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REVIEW

Review of energy management systems and optimization methods for hydrogen-based hybrid building microgrids

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Abstract

Renewable energy-based microgrids (MGs) strongly depend on the implementation of energy storage technologies to optimize their functionality. Traditionally, electrochemical batteries have been the predominant means of energy storage. However, technological advancements have led to the recognition of hydrogen as a promising solution to address the long-term energy requirements of microgrid systems. This study conducted a comprehensive literature review aimed at analysing and synthesizing the principal optimization and control methodologies employed in hydrogen-based microgrids within the context of building microgrid infrastructures. A comparative assessment was conducted to evaluate the merits and disadvantages of the different approaches. The optimization techniques for energy management are categorized based on their predictability, deployment feasibility, and computational complexity. In addition, the proposed ranking system facilitates an understanding of its suitability for diverse applications. This review encompasses deterministic, stochastic, and cutting-edge methodologies, such as machine learning-based approaches, and compares and discusses their respective merits. The key outcome of this research is the classification of various energy management strategy methodologies for hydrogen-based MG, along with a mechanism to identify which methodologies will be suitable under what conditions. Finally, a detailed examination of the advantages and disadvantages of various strategies for controlling and optimizing hybrid microgrid systems with an emphasis on hydrogen utilization is provided.

KEYWORDS

building microgrids, energy management systems, energy storage, hydrogen storage, optimization methods, reinforcement learning, renewable energy

1 | INTRODUCTION

Based on the ever-increasing demand for energy in modern civilization, new solutions are being developed to meet growing energy consumption and decrease dependence on fossil fuels. The decentralization of power production and distribution has been a key aspect of this approach. One example of this decentralization is the development of building microgrids (BMGs) instead of large monolithic power stations. Recent advancements in MGs and the focus on renewable energy have led to greater penetration of renewable energy technologies in energy systems. However, MGs often rely on intermittent renewable energy sources (RES), whose availability is typically non-deterministic, posing a significant challenge for their large-scale deployment. To ensure MGs integrate seamlessly into existing networks and maintain high reliability, it is essential to develop robust control mechanisms and effective energy management systems. For example, typical building-integrated MGs use solar energy as the primary source of renewable energy (RE).

However, energy production and demand exhibit seasonal disparities, with abundant solar energy during summer and heightened demand during winter when solar availability diminishes. Consequently, it is imperative to efficiently regulate energy production and consumption within MGs. The emerging concept of BMGs is gaining traction, facilitating localized energy production from RES which closely aligns with consumption patterns. This proximity mitigates the losses incurred during energy transmission. When it comes to energy consumption, buildings represent a substantial portion of contemporary energy demand. Buildings represent 40% of energy demand and 36% of CO_2 emissions in Europe [1]. As shown in these figures, heating constitutes a significant portion of the energy demand of BMGs. According to the European Commission, heated buildings constitute 6% of the total energy consumption [1].

Consequently, renewable energy is a fundamental element of BMGs and constitutes a core component of their operational frameworks. Moreover, energy storage systems play a crucial role in guaranteeing uninterrupted energy availability, particularly during intervals characterized by a disparity between energy production and demand. Electrochemical batteries are among the most common energy-storage media. Batteries are an effective solution for energy storage; however, they have several critical limitations. Notably, batteries undergo rapid aging when subjected to deep discharge cycles, leading to a reduced lifespan and limiting their ability to utilize at full potential [2]. In addition, batteries experience capacity degradation over time, with each charge and discharge cycle progressively diminishing the storage capacity.

Lithium-ion batteries (LIBs), one of the most widely used energy storage technologies, are manufactured using rare earth metals. The extraction of these metals involves extensive mining operations that have significant adverse socioeconomic and environmental impacts [3]. Moreover, the scalability of lithium-ion batteries is hindered by the limited availability of these materials. Another limitation is the phenomenon of self-discharge, wherein batteries lose charge even when not in use [4]. This renders them unsuitable for long-term energy storage applications. These challenges highlight the need for continued research and development to explore alternative energy-storage solutions.

Consequently, based on the aforementioned characteristics of conventional storage technologies, hydrogen (H_2) offers a unique alternative for energy storage in distributed MGs [5]. To store excess energy in the form of gaseous hydrogen, a process called electrolysis [6] is used, which involves passing electricity through water using electrodes to break down water molecules and capture released H_2 molecules. Hydrogen can then be used to produce energy when required. Energy storage using hydrogen offers advantages over battery-based storage. The main advantage of this method is that hydrogen can be compressed to higher pressures, thereby increasing the storage density. Another advantage of hydrogen-based storage systems is that they do not suffer from capacity loss over time, similar to electrochemical batteries [7]. Thus, the energy stored in hydrogen can be retrieved later without a significant loss of capacity [8]. However, hydrogen-based energy storage systems exhibit slower response times than batteries [9]. Therefore, using a combination of these storage methods requires the development of optimal control and energy-management strategies for BMG. This paper presents a review of energy management strategies used in residential BMGs based on hybrid storage technologies.

Numerous studies have been conducted to classify and characterize [5] the utilization of energy management systems (EMS) in BMGs. However, research that specifically addresses hydrogen-based BMGs is limited. The primary barrier to the widespread adoption of hydrogen in BMGs is the inefficiency of the hydrogen lifecycle, which includes production, storage, and reconversion. This inefficiency affects the overall energy efficiency and economic viability of hydrogen-based systems in BMGs, highlighting a critical area for further research and technological advancement. A report issued by the US Department of Energy indicated that most fuel cell technologies achieve efficiencies in the range of 40%–60% [10]. However, when evaluating the overall efficiency across the entire hydrogen lifecycle, including production, storage, and reconversion, the figures decrease significantly. Despite this, the utilization of surplus solar energy during the summer months presents an opportunity to leverage seasonal storage within BMGs. This approach can help mitigate the efficiency losses associated with hydrogen storage and reconversion, thereby optimizing energy management in BMGs during periods of high solar irradiance.

Accordingly, existing studies have focused on either rule-based or classical optimization techniques [9]. Over time, the optimization and control methodologies for BMGs have undergone significant evolution. The integration of hydrogen-based storage has increased the complexity of the required control strategies [10]. The domain of EMSs for such BMGs is dynamically evolving and lacks a definitive consensus on the most effective energy management and optimization approach [11]. However, recent research trends indicate convergence towards feedback-based methodologies, which will be further described and justified in the following sections of this manuscript, such as reinforcement learning (RL) [12, 13] and model predictive control (MPC) [14], particularly in scenarios with ample computational resources. Conversely, deterministic methods exhibit superior performance in resource-constrained environments because of their lower computational demands [15]. As discussed here, classical machine learning techniques offer enhanced predictive capabilities by retaining the historical context from training datasets [16], thus outperforming deterministic optimization methods in certain specialized BMG scenarios. Additionally, RL and MPC-based algorithms demonstrate greater robustness against external disturbances owing to their inherent adaptability [17].

Consequently, this paper focuses on presenting the latest state-of-the-art methods for EMSs, particularly for hydrogen-based hybrid MGs.

- Section 2 presents the objectives of this study and challenges in the energy management of hydrogen-based BMGs.
- Section 3 defines the methodology used to classify and categorize EMS strategies.
- Section 4 discusses various energy-management techniques and their strengths and weaknesses in the context of BMGs.
- Section 5 presents the major findings from the review of existing technologies.
- Section 6 concludes the review paper.

2 | OBJECTIVES AND CHALLENGES FOR ENERGY MANAGEMENT

Hydrogen-based hybrid microgrids differ from conventional BMGs in several ways primarily because of the introduction of hydrogen production, storage, and conversion methods. These differences affect the design, operation, environmental footprint, and economic considerations. The storage mechanism is the primary factor that distinguishes hydrogen-based BMGs from conventional BMGs. Excess renewable energy from sources, such as solar and wind energy, is used to produce hydrogen through electrolysis. The energy storage duration in such systems is on a longer timescale, which can last up to several months. Another factor that distinguishes hydrogen-based BMGs is their environmental impact. When using renewable energy for hydrogen production, these BMGs essentially produce zero emissions because the only by-product of hydrogen fuel cells is water. By contrast, depending on the energy mix, conventional BMGs may produce greenhouse gas emissions, especially if fossil fuels are part of the energy supply.

Therefore, hydrogen-based BMGs are considered sustainable. They offer a more sustainable solution by integrating renewable energy sources and creating clean energy cycles. However, conventional BMGs have a larger environmental footprint if they rely on fossil fuels or non-sustainable practices. Hydrogen-based BMGs are costly to build because they require many more components to store the excess energy. They incur high initial capital costs owing to the addition of electrolysers, compressors, storage units, and fuel cells. In addition, the maintenance of these equipments incurs additional costs. Because hydrogen is a highly flammable substance, it is subject to various regulatory requirements, which also increase the cost of such BMGs.

2.1 | Challenges of energy management for hydrogen-based BMGs

Hydrogen-based BMGs contain a multitude of components that are capable of generating, storing, and reconverting energy stored in hydrogen. For such a complex BMG, energy management becomes challenging. Because hydrogen is only produced via excess renewable energy sources such as solar and wind, the operation of electrolysers can be highly challenging owing to the intermittent nature of these resources. These sources are dependent on weather conditions that are difficult to predict; thus, the operation of these devices, particularly electrolysers, requires an approach to match renewable availability, which can be a significant challenge. The lifetime of electrolysers is highly affected by the number of start and stop operations [18], thus it is imperative that an energy management system optimizes the operation of electrolysers in such a way as to achieve a trade-off between the production of hydrogen and the lifetime of the equipment. Similarly, the performances and lifetimes of fuel cells are severely affected by the number of start and stop operations [19]. A well-optimized EMS must ensure that fuel cells operate in a manner that ensures maximum renewable energy consumption while balancing the life of the fuel cell. This becomes extremely complex when there are short bursts of high energy demand during peak periods, for example, on winter mornings when there is a significant energy demand but not much solar availability.

TABLE 1 Control layers in a hybrid BMG.

