatively low computation burden and the availability of specific software packages [10]. In residential EMSs, Annes et al. [57] schedule electric appliances in a smart home community with an LP algorithm. A mixed-integer linear problem (MILP) is proposed by Elazab et al. [24] for load scheduling of an offline smart isolated home and by Koltsaklis et al. [27] for a smart home to minimize cost while determining the optimal day-ahead energy schedule for all load types. In industrial EMSs, LP is used to improve the efficiency of refrigeration systems [60], optimize industrial thermal batch processes [62], identify the potential of combined energy and production scheduling in industrial energy hubs [64], and schedule industrial facilities with PV generation, DR potential, and EVs [71]. Klyapovskiy et al. [65] propose a MILP, considering DR flexibility, from an electrolysis plant, a hydrogen storage tank, an electric battery, and hydrogen-consuming plants. While Lu et al. [66] present an adaptable online EMS based on a MILP for industrial microgrids, Mohy-ud-din et al. [68] formulate an EMS as an LP. Software tools for solving the LP are MATLAB [24], Cplex, and GAMS [27], while time resolutions are 5 min [34], 15 min [27,62], and 1 h [64–66,71].
- **Non-linear programming** either models the underlying criteria, constraints, or both by non-linear relationships. These techniques are more potent than LPs, but computation burdens are more significant [10]. In residential EMS, Rafique et al. [100] model non-linear EMSs in a grid-connected residential neighborhood in Sydney with EVs, ESS, and PV generation. Rao et al. [35] provide a control scheme for the phase balancing of a home EMS, which maximizes self-consumption, user comfort, and grid support with mixed-integer quadratic programming. In industrial EMS, Choobineh et al. [73] apply a multi-objective non-linear mixed-integer problem to improve the operational costs, emission levels, assets lifetime, and sustainable operation level of an industrial plant. Software tools for modeling and solving are MATLAB [52,60] and GAMS [52,73], with an hourly time resolution [52,73].

- **Dynamic programming** (DP) can solve complex problems [19] by dividing optimization problems into simpler sub-problems [17]. In the literature analyzed, only industrial EMSs consider DP. Casini et al. [59] model the control of an industrial microgrid, including EVs, and Dreher et al. [61] use a DP-based unit commitment to finding an upper benchmark for an EMS in the context of CO_2-neutral hydrogen production and storage for industrial combined heat and power application. As a software tool, MATLAB is used [59], and the time resolution is 1 h [61].
- **Stochastic programming** (SP) is an uncertainty-based optimization technique where all or some decision variables follow probabilistic determination [17]. In the literature reviewed, only residential EMSs consider SP. Beraldi et al. [1] present an SP problem for an EMS equipped with an ESS and PV, while Esmaeel Nezhad et al. [33] propose a stochastic MILP for self-scheduling home applications, and Javadi et al. [26] apply an SP to minimize electricity costs in a self-scheduling smart home. The models are solved using MATLAB and GAMS, and the time resolution is 1 h [1].
- **Fuzzy programming** is based upon fuzzy logic [17], which has the main advantage of computational efficiency and simplicity [48]. In the literature reviewed, only residential EMSs use fuzzy programming. Hernández et al. [45] implement a fuzzy EMS for a school in Turkey to increase energy efficiency. Kontogiannis et al. [48] present a fuzzy controller following the forward chaining Mamdani approach and use decision tree linearization for rule generation. Qurat-ul et al. [34] propose a fuzzy inference system that maintains the user's thermal comfort, and Youssef et al. [56] ensure minimal expenditure and maximal profit for the microgrid based on a fuzzy logic controller. The Software tool to model and solve the optimization problems is MATLAB [34,48], and the time resolution is 10 min [48].

