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Energy Management Under Uncertainty for Hybrid Microgrids: From Data to Decision-Making

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ABSTRACT

The increasing adoption of distributed energy resources has greatly amplified interest in microgrids, whose effective, reliable and resilient operation relies on the performance of their energy management systems (EMS). These systems ensure the economic operation and maintain load-generation balance. A practical microgrid EMS (M-EMS) incorporates data monitoring, variable forecasting, resource allocation and online supervision to optimise the system while interacting with electricity markets. However, in the inherently uncertain environment of both stand-alone and grid-connected microgrids, variations in key variables can significantly impact the decision-making outcomes of M-EMS. This review paper explores various sources of uncertainties within microgrids, including forecast errors and uncertainties arising from modelling approximations or monitoring inaccuracies. It also provides insights into handling these uncertainties by thoroughly reviewing the pertinent literature and exploring strategies such as analytical methods and AI-based approaches for capturing them. The eventual goal of handling the uncertainties is to enhance system reliability and security through robust energy management solutions. Furthermore, practical measures to mitigate uncertainties are discussed. The practical implementation of these concepts is illustrated through a review of commercially available M-EMS solutions and real-world projects demonstrating their effectiveness in managing energy resources. This paper aims to help both researchers and industry professionals perceive the uncertainties within M-EMS and how to handle them to achieve accurate, optimal solutions and avoid unexpected costs. Emerging trends and future research directions are also outlined.

1 | Introduction

Energy management systems (EMSs) play a significant role in the efficient operation of microgrids, particularly in the face of increasing complexities and uncertainties. An EMS integrates various components of a microgrid, such as generation sources, storage systems and loads, to ensure optimal performance and reliability. Optimisation techniques are employed to balance supply and demand while optimising objectives like operational costs and enhancing system reliability. Handling uncertainty is crucial in this context, as it allows for better decision-making in the face of variable renewable energy sources (RESs), fluctuating demand patterns and potential system failures. By effectively managing uncertainty, microgrids can maintain stability and performance, ultimately supporting a more resilient and sustainable energy future.

Generally, utilising distributed energy resources (DERs) enhances the microgrid's resilience and reliability, particularly during periods of grid isolation [1]. However, any malfunction in DERs can pose significant challenges unless a sufficient backup system is in place. Furthermore, the intermittent nature of RESs introduces complexities in maintaining a balanced supply and demand, given the influence of unpredictable variables like weather conditions. It is important to note that RESs are not the only source of uncertainty within the system. Load demand, the other source of uncertainty, exhibits variability due to unforeseeable consumption behaviour across different operational scenarios of the microgrid. The consumption is influenced by factors such as electricity pricing, weather variations, load type, cluster specifics and special events. Although historical consumer behaviour data aid in capturing some of these uncertainties, the exact consumption patterns remain inherently uncertain. Consequently, an effective EMS for microgrids is imperative not only to incorporate forecasted data of load, prices and RESs but also to address unforeseen alterations during microgrid operation. The energy management in this scope serves as a crucial bridge, managing deviations between actual and projected data. Therefore, microgrids necessitate sophisticated EMSs capable of orchestrating both optimal day-ahead and real-time DER operations [2]. These systems are indispensable in meeting the stability and operational requisites of microgrids [1].

This study aims to bridge critical gaps in the current literature by systematically examining the sources, propagation and management of uncertainties within microgrid energy management systems (M-EMSs). Such uncertainties, arising from data acquisition, forecasting, modelling and real-time operation, can propagate across system layers, potentially compromising the optimality and reliability of energy management decisions. The methods used to capture and mitigate these uncertainties differ depending on their source and temporal characteristics. Unlike previous reviews that primarily emphasise algorithmic frameworks or isolated system components, this work focuses on the integration of academic methodologies with real-world industrial M-EMS implementations, highlighting the operational complexities associated with real-time decision-making under uncertainty. In particular, it explores the interaction between forecasting modules and system-level optimisation, offering a detailed perspective on how prediction errors and modelling approximations influence operational outcomes. Furthermore, the study incorporates an AI-driven perspective, examining the role of machine learning, probabilistic forecasting and predictive analytics in enhancing decision-making robustness under uncertain conditions. To ensure a holistic understanding, the review also provides an overview of commercially deployed M-EMS solutions, identifying practical challenges, technology trends and implementation barriers. Table 1 summarises the novel contributions of this study relative to existing reviews, underscoring how it extends prior work by combining theoretical advancements with practical insights from operational and commercial EMSs.