Level	Timescale	Equipment
Primary level	Order or micro and milliseconds	Hard real-time embedded systems based on RTOS (microcontroller-based)
Secondary level	Order of seconds	Soft real-time systems (PLCs)
Tertiary level	Minutes, hours, and days	General purpose systems (Linux, PLCs etc.)

The heightened complexity arising from the intermittent nature of DERs coupled with the hybridization of energy sources presents novel operational challenges for BMGs. Optimal control is essential for BMGs to achieve enhanced self-consumption and autonomy, thereby minimizing their dependence on the main grid. This review presents a comparative analysis of the diverse optimization and control methodologies utilized in BMGs with a specific focus on hydrogen-based hybrid storage systems. Figure 1 shows a schematic of a typical hybrid hydrogen-based BMG.

In a BMG, various components collaborate to ensure its functionality. Renewable energy sources (RES), typically solar panels and occasionally wind turbines, are employed to supply power to grids. A battery pack serves as a short-term energy reservoir, owing to the intermittent nature of renewable energy. Additionally, an electrolyser is used to generate H_2, which can be employed when required to retrieve energy via a fuel cell. Control mechanisms within most systems rely on a local controller, tasked with maintaining the power balance in the BMG and ensuring continuous energy availability for end users. These controllers are commonly embedded devices engineered to provide real-time responses and often leverage real-time operating systems (RTOS) to satisfy stringent timing constraints. The subsequent sections delve further into the various control levels within the BMG. In the next section, an overview of various control levels in the BMG is presented.

2.2 | Control levels in a building microgrid

The EMS in a BMG acts as a supervisor and control system and performs several important tasks. These include monitoring, data and energy analytics, energy optimization, control, and system safety. Performing these tasks requires the EMS to be robust and flexible. The MG control can be divided into three levels that act on different time scales, as shown in Figure 2.

As listed in Table 1, the three control levels work on three different timescales. The fastest control response occurs on the millisecond and microsecond time scales and is used for frequency control and power sharing among devices in the BMG.

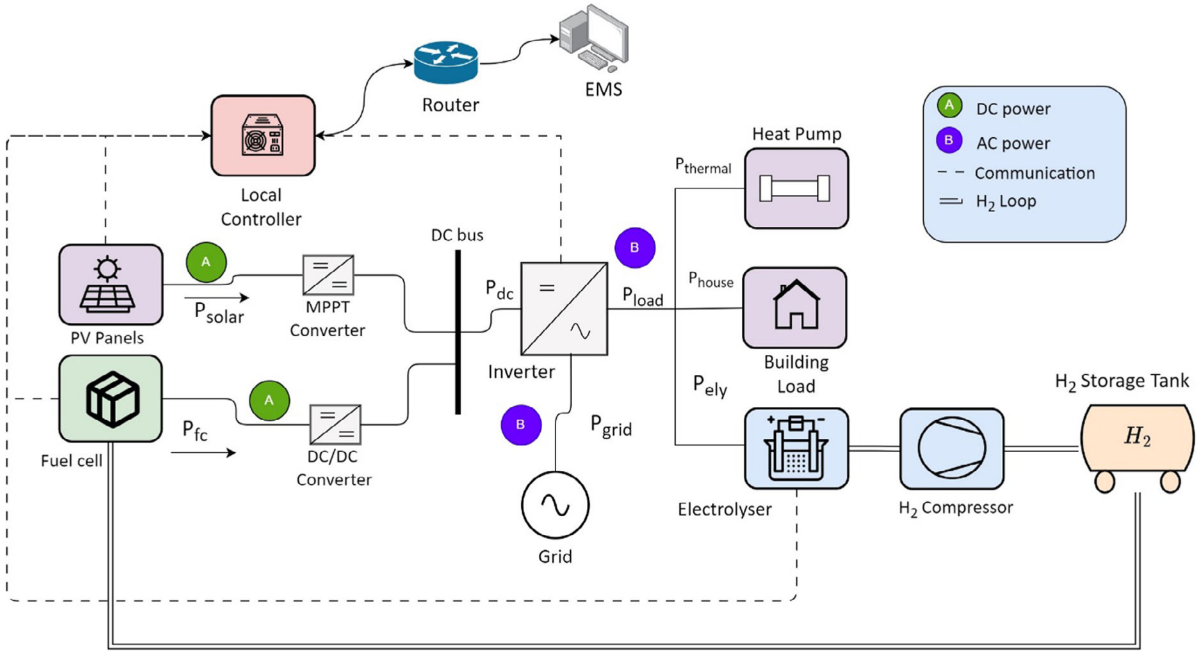

FIGURE 1 Overview of a hybrid hydrogen-based building microgrid (BMG).

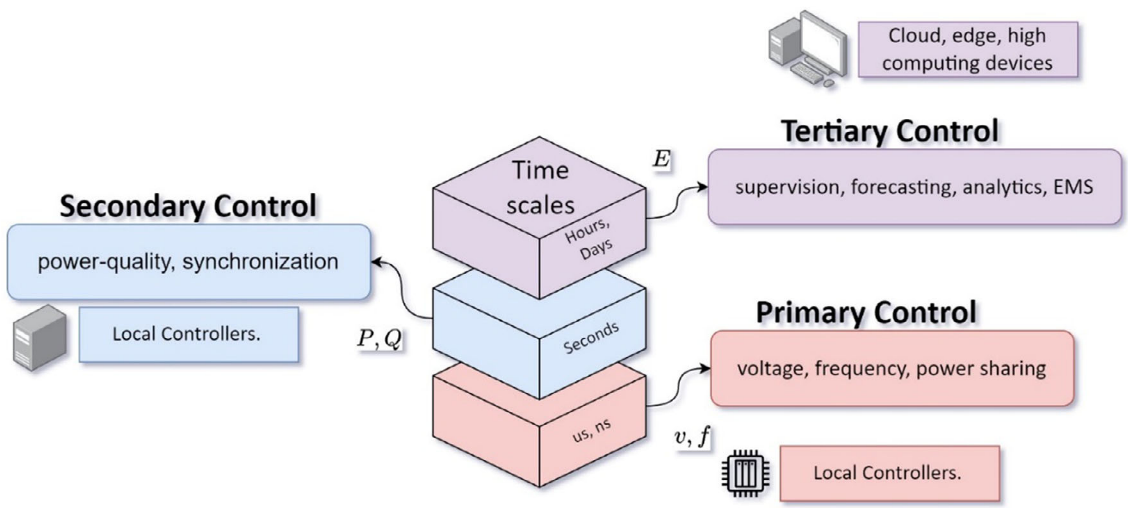

FIGURE 2 Microgrid control levels.

In addition [20], investigated voltage sags in power systems and proposed integrating hydrogen fuel cells with a D-STATCOM to mitigate these fluctuations and enhance power quality. Using simulations and a Type-3 Fuzzy system, this study demonstrates that the proposed approach, validated using MATLAB, outperforms conventional PI and ANFIS controllers in terms of reliability and effectiveness. A real-time energy management strategy for a smart home was proposed in [21], which contained an electric vehicle (EV) and hydrogen production system to achieve flexible demand-side control.

The key objective of this study is to focus on optimization and energy management techniques that work over longer time scales; therefore, only tertiary-level control and optimization methods will be discussed in this case. In the next section, the main functions of an EMS are discussed.

2.3 | Key functions of the EMS

EMSs are designed to perform a variety of tasks, depending on the systems with which they are integrated. The majority of EMS functionalities can be divided into five main categories: monitoring, analysis, forecasting, system optimization, and real-time control (Figure 3). As the name indicates,

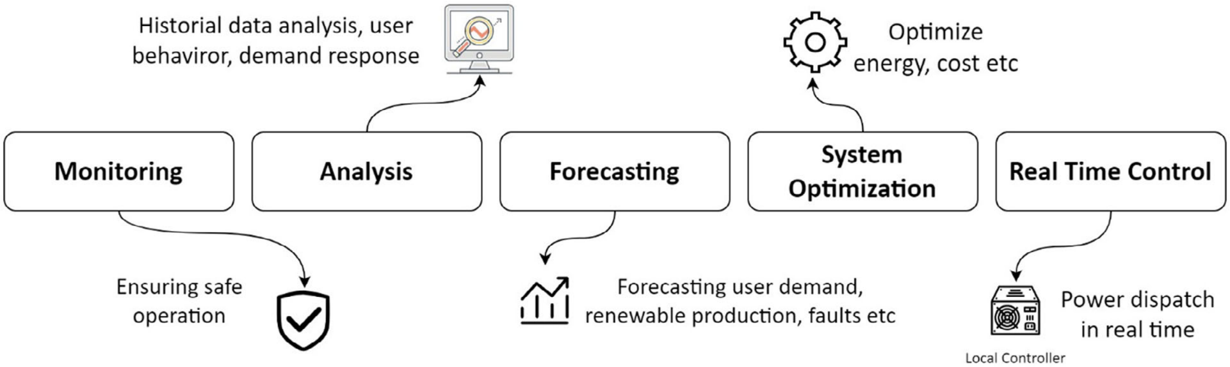

FIGURE 3 Overview of different EMS functionalities and controls.

real-time control allows BMGs to be controlled in real-time through power balance and power-sharing mechanisms. The EMS can determine the manner in which power can be shared among the different components of the BMG. The core functionality of an EMS within a BMG encompasses operational optimization, enabling the BMG to function in an optimized manner. This optimization entails strategies to minimize the operational and maintenance costs and enhance the equipment lifecycle, among other factors. Various optimization methodologies are elaborated subsequently. Furthermore, the forecasting capabilities of the EMS enable the anticipation of future system states, facilitating predictive analysis and necessary control actions. Accordingly, the forecasting function can focus on either the BMG load demand or the future RES production [22]. EMSs are also capable of analysing user behaviours in the BMG as well. In [6], a community-based analysis of energy management in a BMG. A novel power dispatch methodology is proposed to yield minimum energy cost and integrate hydrogen for energy storage. In [23], bi-objective optimization was performed using dynamic programming for energy optimization in a hydrogen-based BMG. The results for two typical cases indicate the proposed strategy can improve photovoltaic utilization by 0.95% and fuel economy by nearly 50%. Moreover, the work presented in [24] proposed a dual model predictive control and hybrid programming approach to realize the economic operation of a BMG. Based on the ultrashort-term forecast, the renewable power output and load demand were predicted to optimize the economic operation of the system. The results showed the operating cost of the BMG was reduced by 22.7% when the prediction horizon was increased to 90 min from 60 min.