Metaheuristic optimization is suitable for problems where it is easy to find one suboptimal solution but difficult to find a global solution [10]. Table 7 shows various nature-inspired optimization techniques in both *industrial* and *residential* EMSs. In addition, some publications in the literature on residential EMSs combine different techniques to create hybrid metaheuristics. Ali et al. [43] propose a hybrid algorithm to increase efficiency and convergence speed by combining the flower pollination algorithm with MILP. Iqbal et al. [55] present three hybrid algorithms to reduce electricity costs and the peak-to-average ratio of an EMS. First, they combine the genetic algorithm, inspired by the genes of living organisms [55], and the wind-driven optimization algorithm, which works based on the atmospheric motion of air parcels [55]. Secondly, they combine wind-driven optimization with the grey wolf optimization technique, representing grey wolves' hunting mechanism and leadership hierarchy [55]. Thirdly, they combine the binary particle swarm optimization with the wind-driven optimization. Particle swarm optimization is based on a group of birds searching for food [38], and binary particle swarm optimization is a discrete variation [36]. The various nature-inspired metaheuristics impede the selection of an appropriate metaheuristic. While some authors compare the performance of selected nature-inspired optimization techniques [38,40,43,55,70], the high variability of the best-performing algorithms indicates that the performance is dependent on the underlying data and cannot be generalized to other data sets. All nature-inspired metaheuristics are modeled in MATLAB, while the time resolution differs between 15 min [54], 30 min [32], and 1 h [55].

RL is based on an intelligent agent that iteratively learns how to best act in a dynamic environment while performing a given task. An agent aims to maximize rewards or their expected values [10]. In *residential EMSs*, Lissa et al. [29] propose an RL algorithm for indoor and domestic hot water temperature control, and Ul Haq et al. [39] present an RL algorithm for monitoring household electric appliances to lower energy consumption. In *industrial EMSs*, Dreher et al. [61] present an RL-based EMS for CO_2-neutral hydrogen production. All the RL models are simulated via MATLAB and are validated by different use cases with a time resolution of 30 min [29].

Table 7. Metaheuristic optimization techniques for energy management systems.

Algorithm	Ref. Residential	Ref. Industrial
Metaheuristic optimization algorithm		
Genetic algorithm	[38,40,55]	[63,69]
Firefly algorithm	[40]	[70]
Moth-flame optimization	[40]	[70]
Cuckoo search algorithm	[40]	[70]
Ant colony optimization	[40]	[70]
Grasshopper optimization algorithm	[43]	[70]
(Binary) Particle swarm optimization	[2,32,36,38,55]	
Simulated annealing	[43]	
BAT algorithm	[43]	
(Two-cored) Flower pollination algorithm	[43]	
Slap swarm algorithm	[43]	
Polar bear algorithm	[43]	
Coyote optimization algorithm	[43]	
Grey wolf optimization	[55]	
Wind-driven optimization	[55]	
Sine cosine algorithm	[38]	
Whale optimization algorithm	[38]	
Hybrid nature-inspired optimization techniques		
MFPA-MILP	[43]	
WDGA	[55]	
WDGWO	[55]	
WBPSO	[55]	
TG-MFO	[40]	

Game theory approaches are usually employed within a multi-agent framework, where each agent chooses a strategy to maximize an individual utility function [10]. This approach is only used for *industrial EMS* by Lu et al. [67], who propose an industrial manufacturing system initially formulated as a partially-observable Markov game. Then, a multi-agent deep deterministic policy gradient algorithm is adopted to obtain the optimal schedule for different machines.

4. Challenges, Trends, and Future Research Directions

Building on the literature review, in this chapter, we identify trends and future research directions for residential and industrial EMSs. It is worth mentioning that our results depend on the literature analyzed. Thus, selecting different databases could lead to complementary results and future research directions.

Design of the energy management system infrastructure:

- **A trend towards aggregated and coordinated EMSs**: The increased demand for flexibility leads to aggregating residential and industrial EMSs. Therefore, future work should focus on: (i) proposing standardized interfaces and communication architectures to aggregate EMSs within and between the residential and industrial domains [18]. (ii) Introducing load classifications for the industrial domain, including industrial dependencies in time, materials, and workflows. (iii) Addressing standardized communication of flexibility potentials between different local EMSs to coordinate demand and supply flexibility over geographically distributed spaces with heterogeneous applications [11]. (iv) Proposing new business models and interoperable interfaces to offer aggregated flexibility to the utility [57]. (v) Considering multi-energy EMSs and sector coupling, including heat flows, industrial hydrogen production, and large-scale integration of EVs with V2G capabilities [65]. (vi) Addressing industrial participation in DR by further nudging user behavior and integrating human interaction factors.
- **A trend towards resilience, security, and advanced metering**: The need for secure and resilient EMSs increases with the rising system's complexity and interdependency. Future work should focus on: (i) increasing local resilience of industrial sites, private households, and neighborhood solutions in terms of black start and off-grid capabili-