To conduct this review, the IEEE Xplore and Scopus databases were searched for studies addressing uncertainty management in microgrid energy systems. Additional relevant studies were also included to ensure comprehensive coverage of the topic. To visualise the research scope and dynamics of the field, a keyword co-occurrence map was generated using VOSviewer, based on bibliographic data from the reviewed literature. As shown in Figure 1, this visualisation highlights the most prominent and frequently co-occurring terms within the research domain. Node sizes represent keyword frequency, while colour gradients indicate the average publication year (2017–2025). To ensure consistency, keywords with different spellings or abbreviations representing the same concept were standardised. Larger nodes correspond to dominant research themes such as 'microgrid', 'EMS', 'DERs', 'renewable energy', like 'PV' and 'wind', as well as 'optimisation', 'uncertainty', 'real-time control', 'artificial neural networks (ANN)' and 'demand response'. Emerging themes, including 'integrated energy systems,' 'flexibility,' 'hydrogen technology,' 'rolling horizon strategies,' 'deep reinforcement learning' and 'probabilistic forecasting' appear in lighter colours, indicating recent research attention. The map effectively reveals both established and evolving trends, offering an intuitive overview of how key concepts interconnect across the literature and guiding the thematic organisation of this review.

In addition, Figure 2 presents the temporal distribution of the reviewed publications, highlighting research evolution over the examined period. Although the review prioritises the most recent advancements, certain very recent papers were filtered out to maintain alignment with thematic keywords and the study's focus. Consequently, while the number of publications in the most recent years may appear slightly lower, the selection remains representative of current and influential work. Figure 3 shows the top ten most cited journals contributing to the reviewed literature, underscoring their relevance to the topic. IEEE Transactions on Smart Grid and Applied Energy emerge as the most influential, contributing 17 and 11 papers, respectively.

The remainder of the paper is structured as follows: Section 2 discusses microgrid monitoring systems as a foundation for data collection; Section 3 examines forecasting approaches for M-EMS applications, comparing deterministic and probabilistic methods; Section 4 explores operating timescales relevant to uncertainty management; Section 5 outlines practical strategies and techniques for handling uncertainties; Section 6 reviews the state-of-the-art in M-EMS uncertainty management; Section 7 examines real-world implementations and commercially available systems; and finally, Section 8 concludes the study with key insights and implications.

2 | Microgrid Monitoring Systems

Monitoring systems are crucial elements of M-EMSs, enabling real-time data collection and analysis of various variables and components. With advancements in technology, monitoring systems have evolved significantly, incorporating Internet of Things (IoT) devices, cloud computing, supervisory control and data acquisition (SCADA) systems and smart meters. These innovations enhance the ability to manage and optimise energy resources, reduce operational costs, improve response times, ensure system security and enhance real-time awareness of the voltage, current, frequency and phase angle [14, 15]. Particularly, the development and integration of smart meters have transformed consumer-operator relationships by enabling reliable, rapid communication and electronic invoicing. Transitioning from automated meter reading to advanced metering infrastructure has allowed for bidirectional communication and power flow, enhancing the efficiency and reliability of distribution systems. Smart meters equipped with memory chips and software interfaces enable users to monitor energy consumption and support distribution automation, improving overall system security and reducing power theft. These advancements allow consumers to manage energy loads more effectively, contributing to cost savings and efficient energy use. Combining cloud computing

TABLE 1 | Overview of prior studies and novel insights provided by this review paper.