In addition to real-time control, an EMS plays a pivotal role in optimizing the long-term operational aspects of an MG. For instance, in [25], a methodology employing online learning-enabled hierarchical distributionally robust model predictive control (OL-DRMPC) with day-ahead scheduling was proposed to enhance the power dispatch efficiency within the BMG. Precise forecasting of renewable energy is of paramount importance for ensuring the optimal operation and energy management of renewable energy source (RES) MGs. The research performed in [26] focused on the implementation of stochastic model predictive control of a hybrid BMG. The proposed strategy extends the lifecycle of batteries and hydrogen devices. Managing hydrogen storage in hybrid MG is a newly researched topic in BMGs. Both data-driven and model-based approaches have been used to optimize hydrogen storage. In [27] a unique control method using a data-driven modelling approach was proposed to achieve frequency regulation in an MG.

2.4 | Objectives and comparison with existing research

Recent studies have compared the energy management strategies for hydrogen-based BMGs. The work presented in [28] summarizes the multiple energy management systems used for BMGs. This study focuses on different optimization methods used for energy management in BMGs. However, the research in this study did not consider the impact of energy optimization on BMGs. Similarly, the researchers in [29] presented a review of EMS for residential BMGs, but their scope of work was limited to hierarchical-based hybrid BMGs. Numerous works have focused on summarizing the energy management strategies utilized for conventional BMGs. One such study [30] examined forecasting methods, control methods, uncertainties, and tariffs; however, it did not consider the aspects of hydrogen storage or BMGs. The work done in [31] also focused on conventional BMGs, with a focus on artificial intelligence (AI) and machine learning-based management strategies. Similarly [32], presented a state-of-the-art energy-management system for conventional BMG. A systematic review of various energy management strategies, optimization scheduling frameworks, and multi-BMG voltage and frequency control strategies was presented; however, they only focused on battery-based storage systems and did not consider hybrid storage mechanisms. The work published in [33] discusses energy management and control strategies for hydrogen-based systems; however, it focuses only on electrical vehicle usage rather than in the context of a BMG. The research in [34] also aims to present a summary of EMS for energy usage optimization in MGs. A unique aspect of this study is that it discusses MGs in residential, commercial, and industrial buildings. The literature suggests that integrating fuel cells (FCs) with renewable and storage systems can justify their high investment costs by lowering the levelized cost of energy (LCOE), reducing the loss of power supply probability (LPSP), shortening the payback period, and increasing the renewable energy fraction, particularly for remote or combined loads. Reported LCOE ranged from \$0.0462 to \$1.0864 per kWh, LPSP from 0% to 20%, payback periods averaged over six years, and renewable fractions ranged from 26.77% to 100%, depending on the case study.

The objective of this study was to provide a comprehensive analysis and comparison of various energy management strategies and methodologies used in the context of BMGs. A detailed review of the existing methodologies was performed to compare their predictive capabilities and computational complexities. Finally, a ranking criterion was determined to establish the applicability of the different methodologies to different microgrid scenarios.

3 | METHODOLOGY FOR EMS CLASSIFICATION

The development of EMSs has evolved over the past few years. The need to develop an efficient EMS is continuously evolving from the simplest rule-based EMS to complex multi-agent management systems, the need for developing efficient EMS is continuously evolving. As the current state-of-the-art approaches focus on hydrogen-based building MG, the following criteria will be used to perform a comparative analysis:

- Predictive capabilities
- Computational complexity
- Data dependency
- Model dependency
- Multisystem consideration
- Robustness and flexibility

3.1 | Criteria

In the following section, a comparison criterion is discussed, which is used to analyse the different EMS for hydrogen-based systems. Using these criteria, each methodology was analysed to test its suitability. A comparison was made of how different approaches offer different trade-offs for their applicability.

3.1.1 | Predictive capabilities

A primary feature of contemporary energy management systems (EMS) lies in their robust predictive capabilities, encompassing load forecasting, renewable energy availability estimation, and control/optimization parameter prediction. The accelerated integration of artificial intelligence and machine learning techniques in EMS development and control stems from their reduced reliance on complex models and decreased computational burden. Machine learning offers distinct advantages over conventional methods by leveraging historical data to provide highly specific predictions, thereby enhancing accuracy. Additionally, artificial intelligence solutions deliver robust and expedited outcomes, fostering greater flexibility and scalability of EMS, particularly when scaling up to larger MGs.

In terms of predictive capabilities, machine learning and artificial intelligence are best suited for this objective. Many studies have focused on the application of machine learning and its different domains for the predictive control of MGs. The work done In [35], a novel neural network-based genetic optimization method for net-zero-energy buildings was proposed. The optimization resulted in the lowest installation cost, CO_2 production, and loss of power supply probability. In [36], a cloud-based architecture was proposed for supervised machine learning approaches applied to MG clusters for energy management. Using this machine learning-based approach, a faster data-sampling rate was achieved to overcome the limits of network congestion. This leads to significant cost reductions in the BMG of up to 100 USD for grid consumption per week [36, 37] performs an evaluative analysis of the performance of machine learning strategies for the predictive control of hybrid BMGs. It uses machine learning methods are used for the predictive assessment of faults in energy storage.

Load forecasting is another important aspect of energy management in a BMG. Accurate load forecasting is paramount, particularly for BMGs. Recent trends indicate that this topic is gaining considerable attention in the research community because of its impact on MG performance. In [38], the authors discussed proposals for short-term load forecasting based on deep learning models. Electrical features and environmental data were used as inputs to forecast the day-ahead electricity loads. The research conducted in [39] used different machine learning algorithms such as ANN, multi-layer perception, support vector machine, and other tree-based models to predict the heating demand in a household.

Another method used for the optimal and predictive control of a BMG is model predictive control (MPC). MPC has been effectively used for the optimal control of MGs in various scenarios. The work in [40] focused on the resilience-oriented control of a BMG based on a stochastic model predictive controller. The work done in [41] proposes a novel two-level hierarchical model predictive controller. The two-level data-driven design of this controller improves the accuracy of energy storage. This study also focused on integrating hydrogen-based energy storage. The model proposed a scheduling strategy based on yearly self-consumption and energy storage costs for energy storage devices. In [42], an artificial intelligence-aided model predictive control for a grid-tied hydrogen fuel cell system was proposed. This work combines multiple methodologies to achieve optimal power dispatch in a BMG using MPC, particle swarm optimization (PSO), and genetic algorithms (GA).

Forecasting the energy demand in a BMG is an important aspect of energy management. Accurate predictions can help properly schedule energy strategies and optimize storage systems. Reference [43] proposes a deep learning and forecasting method for renewable energy prediction. Reference [44] proposed a novel deep-learning-based energy management strategy for fuel cells although the research focused only on fuel cells for vehicles. Most of these results are applicable to energy management in BMGs. Artificial and recurrent neural network models have proven to be highly effective in this domain. In [45], the researchers proposed an ANN-based model for load prediction in BMG. Real-time load forecasting has a significant impact on the performance of BMG and is being developed using data available at edge points. Deep-learning models have been used to predict and forecast hydrogen production based on renewable energy. One such study in [46], presents an overview of deep learning and neural network-based schemes for predicting hydrogen production. This paper presents a summary of numerous deep-learning-focused EMS for hydrogen storage.

Determining the amount of renewable energy available is a core aspect of MG energy management. This feature is even more important in hydrogen-based hybrid MGs because hydrogen production is directly related to excess renewable energy production. Researchers in [47] proposed a network-pruning technique based on feedforward neural networks to forecast renewable energy availability. Reference [48] presents a review of artificial intelligence-based methods used in hydrogen-battery-based systems. This review explored the transformative potential of artificial intelligence (AI) in the hydrogen and battery technology sectors. It emphasizes how AI techniques, such as artificial neural networks, machine learning, support vector regression, and fuzzy logic models, enhance hydrogen energy production, storage, and transportation. The role of AI in smart battery technology has been highlighted, particularly in material discovery, battery design, manufacturing, diagnostics, and management systems. This review underscores the significant impact of AI on optimizing these technologies, with implications for their applications in modern robotics, electric vehicles, aerospace, and other fields.

3.1.2 | Computational complexity

The computational complexity of the control of a BMG is an important aspect of EMS design. This depends on multiple factors, including the existing infrastructure, choice of algorithms, and features of the EMS. Computational complexity plays a key role in the design and selection of an MG EMS. Ideally, the aim is to design an EMS with lower computational requirements, while achieving the highest level of optimization and flexibility. However, these criteria usually work in opposite directions. A higher-complexity system tends to yield better optimization results. Deterministic-based optimizations such as linear programming tend to have low computational complexity; however, their performance is not robust, which restricts their use in more complicated EMS. On the other hand, advanced techniques, for example, MPC, are more computationally expensive; however, they offer superior performance [41].

Computational complexity is an important criterion for EMS comparison because, in BMGs, it is important to have an energy management strategy that is computationally expensive. Because BMGs typically have low output power, the associated computational power available is also limited. Therefore, the selected strategy must also be computationally low to moderate. In the case of hydrogen-based systems, managing dual-energy storage also requires some level of computational complexity inherent in the BMG thus, balancing the computational complexity with the optimal operation and management of BMG is extremely important.

The higher complexity of EMS means that the computational requirements of EMS hardware are also very high. For instance, for a BMG to use machine learning to achieve energy optimization, the required processing power must be greater than that of a simple rule-based method. First, the data needs to be acquired, and stored in a database, next the data needs to be cleaned and features need to be extracted. Depending on whether the dataset is labelled, either supervised or unsupervised learning can be applied. This requires high computational power for the EMS.