ties [10]. (ii) Proposing architecture requirements and frameworks for a data secure aggregation of the bidirectional charging processes and load profiles [14]. (ii) Investigating industrial communication protocols and standards. (iii) Comparing different sensors and meters based on security, data privacy, accuracy, and costs. (iv) Proposing new business models for smart meters.

Data-driven analysis and monitoring:

- **A trend towards improved data quality**: With the increasing data volume of EMSs, the importance of data quality is rising. Therefore, future work can focus on: (i) Publishing residential and industrial datasets that are openly available, in high resolution, and over a multi-year horizon to compare seasonal effects [9]. (ii) Proposing frameworks to publish high-resolution industrial datasets without violating security standards. (iii) Introducing benchmark datasets for specific applications, such as load profiles, PV generation, or EV charging, to compare different algorithms and the influence of data quality [9].
- **A trend towards automated and adaptive algorithms**: Data supporting techniques, such as feature selection, extraction, clustering, and the automation and adoption of algorithmic optimization, are increasingly important. Therefore, future work can focus on: (i) proposing a methodology for robust and real-time semantic feature selection [7]. (ii) Automating data preprocessing, feature generation approaches extraction techniques and hyper-parameter tuning [9]. (iii) Improving forecasting algorithms by deep learning and hybridization techniques. (iv) Analyzing unsupervised learning approaches for temporal energy pattern characterization [7]. (v) Automating the integration of domain and expert knowledge into the optimization process. (vi) Addressing modular and automated setup processes for RL and multi-agent systems [7]. (vii) Reviewing working NILM use cases to decrease the sensor's installation costs and time. (viii) Analyzing automated cyber-attack and error detection.

Decision making:

- **A trend toward multi-objective optimization**: While various objectives exist for energy systems, future research should focus on: (i) finding frameworks to balance the objective functions correctly and automatically. (ii) Improving robust multi-objective optimization [8]. (iii) Analyzing further objectives such as frequency, voltage stability, and total harmonic distortion [17].
- **A trend towards transferrable, robust, and scalable optimization**: Regarding the scheduling algorithms, future work should focus on: (i) RL, considering data efficiency, safety, generalization, and robust adaptability [15]. (ii) Cooperative learning, robust coordination, federated RL, and self-learning artificial intelligence techniques to replace user involvement [8]. (iii) Benchmarking different optimization techniques for specific use cases to evaluate the performance, robustness, and generalizability. This is especially important as nature-inspired optimization techniques, and hybrid algorithms are often only applied to one use case [43]. (iv) Including game theory in EMSs. (v) Implementing the EMS, as many publications only simulate the decision-making process and optimization. (vii) Stochastic and fuzzy optimization for industrial EMS. (viii) Analyzing the effect of physics-informed learning algorithms.

5. Conclusions

This systematic literature review comprehensively reviews the state-of-the-art research on residential and industrial EMSs to identify trends, challenges, and future research directions. First, we analyzed the design of the EMS infrastructure, differentiating between flexible and non-flexible energy demand, incentive-based, and pricing-based DR programs. Further, considering smart meters, sensors, and wired and wireless communication, we briefly addressed PV, WTs, and heat pumps as essential RESs, different ESSs, and AMI. Building upon the EMS's infrastructure, we reviewed the literature on data-driven monitoring, considered historical and real-time data for various applications, and presented data preprocessing techniques. Next, we focused on data-driven analysis, including advanced forecasting and classification techniques.

Regarding the decision-making process, we differentiated between economic, technical, environmental, and social objectives and considered single- and multi-objective optimization. Further, we grouped the optimization techniques into rule-based optimization, mathematical optimization, metaheuristic optimization, RL, and game-theory-based optimization. Finally, we presented several trends and future research directions.

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