Consequently, the computational complexity of machine learning algorithms is more difficult to understand. This depends heavily on multiple factors, including the choice of the algorithm (supervised or unsupervised). Advanced approaches, such as deep neural networks (DNN) and ANN, depend on various factors, such as the number of layers in a neural network. Research in [49] discusses the computational limits of deep neural networks. This study shows that the computational limits for deep learning will soon be constrained for certain applications and can create bottlenecks for certain applications. Reinforcement learning has also been studied recently because of its several advantages over traditional machine learning and AI-based approaches [50]. It offers a suitable middle ground because of its ability to adapt and improve over each cycle, making it a suitable solution for systems with frequent changes. Many optimization methodologies have an objective function, which is defined as minimizing the production cost of energy. This is performed while considering other constraints, such as voltage and power generation. Cost can be composed of various aspects such as capital costs, installation costs, maintenance costs, cost of production, and sometimes selling costs to the grid (which need to be maximized to obtain a financial advantage). Another important factor in optimization is the objective function related to the reliability of the network. For example, a network should be reliable and provide the required power for its loads. Constraints regarding different energy sources, such as solar energy, fuel cells, and energy storage systems, must be defined for optimal system optimization.

3.1.3 | Data dependency

Data dependency refers to the requirement for data availability for the optimal performance of an EMS. Different models require different data. Techniques such as linear programming (LP) and dynamic programming (DP) require only recent real-time data. However, other approaches that depend heavily on data availability include classical machine learning techniques such as supervised learning. Recently, reinforcement learning has been increasingly used in EMS development. Its advantage is that there is no need for training data. The model learns based

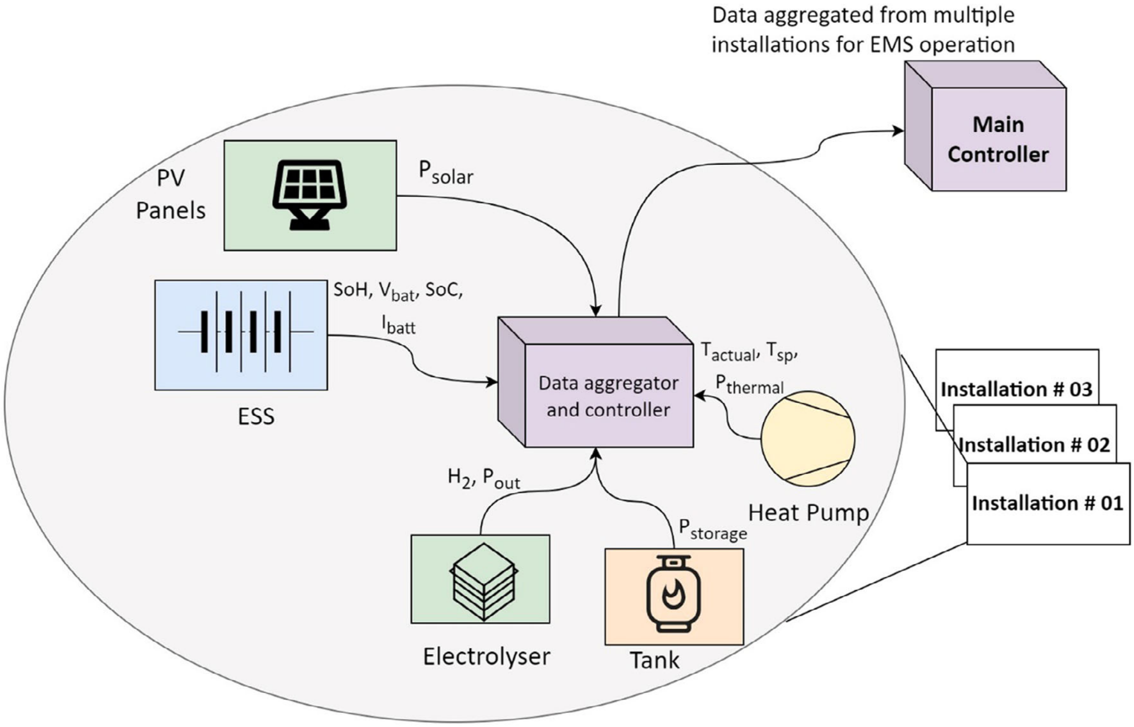

FIGURE 4 Data dependency of distributed EMS.

on an action-and-reward approach in which a correction action is preferred over an incorrect action. Classical machine learning algorithms require large amounts of historical data to function properly. The accuracy of these models is heavily dependent on the availability of correctly labelled data, making them less suitable for systems with lower data availability.

A lot of focus and attention is diverted towards data-based approaches for energy management, both on the residential as well as industrial scale. With the advent of the IoT and Big Data, these technologies have been rapidly adapted for energy management. For example, in [51], a data-based energy management framework was proposed to optimize data usage and energy consumption in the industrial sector.

The accuracy and integrity of the data injected for the internal operation of an EMS are critical for the operation and safety of an MG. Very few studies have been conducted to address this aspect. In [52], a deep long short-term memory (LSTM)-based EMS resilient to data integrity attacks was proposed. It uses decentralized controllers for load forecasting and sets set-points for energy dispatch.

Figure 4 shows how the data from multiple sections of an MG are aggregated and used by a centralized EMS to perform its optimization and control functions for a BMG. In [53], a multistage and multi-time-horizon energy management strategy was proposed for the dual control of a hybrid BMG. In [54], a data-driven energy optimization strategy was proposed. In this study, a multi-energy hub that integrates renewable energy and large-scale storage using hydrogen and ammonia as carriers via the P2 × 2P and B2 × 2P pathways was developed. The results showed that B2 × 2P is more profitable, whereas P2 × 2P offers greater flexibility, with ammonia favouring mass production and storage, and a modified deep Q-network framework proved effective for scheduling optimization.

The availability of data and corresponding data-dependent strategies for energy management are essential for optimized operation and increasing the lifetime of the components used in the BMG. With the availability of historical performance data for hydrogen-based components such as electrolysers and fuel cells, a more accurate representation of the state of health of these components can be established, which can be incorporated into energy management strategies to ensure the longevity of the components.

3.1.4 | Model dependency

EMS development often requires an accurate system model to work properly. The optimization methods used in the EMS can have a very high model dependency, and their outcomes can be skewed if an appropriate model is not used. Different methodologies have different levels of model dependence. For example, classical machine learning techniques are completely independent; however, control techniques such as MPC require an accurate model for the system to run properly. The model-based EMS performed best when the modelled system was accurate. Deviations from environmental conditions or changes in model behaviour can significantly affect the performance of the EMS strategy applied to the MG. In hydrogen-based BMGs, the dependence of EMS strategy on the BMG model can affect the behaviour of BMG. In this case, dynamic modelling, which adjusts the system model by learning feedback, has been proposed to counter this issue. One such example is presented in [55], which presents a multi-energy BMG model to supply both electric- and hydrogen-based loads. This work focuses on the detailed modelling of electrolysers, compressors, and hydrogen vehicles (HV) using conventional models, such as photovoltaic (PV) and battery systems. The development of appropriate BMG models is necessary for the operational design and performance of hybrid BMGs, in [56], a unique model of the BMG is proposed with a state-flow-based energy optimization strategy. The results showed that the energy management strategy provided the following advantages: (1) the power supply and demand in the BMG were balanced, (2) the lifespans of the electrolyser and fuel cell were extended, and (3) the state of charge of the battery and the stored level of hydrogen were appropriately ensured. The work in [57] addresses the cooperative operation of batteries and hydrogen-based storage systems were addressed in [57]. It considers the cycling impact of both technologies on the economic signals for energy trade.

3.1.5 | Multisystem consideration

The addition of hydrogen-based energy storage systems to small residential buildings is a relatively new concept. The design of EMS has been considered in the past and has only focused on large-scale industrial or commercial applications. In the BMGs, the energy expenditure margin was relatively small. For this reason, it is of paramount importance that energy management be performed while maintaining the overall energy expenditure of buildings. One of the main sources of energy expenditure in buildings is the thermal demand to provide a thermal comfort level for users. Various combined approaches have been used to address this issue. In the work done in [58], a stochastic optimization approach for the multi-objective optimization of combined heating, cooling, and hybrid BMGs was discussed. Optimization was performed using the mixed integer linear programming (MILP) approach. Using an incentive-based demand response, the optimization results in the reduction of system operation costs by 15%. Thermal heat recovery from electrolysers and fuel cells can be utilized to meet the thermal demands of buildings. In [59], a novel EMS with fuel cell heat recovery was proposed to supply the thermal loads of the MG. The study observes a BMG for a university campus where thermal energy is recovered from the operation of the fuel cell and applied to the heat storage system. Reference [60] proposes a unique EMS that aims to recover the excess heat generated by electrolysers and supply it to the BMG. The work done in [61] focused on the implementation of hydrogen-based MGs for residential applications and discussed both the thermal and electrical demands of buildings. Similarly, in [62], a multiobjective optimization strategy was proposed for the combined optimization of an off-grid power and heat system. A two-stage energy management strategy was introduced to optimize power flow and maximize solar energy utilization, minimizing disruptions in power and hot water supply, energy waste, and costs over 20 years using a multi-objective NSGA-II algorithm with MATLAB and TRNSYS. Optimization reveals trade-offs between competing objectives. Dynamic simulations indicate that water tank temperatures fluctuate between 20 and 100°C, with mean values slightly decreasing in later years due to battery degradation.

3.1.6 | Robustness and flexibility

An EMS is designed to handle the fluctuations and variability of numerous variables such as renewable energy, MG faults, and user behaviour. Considering these variables in the operation of an MG is a challenging task and requires the development of control systems that can handle such scenarios. Data-driven robust energy management strategies have been studied for their effectiveness in energy optimization. In [63], a similar data-driven approach was proposed to overcome the challenge of random source-load fluctuations in integrated energy systems (IESs) in the operational scheduling problem of integrated energy production units (IEPUs). In [64], a robust energy management strategy was proposed for hydrogen storage and demand response in an isolated BMG. This study proposes a robust energy management methodology for isolated BMGs using hydrogen storage and demand response initiatives structured as a nested max-min optimization framework. The methodology employs a master-slave scheme and a constraint-and-column generation algorithm, validated through a benchmark BMG, demonstrating that flexible demand reduces costs by 6 % compared with hydrogen storage. Hydrogen has great potential for flexible applications in a microgrid. A strategy for testing the resource and demand flexibility for energy management in an MG was presented in [65]. To cope with the fluctuations in renewable energy sources (RES) and the impact of random charging loads of electric vehicles (EV), reference [66] proposed a hierarchical co-optimal planning framework for flexible energy management of an MG. A novel finding is that hydrogen, as a zero-carbon fuel supplied to hydrogen-fuelled vehicles, provides significant flexibility values comparable to energy storage, as demonstrated by an additional 68.52% reduction in the renewable energy curtailment ratio (RECR) than hydrogen only used for energy storage. Similarly, in [67], a stochastic mechanism for the optimization of MGs was proposed that provides flexible services to system operators (SOs) using uncertainties in the forecast. Consequently, the problem is addressed using stochastic model predictive control and mixed-integer quadratic programming.

3.2 | EMS control methods

As the complexity of MGs has increased, the control methods (Figure 5) used for energy optimization and dispatch control have also become increasingly complex. In practice, there are multiple energy management domains. Computational-modelling-based control methodologies for hybrid MGs have gained momentum in recent years. Multi-agent-based control has been extensively used in MG control applications.

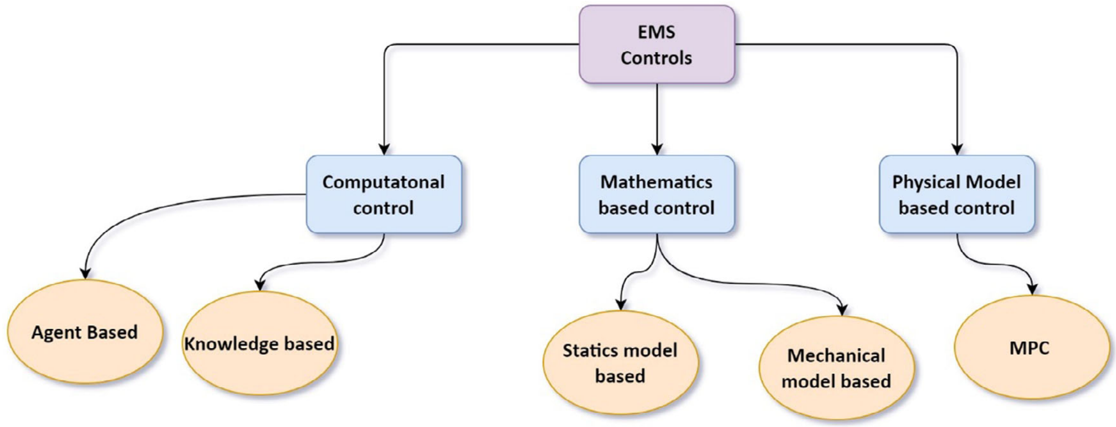

FIGURE 5 Energy management system's control methods.

Accordingly, multi-agent-based control methods have been successfully implemented for hydrogen-based hybrid BMGs. Feedback-based methodologies have been very successful in the robust control of hybrid BMGs; particularly, reinforcement learning has shown good results. In [68], a multi-agent-based deep reinforcement learning-based control methodology was proposed for grid-connected BMGs. Physics-based models have been extensively used for BMG control, particularly for hybrid BMGs. This paper [69] introduces a two-level hierarchical model predictive controller combined with an autonomous observer of hydrogen storage (AOHS) to improve BMG flexibility. Using instantaneous data measurements, AOHS accurately estimated hydrogen levels with an error below 2%, outperforming fixed-parameter models in self-consumption, noise robustness, and energy planning, as demonstrated in simulations based on a developing building BMG case study. The work in [70] proposed a two-stage energy management strategy with demand response and hydrogen storage. It utilizes a modified student-based-psychology-optimization (MSBPO) method to improve issues such as slow convergence, low solution accuracy, lack of diversity, and becoming stuck in local optima.

The computational intricacy of these control methodologies varies considerably. The integration of model predictive control (MPC) with real-time optimization has demonstrated notable effectiveness in ensuring robust control in residential settings. In [71], a hierarchical model for predictive control is presented. This study introduces a novel energy management strategy for a wind-hydrogen MG featuring a wind turbine and hydrogen-based energy storage system (HESS). Utilizing a hierarchical model predictive control (MPC) approach, it optimizes long-term operations through high-level MPC for load forecasting and market participation and manages short-term operations with low-level MPC to handle real-time dynamics. The system's efficacy, modelled with a mixed-logic dynamic (MLD) framework and simulated using wind forecasts and spot prices from an Italian wind farm, demonstrates its potential for integrating wind energy into the grid and optimizing energy supply. Similarly, in [72], a decentralized multi-agent EMS was proposed using fuzzy cognitive maps. Such a system scales well to larger MGs because each MG acts as a single agent for the other distributed BMGs. This methodology is highly flexible because any number of agents can be added to or removed from the system.

4 | EMS CLASSIFICATION

Generally, EMSs can be categorized using multiple methods. Numerous attempts have been made to classify and categorize these energy management systems. However, most of these classification methods focus on conventional MG systems with DERs and battery storage, whereas a deeper classification of BMGs and hydrogen-based MGs has not been extensively studied. There have been some attempts to classify the EMS for example [73], tried to categorize the existing smart energy management systems for homes; however, it did not consider hybrid storage systems incorporating hydrogen storage.

Broadly, EMSs can be categorized into the following three categories:

- Deterministic optimization
- Stochastic and metaheuristic approaches
- Machine learning (ML) and artificial intelligence (AI)

4.1 | Deterministic optimization

By definition, deterministic algorithms are a class of simple optimization algorithms. In this domain, approaches such as linear programming have been used to achieve energy management and optimization in MGs. More recently, mixed integer linear programming (MILP) has been extensively used to develop EMSs for MGs. A dual optimization technique was proposed in [74] that utilizes multi-layer optimization for the self-scheduling of the BMG. Additionally, it contains a hydrogen refuelling station capable of exchanging power with an MG. A combined heat and power unit was also considered to validate the applicability of the proposed model. In [75], a mixed integer linear programming-based scheduling approach for the energy management of an MG was proposed to solve the generational dispatch problem. It transforms transmission dispatch into a

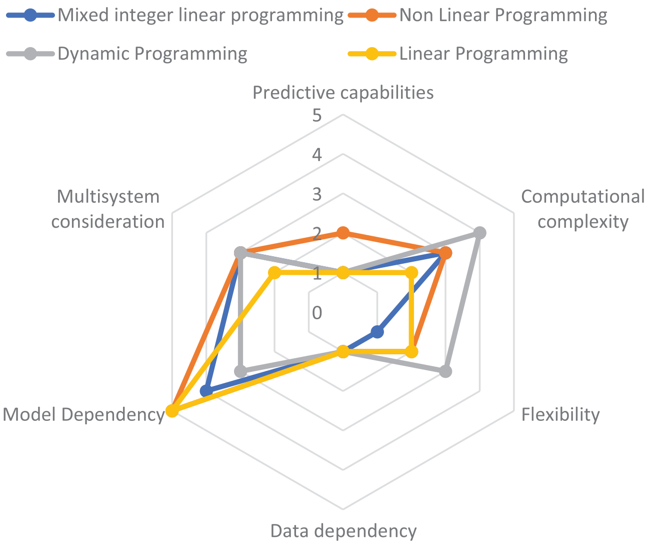

FIGURE 6 Deterministic optimization comparison with regard to a predefined criterion.

quadratic mixed integer linear programming approach. The results show that transmission losses can be reduced using this approach. In [76], a dynamic programming-based energy management strategy was proposed based on an integrated fuel cell and thermal management of integrated buildings. In [77], a unique MILP-based approach was proposed for optimization aimed at minimizing the total life cost and loss probability of the power supply. Similarly, in [27], an MILP-based approach was used for the schedule planning of a hybrid MG. A combination of MILP and MPC was used to optimize the energy storage of the system.

Accordingly, Figure 6. shows how deterministic optimization is compared with the criteria defined earlier. A rating of 0 indicates no capability, whereas 5 indicates the highest capability.

Based on the literature review and existing methods, the comparison results presented in Figure 6 show that linear programming is heavily dependent on the accuracy of the given model, whereas dynamic programming is more computationally expensive. The scale represents values from 1 to 5 with 1 representing the least dependent and 5 representing the most dependent compared to other methods.

4.2 | Stochastic and metaheuristic approaches

A metaheuristic or stochastic approach to an optimization problem is a procedure for obtaining solutions with incomplete knowledge of the system. These algorithms typically rely on a search algorithm. Accordingly, metaheuristic optimization can be classified into the following broad categories:

- Swarm-based optimization
- Biology-inspired optimization algorithms
- Physics-inspired algorithms

These optimization methodologies include either swarm-based optimizations [78], such as particle swarm optimization, or other biology-inspired algorithms, such as genetic algorithms [79]. There are other physics-inspired algorithms such as gravitational search algorithms [80]. Hybrid approaches combining multiple optimization techniques have been reported in the literature. An example of a hybrid genetic particle swarm optimization algorithm for scheduling energy resources is presented in [81]. In addition, in [82], a particle swarm optimization approach was used for advanced asynchronous energy management. The research in [82] focused on the layered architecture between multiple components of an MG and considered very limited data sharing of only the state variable between the supervisor and agents in the system. This leads to flexible control and low computational complexity. A summary of various metaheuristic approaches was presented in [83], although it focused only on conventional BMG without hybrid storage. This study reviews the application of metaheuristic algorithms in MG management, focusing on highly cited articles and typical cases, and demonstrates their advantages over traditional methods in the deployment and operation phases. Metaheuristics have been shown to be superior in MG optimization, which requires an interdisciplinary knowledge of MGs and optimization algorithms. The insights provided will aid future research on the integration of metaheuristic algorithms with MG management.

Additionally, the work done in [84] proposed a stochastic point estimate method (PEM) to capture different uncertainties in a system caused by solar, wind, and other types of energy sources. The optimization was performed using a teacher-learning algorithm (TLA). The results were then compared with PSO and GA, which showed improved algorithm performance. Various studies have focused on the optimal scheduling of energy resources in MG. The study in [85] focused on scheduling using metaheuristic approaches. The authors presented the day-ahead scheduling of energy resources based on genetic algorithm and particle swarm optimization. The results show that a cost reduction of up to 11% is achieved using this method compared to the net power-based algorithm (NPBA).

Accordingly, Figure 7 presents an overview of the stochastic approaches and their suitability for predefined criteria. Again, a rating of 0 refers to no capability, whereas 5 refers to the highest capability.

4.3 | Machine learning (ML) and artificial intelligence (AI)

ML and AI have recently gained popularity in various domains, and renewable energy is no exception. Based on the literature review, ML can be broadly classified into the following categories:

- Supervised learning
- Unsupervised learning
- Deep learning
- Reinforcement learning

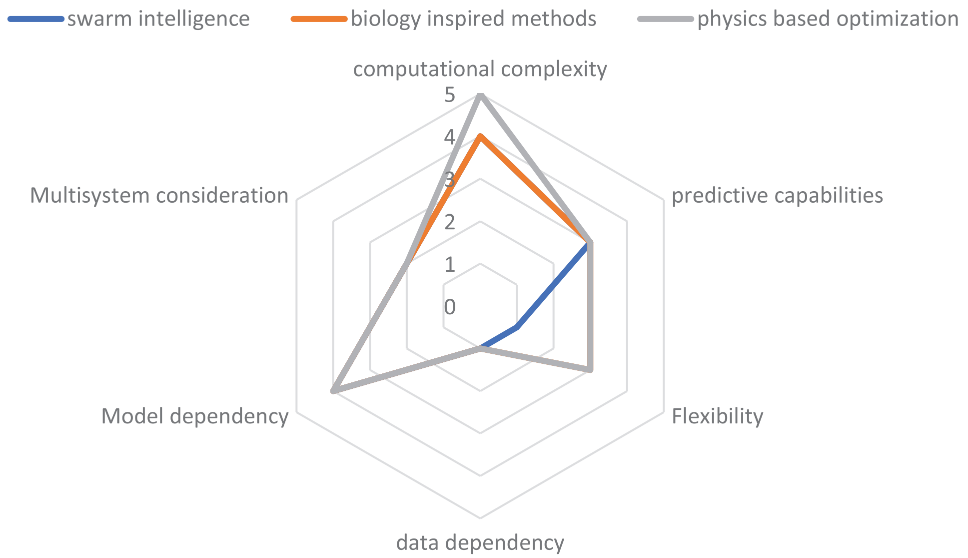

FIGURE 7 Comparison of stochastic and metaheuristic optimization methods with predefined criteria.

4.3.1 | Supervised learning

Supervised learning is a subcategory of machine learning in which a labelled dataset is already available to train the model. This trained model can then predict the outcomes related to an unseen data point using labelled data as the context. These algorithms were relatively simple to implement. In [86], an energy management strategy for a multi-objective EMS was proposed based on random forest (RF) and support vector machine (SVM) algorithms. Supervised learning techniques work relatively well when sufficiently labelled data are available. However, in cases where no data or unlabelled data are present, these techniques are not applicable and tend to rely heavily on the correctness of the dataset and the features represented by the dataset. Machine learning algorithms are particularly effective for forecasting given historical data, and numerous studies have been conducted to summarize the performance of machine learning applications for forecasting energy demand and production for BMG applications. One such study focused on load forecasting in MGs based on machine learning methods [87]. This study discusses various time horizons for prediction, including short-, medium-, and long-term. The work done in [88] focused on the demand-side management of an MG. Demand side management (DSM) is crucial for optimizing loads in smart islanded MGs with batteries and distributed photovoltaics. This study combines the elephant herding optimization algorithm (EHOA) and support vector machine (SVM) to reduce electricity bills, achieving an 11.2% cost reduction compared with current methods. Although supervised learning-based models have been applied in the past to conventional BMGs, the lack of research on hydrogen-based BMGs indicates that owing to the complexity of hybrid MGs, supervised learning may not be the best choice. Supervised learning techniques perform best when carefully crafted label data are present and the data to be predicted conform to the labelled data. If the data to be predicted are sufficiently random and do not conform to the training data, the accuracy of supervised methods decreases rapidly.

4.3.2 | Unsupervised learning

Unsupervised learning is a class of machine learning that identifies patterns and similarities in a dataset without preexisting labels. It typically works on raw data without the need for human involvement to label a dataset properly. The work done in [89] focuses on demand-side management using unsupervised learning techniques for the clustering of demand levels. Unsupervised learning techniques are only applicable for clustering unknown data and thus are not relevant to the main aim of this review. Unsupervised learning is generally not applicable to energy management in MGs for several reasons. First, energy management tasks require specific outcomes or labels, such as cost minimization or load balancing, which unsupervised learning does not utilize because it focuses on identifying patterns within unlabelled data. Second, energy management involves clear goal-oriented tasks that are better addressed by supervised learning or optimization techniques capable of directly targeting these objectives. Additionally, effective energy management requires complex decision-making based on multiple variables and constraints such as energy prices, demand forecasts, and storage capacities. Supervised learning and optimization frameworks can explicitly model these complexities, whereas unsupervised learning lacks the mechanisms to incorporate and act on such constraints. Finally, energy management often relies on precise predictions of future energy production and consumption, tasks that are well-suited to supervised learning models trained on historical data. By contrast, unsupervised learning is not designed for prediction tasks, making it less suitable for accurate energy forecasting.

Thus, the goal-oriented, predictive, and decision-making nature of energy management in BMGs better aligns with supervised learning and optimization techniques.

4.3.3 | Deep learning

At its core, deep learning is a machine learning technique that uses ANN to mimic the structure and function of a human brain. A deep neural network, represented in Figure 7, contains a complex network of nodes called neurons that mimic the functioning of the human brain. Each neuron forms a network with the other nodes using a link that carries a weight. This weight determines the strength of the relationship between the nodes. The output layer provides a prediction based on the relative strengths and weaknesses of the relationships between the nodes. Deep learning, which uses hidden layers to abstract patterns for learning higher-level features, has been effectively used to optimize and control BMGs. In [90], a deep learning-based embedded forecaster and optimizer were developed. Using this approach, the EMS can minimize the power drawn from the grid and improve the system autonomy rate. In [91], a hybrid EMS that considered offline optimization along with a real-time rule-based engine was proposed. Optimization is performed in the receding horizon with load and solar generation forecast profiles using the deep learning-based long short-term memory (LSTM) method in the rolling horizon to reduce daily electricity purchase costs.

In [92], a deep-learning-based EMS was proposed for the combined heating, cooling, and energy management of a BMG. In [93], a deep-learning-based optimization technique was proposed for the joint operation of PV, hydrogen, and wind-based systems. Based on wind energy, photovoltaic energy generation, and load forecast information, the method uses a deep Q network to simulate the energy management strategy set of the hydrogen-electric coupling system and obtains the optimal strategy through reinforcement learning to finally realize the optimal operation of the hydrogen-electric coupling system based on the demand response.

Figure 8 shows the operation of the neural-network-based EMS controller. This type of EMS is typically suited for hierarchical control, in which data are received from multiple local controllers. These controllers aggregate data and send the resulting dataset to a centralized controller. The centralized controller then uses these data as inputs for the computational block of the neural network. This block then computes the required parameters such as the power dispatch for local environments. This is performed using neural paths with weights assigned to each path. Over time, neural networks adjust their learning paths to determine the optimal state of the system.

4.3.4 | Reinforcement learning

In reinforcement learning (RL) the model iteratively learns to adapt. Each positive action provided positive reinforcement for the model. Figure 8 shows the operation of the reinforcement algorithm. In [94], a residential EMS based on reinforcement learning techniques was proposed. It uses a dual-targeting algorithm to simultaneously control energy storage and HVAC systems. In [95], a novel reinforcement learning approach for distributed residential buildings was proposed using an agent-based approach. The agents control the flexibility of the EVs, space heating, and flexible loads. Accordingly, Figure 9 shows the operation of reinforcement learning in hybrid BMGs. The RL agent takes the input from the environment, which in most cases is the BMG (it can be an external factor such as weather), with the objective of reaching the desired state (power balance, cost minimization) takes action. Over a cycle or episode, in RL terms, it measures the response generated by the environment, and based on the rewards (penalties), it can adjust its set points (dispatch power etc.) to optimally run the MG.

In [96], optimal energy management was achieved in real-time based on deep reinforcement learning techniques. The results indicated that using a reinforcement-based approach led to a more stable update rate for the parameters. This also demonstrates that the approach is more suitable for handling uncertainties in the system. For multiple input multiple output (MIMO) systems, Other techniques have been used for the optimization and control of multiple-input multiple-output systems. Model predictive control is one such technique used for the predictive control of MGs. MPC uses a model of the system to predict the system's behaviour. In [97], an MPC was proposed for residential BMG. The objective of this study was to optimize and find suitable configurations for cost-effective solutions. In [98], demand response energy scheduling was presented, which takes advantage of combined Q-learning-based reinforcement and MPC to ensure optimal scheduling.

4.3.5 | Model predictive control

Model predictive control (MPC) is a control technique that offers an operation similar to reinforcement learning. MPC relies on the dynamic models of the system, as shown in Figure 10. It contains a central controller with a predictive model and optimizer. The MPC block applies control inputs to the plant and measures its effects. Based on these effects, the controller behaviour was adopted, and system disturbances were considered. MPC techniques have been extensively used for the operation and control of BMGs. In [99], an MPC-based scheduling methodology was proposed for the seasonal storage of hydrogen. The strategy utilizes data-driven predictions of an industrial power plant's energy production and consumption and optimizes energy flows via a digital twin optimizer. Seasonal operations were facilitated by incorporating storage charge costs into the optimization target function using a hybrid control scheme based on rule-based heuristics to mitigate prediction inaccuracies. Achieving balanced hydrogen production and consumption annually, the strategy meets all energy demands with only a 6% oversizing relative to the optimal system layout. In addition, [41] developed a two-level hierarchical model predictive controller for the optimal scheduling of a BMG with

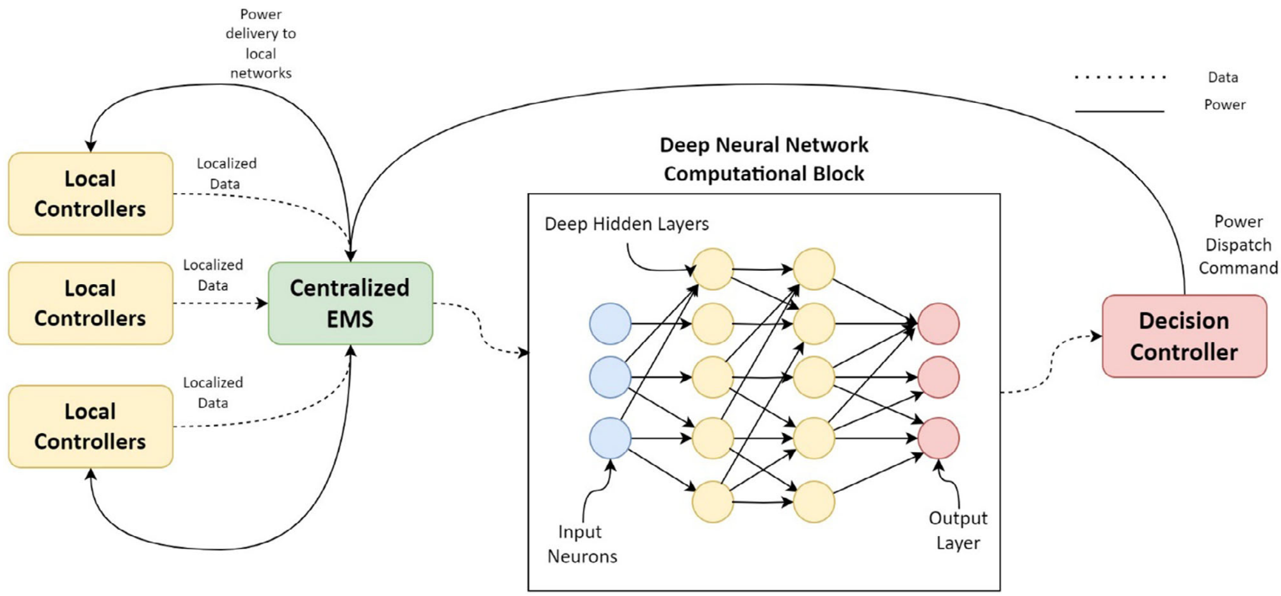

FIGURE 8 Distributed EMS running a deep neural network optimizer for power dispatch.

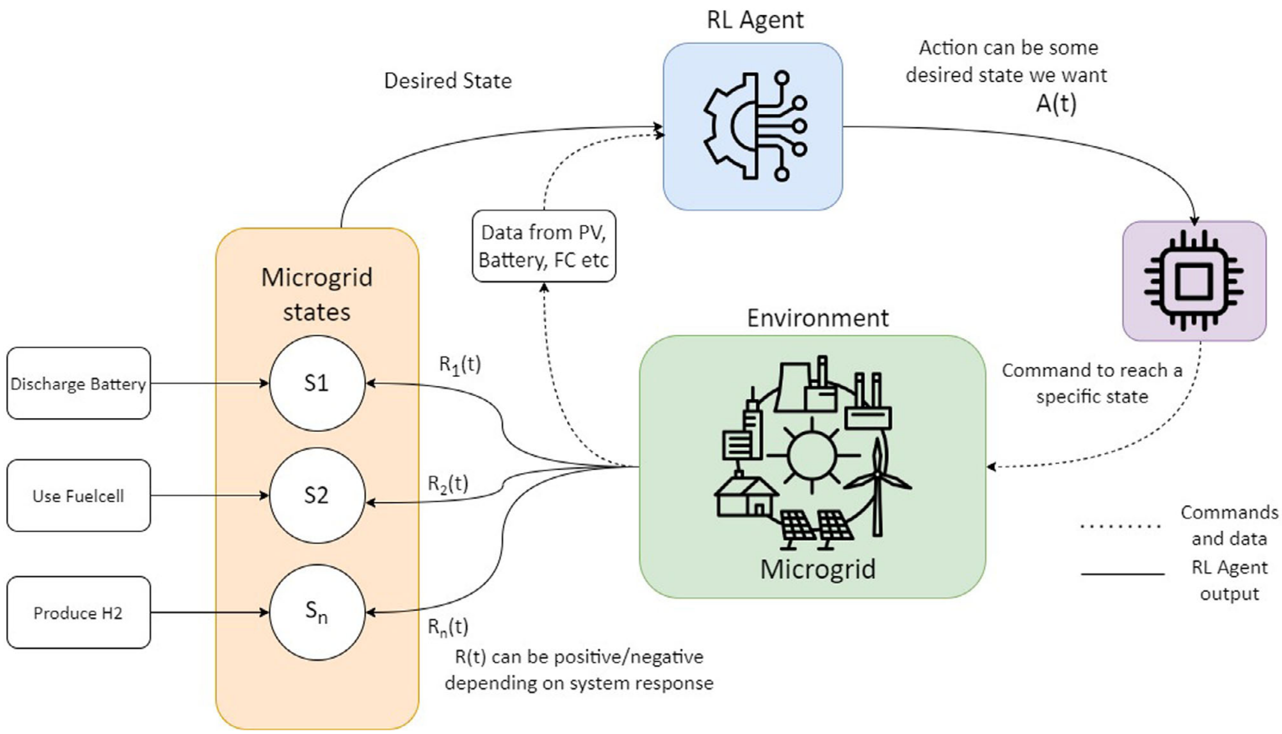

FIGURE 9 Reinforcement learning mechanism for a hybrid microgrid.

batteries and hydrogen storage. Compared to a standard rule-based strategy, the proposed controller reduces annual costs by up to 5% in residential buildings and 9% in non-residential buildings. Based on the MPC controller mechanism shown in Figure 10, MPC typically consists of an optimizer along with a model of the system. Using a plant model (MG), the MPC controller can predict future plant outputs, trying to reach the desired reference state as closely as possible.

In [100], a closed-loop MPC model was proposed for the energy management of a hybrid system. This study evaluates potential improvements in the operational strategy of a hybrid battery-hydrogen energy storage system using mathematical optimization techniques. A simulation model of the hybrid energy storage system and a custom mixed-integer linear programming (MILP) optimization model were employed within a model predictive control (MPC) framework. The operational

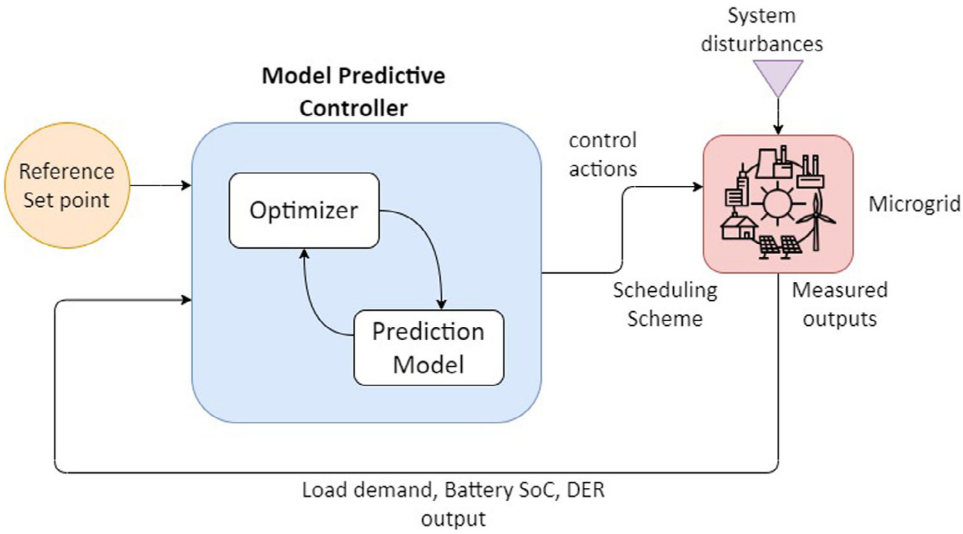

FIGURE 10 MPC controller for a hybrid BMG.

strategies derived from various MPC settings were compared with those generated by a rule-based controller, demonstrating the potential advantages of MPC over traditional methods. A comprehensive analysis was conducted to examine the factors influencing the effectiveness of MPC, including a sensitivity analysis of different electricity demand scenarios and resource sizes. The findings indicate that the MPC reduces energy consumption by at least 3.9% and up to 17.9% compared to the rule-based controller.

4.4 | Fuzzy logic-based EMS

Fuzzy logic is an approach to variable processing that allows multiple possible truth values to be processed using the same variables. Fuzzy logic attempts to solve problems with an open and imprecise spectrum of data and heuristics, which makes it possible to obtain an array of accurate conclusions. Fuzzy-logic-based energy management strategies are a recent trend in BMG management. Recent studies have shown that this approach can provide several improvements in energy management. The application of fuzzy-logic-based controllers has shown promising results in the energy management of smart homes. In [101], a type 2 fuzzy logic controller was proposed. The objective is to achieve demand-side energy management. The results showed that by using the fuzzy logic controller, the energy costs were reduced by 71.5%.

Figure 11 shows a global overview of the EMS technologies used in different hybrid BMGs. Deterministic and rule-based approaches to hydrogen-based BMGs, such as linear programming and MILP are suitable for simpler systems. When hydrogen production is stable and predictable, deterministic methods are sufficient for optimizing the BMG. When either user demand or solar availability is subjected to sufficient randomness, stochastic methods are better tools for achieving energy optimization in a BMG. As discussed previously, they can be broadly classified into three main categories.

Based on the aforementioned analysis, Table 2 provides an overall summary of the different EMS categories according to the previously defined criteria. Three different approaches were compared with respect to the criteria listed in the columns. For simpler systems, deterministic approaches are sufficient and do not require significant computational resources for the EMS to operate. However, their simplicity implies that in highly dynamic systems, they may not live up to the desired performance levels. For predictive applications and BMGs with more uncertainty, reinforcement learning- and machine learning-based approaches are better suited because they can handle disturbances and deviations in a much more robust manner. The * in Table 2 refers to the level of dependence on a particular criterion. For example, linear programming with 1 * for predictive capabilities means that linear programming is not a suitable candidate if the goal is to have high predictive capabilities. Similarly, five * signify the most correlation of that characteristic with a given methodology.

5 | MAJOR FINDINGS AND FUTURE RECOMMENDATIONS

Over time, the optimization and control domains in BMGs have evolved, particularly with the advent of hydrogen-based storage, leading to an increased complexity of the control methodologies. The energy management systems (EMSs) field for such BMGs is changing dynamically, with no definitive consensus on the most effective energy management and optimization approach. However, contemporary research is gravitating towards feedback-based methods, such as reinforcement learning (RL) and model predictive control (MPC), particularly for scenarios with ample computational resources. RL enables agents to learn optimal behaviours through interactions with the

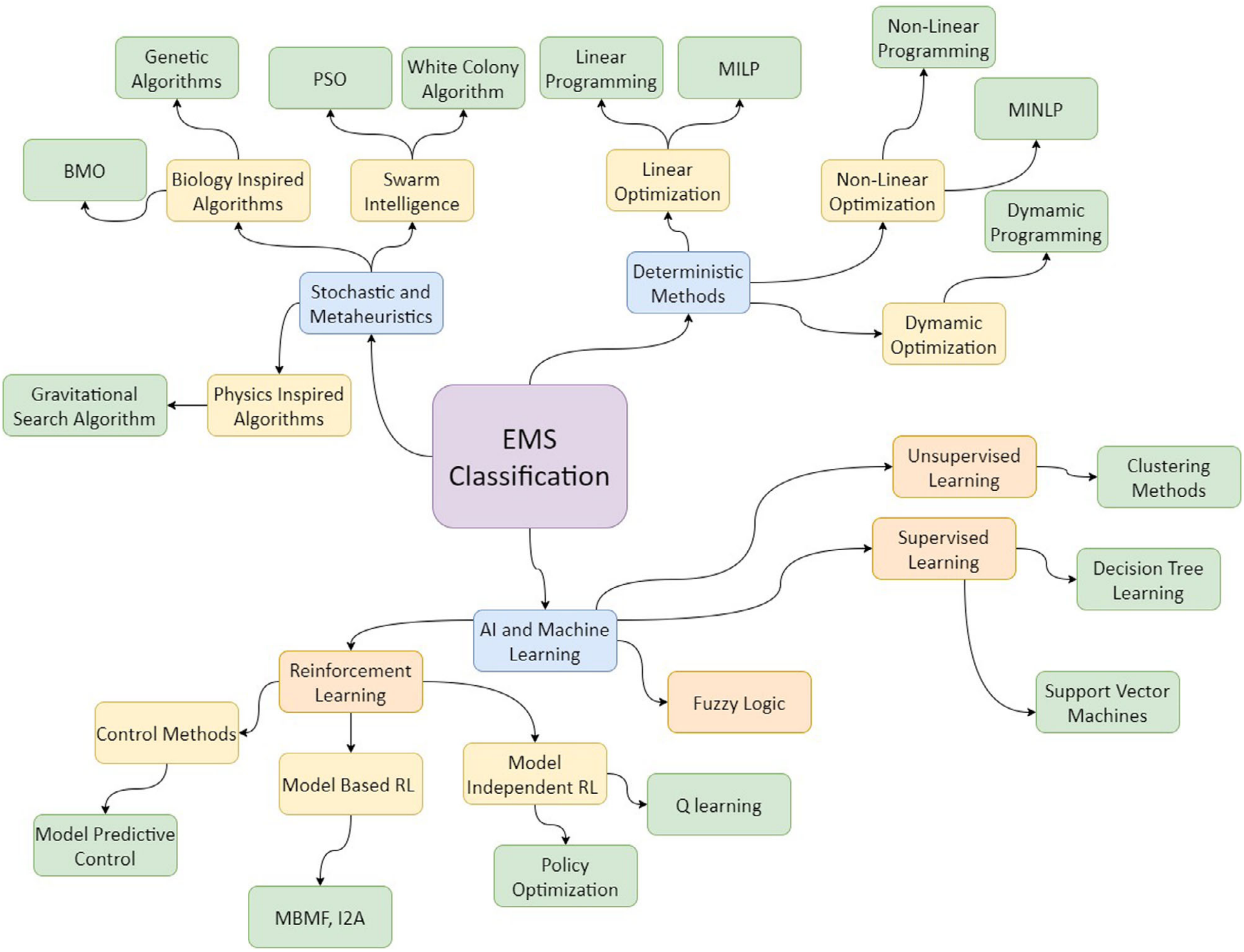

FIGURE 11 EMS methodologies used for hybrid BMGs.

TABLE 2 Global comparison of EMS algorithms with predefined criteria.

EMS methodology	Predictive capabilities	Computational complexity	Flexibility	Data dependency	Model dependency	Multisystem consideration
Linear programming	*	* *	* *	*	* * * * *	* *
Mixed integer linear programming	*	* * *	*	*	* * * *	* * *
Non-linear programming	* *	* * *	* *	*	* * * * *	* * *
Dynamic programming	*	* * * *	* * *	*	* * *	* * *
Genetic algorithm	*	* * *	* * *	*	* * * *	*
Particle swarm optimization	* *	* *	* * *	*	* * * *	* * *
Reinforcement learning	* * *	* *	* * * * *	*	*	* * * *
Fuzzy logic	* * * *	* * * *	* * * *	*	* * *	* *
Q-learning	* * * *	* * * *	* * *	* * *	**	**
Model predictive control	* * *	* * * * *	* * *	* *	* * * *	* * * *
Supervised learning	* *	* *	*	* * * * *	*	* * *

environment without requiring explicit supervision or labelled data. The agent learns from the consequences of its actions, which fosters autonomous decision-making. RL agents can adapt to dynamic and uncertain environments. As they learn continuously from new experiences, they can adjust their strategies to accommodate changes and unforeseen circumstances. RL inherently balances exploration (testing new actions) and exploitation (utilizing known actions to maximize rewards). This balance helps discover optimal policies, even in complex and unfamiliar environments.

In resource-constrained environments, deterministic methods tend to exhibit superior performance owing to lower computational demands. Although RL and MPC may lack historical data context for accurate long-term predictions, classical machine learning approaches offer better solutions by leveraging the historical context from training datasets. Given sufficient data, machine learning (ML) models can surpass RL or deterministic optimization methods, which may overlook specialized BMG scenarios. RL and MPC-based algorithms also demonstrate heightened robustness to external disturbances owing to their inherent adaptability. In complex systems involving various prosumers, a hybrid approach combining different methodologies can yield superior results. This mix leverages the strengths of each approach, thereby enhancing overall system performance and reliability.

In the case of hydrogen-based microgrids, owing to their particular demands regarding the interaction of multiple components such as electrolysers, fuel cells, and batteries, RL and MPC are well suited for such BMG because of their ability to interact with systems in near real-time and adapt their behaviour according to the changes faced by the BMGs. The disadvantage of these approaches is their limited ability to make future predictions. MPC can predict the future state of a system within a predefined time window. In the case of RL, a well-defined RL agent must be trained with a well-crafted reward function that incorporates the desired energy management strategy. A limitation of RL-based methods is the suitability of their reward mechanisms. The reward function must incentivize the desired outcomes for BMG, for example, increasing the autonomy or lifetime of components and penalizing the undesired conditions for energy management in a BMG, for example, decreased performance of lower efficiency. Thus, for hydrogen-based BMGs, it is recommended to focus on the development of an all-encompassing reward function for RL before an agent is trained for energy optimization in a BMG.

6 | CONCLUSION

As previously reviewed, the EMS is the backbone of the most modern hybrid BMG. Hydrogen along with batteries has the potential to play a transformative role in building resilient, sustainable, and efficient BMGs, offering a range of benefits to both energy consumers and broader energy systems. However, with the increasing complexity of MGs, an adapted and optimized operation is essential.

The literature review indicates that, to date, there have been very few attempts to classify optimization and control methods specifically for these scenarios. The novelty of the work presented in this paper lies in its focus on EMS applications for BMGs with combined heat and electrical demands from a hydrogen application perspective. This study also focuses on hydrogen applications in the context of building MGs. A comparative study was performed on strategies for energy management for such MGs and on how some approaches, such as RL and MPC are better for such MGs owing to their adaptability and flexibility.

The algorithms presented in this paper were compared according to predefined criteria, and their relative strengths and weaknesses were assessed. The complexity of systems with multiple indeterministic components suggests that certain approaches are better suited for achieving higher self-consumption and autonomy levels.

A literature review revealed that the combination of MPC and RL techniques offers an optimal strategy for managing MGs. Considering the practical constraints and existing infrastructure, these methods appear to be the most suitable for such systems. However, there is a significant trade-off between the computational complexity, predictive accuracy, and robustness of the EMS. The choice of the control method should be tailored to a specific system size and economic considerations.

NOMENCLATURE

AI	Artificial intelligence
ANN	Artificial neural network
BMG	Building microgrid
CNN-GRU	Convolutional neural network-based gated recurrent unit
CoH	Cost of hydrogen
DER	Distributed energy resources
DG	Distributed generation
DHW	Domestic hot water
DNN	Deep neural network
DP	Dynamic programming
EMS	Energy management system
ESS	Energy storage system
GA	Genetic algorithm
HV	Hydrogen vehicle
IDA-PBC	Interconnection and damping assignment passivity-based control
IEHCCS	Integrated electricity hydrogen conversion and charging station
LP	Linear programming
LSTM	Long short-term memory
MG	Microgrid
MILP	Mixed integer linear programming
MIMO	Multiple input multiple output
ML	Machine learning
MPC	Model predictive control
MPG	Micro power grid system
NPBA	Net power-based algorithm

P_{ely}	Electrolyser power
PEM	Point estimate method
PSO	Particle swarm optimization
PV	Photovoltaic
RES	Renewable energy sources
RF	Random forest
RF	Reinforcement learning
RL	Reinforcement learning
RTOS	Real-time operating system
SO	System operators
SoC	State of charge
SoH	State of health
STLF	Short-term electricity load forecasting
SVM	Support vector machines
TLA	Teacher learning algorithm
T_{sp}	Set point temperature
V_{batt}	Battery voltage

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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