Study	Year	Description	Integrated monitoring system	Data fore-casting	Optimi-sation insights	Uncertain environ-ment	Real-time operation	AI vision	Real-world initiatives
[3]	2024	This study evaluates rule-based, model predictive control (MPC) and deep reinforcement learning (DRL) real-time control methodologies for a grid-connected microgrid under solar and load uncertainties.	—	—	✓	✓	✓	—	—
[1]	2023	This work examines energy management optimisation methods, covering objectives like cost reduction, carbon footprint minimisation and profit maximisation through grid trading.	—	✓	✓	—	✓	✓	—
[2]	2023	This paper reviews the application of artificial intelligence (AI) technologies in M-EMS, focusing on how they address challenges arising from the variability of renewable energy sources.	—	—	✓	✓	—	✓	—
[4]	2023	Emphasising the crucial role of EMS within the microgrid control hierarchy, this paper covers essential aspects like objectives, constraints and provides insights into deterministic and probabilistic methods.	—	—	✓	✓	—	—	✓
[5]	2023	It covers the configuration of distributed generation units, control strategies and optimisation techniques.	—	—	✓	—	✓	—	—
[6]	2023	This review paper examines various energy management techniques in microgrids with hydrogen technologies.	—	—	✓	✓	—	—	—
[7]	2023	This review paper focuses on the transition to low-carbon futures driven by local renewable energy resources and energy storage systems. It emphasises the need for innovative architectures and explores the integration of energy storage systems into energy management models.	—	—	✓	✓	—	—	—
[8]	2022	This review paper focuses on the role of M-EMS in enhancing energy efficiency, power quality and distribution system reliability. It introduces key elements of multi-microgrids, including physical network structures, energy trading mechanisms and various energy scheduling strategies.	—	—	—	✓	—	✓	—
[9]	2022	This work examines various energy management strategies, including MIP, heuristic optimisation, rule-based, fuzzy logic control and MPC methods, highlighting.	—	—	✓	✓	—	✓	—
[10]	2022	This survey provides an assessment of EM strategies for microgrids with a focus on demand response programs and EMS constraints. It categorises EMS based on decision-making methods and outlines methods for handling uncertainties.	—	—	✓	✓	✓	✓	—

(Continues)

TABLE 1 | (Continued)

Study	Year	Description	Integrated monitoring system	Data fore-casting	Optimi-sation insights	Uncertain environ-ment	Real-time operation	AI vision	Real-world initiatives
[11]	2020	This study conducted a review of recent research concerning M-EMSs. It specifically emphasised various control strategies aimed at optimising the operation of MGs.	✓	—	✓	—	—	✓	—
[12]	2019	The paper gives an overview of energy management in multi-microgrids and covers topology structures, optimisation objectives, operational timescales and decentralised strategies.	—	—	✓	—	✓	—	—
[13]	2018	This review explores effective methods to attain energy management objectives, considering their suitability, practicability and feasibility for optimal operation.	—	—	✓	✓	—	✓	✓
		This study	✓	✓	✓	✓	✓	✓	✓

with IoT and smart meter technology creates a robust framework for real-time microgrid monitoring and management, paving the way for more intelligent and efficient energy systems.

In the literature, particular emphasis is placed on the monitoring of photovoltaic (PV) systems [16, 17] and BESS [15, 18]. Monitoring these components is vital for assessing operational status and performance. Specifically, for batteries, this includes monitoring longevity and managing charge and discharge cycles. A battery monitoring system includes instruments that measure key parameters such as voltage, current and temperature. These measurements are processed to estimate the battery's state of charge (SoC) and state of health.

Generally, monitoring systems today are faced with challenges related to interoperability and the reliability of communication networks. Selecting the right communication interface to ensure effective interoperability is an important decision that significantly influences economic costs, maintainability, scalability, security and resilience [16].

2.1 | SCADA Systems

A SCADA system offers an effective solution for monitoring and managing energy in microgrids across various settings, including residential, commercial and industrial buildings. SCADA systems consist of two main components: hardware for data collection, communication, control and operation and software for data storage, elaboration, visualisation, optimisation and management [19, 20]. The hardware component of a SCADA system includes four major functions. The first is the remote terminal unit (RTU), which is responsible for gathering data from the microgrid. The second component is the communication platform that establishes data links between devices, ensuring seamless data flow. The third function involves the programmable logic controller (PLC), which is essential for ensuring proper operation of the microgrid in both grid-connected and islanded modes [21, 22]. The software component of SCADA, particularly the human-machine interface (HMI), is crucial for monitoring and control. The HMI enables operators to interact with the system, providing a user-friendly interface for real-time monitoring and control of microgrid operations. Typically, the SCADA system follows a server-client architecture, where the primary SCADA application runs on the server and the HMI operates on the client side [23].

SCADA systems serve as middleware in intelligent monitoring systems, primarily used to read and manage bundled microgrid data. This data is accessed by the SCADA system and stored in databases like MySQL for further analysis and optimisation [20]. The integration of all four SCADA components, RTU, PLC, HMI and communication platform, aims to achieve advanced energy management objectives, contributing to the intelligent and efficient operation of microgrids.

2.2 | IoT-Based Systems

The IoT represents the evolution of SCADA, serving as a system for monitoring and controlling operations via Internet connectivity. IoT represents a significant advancement in network

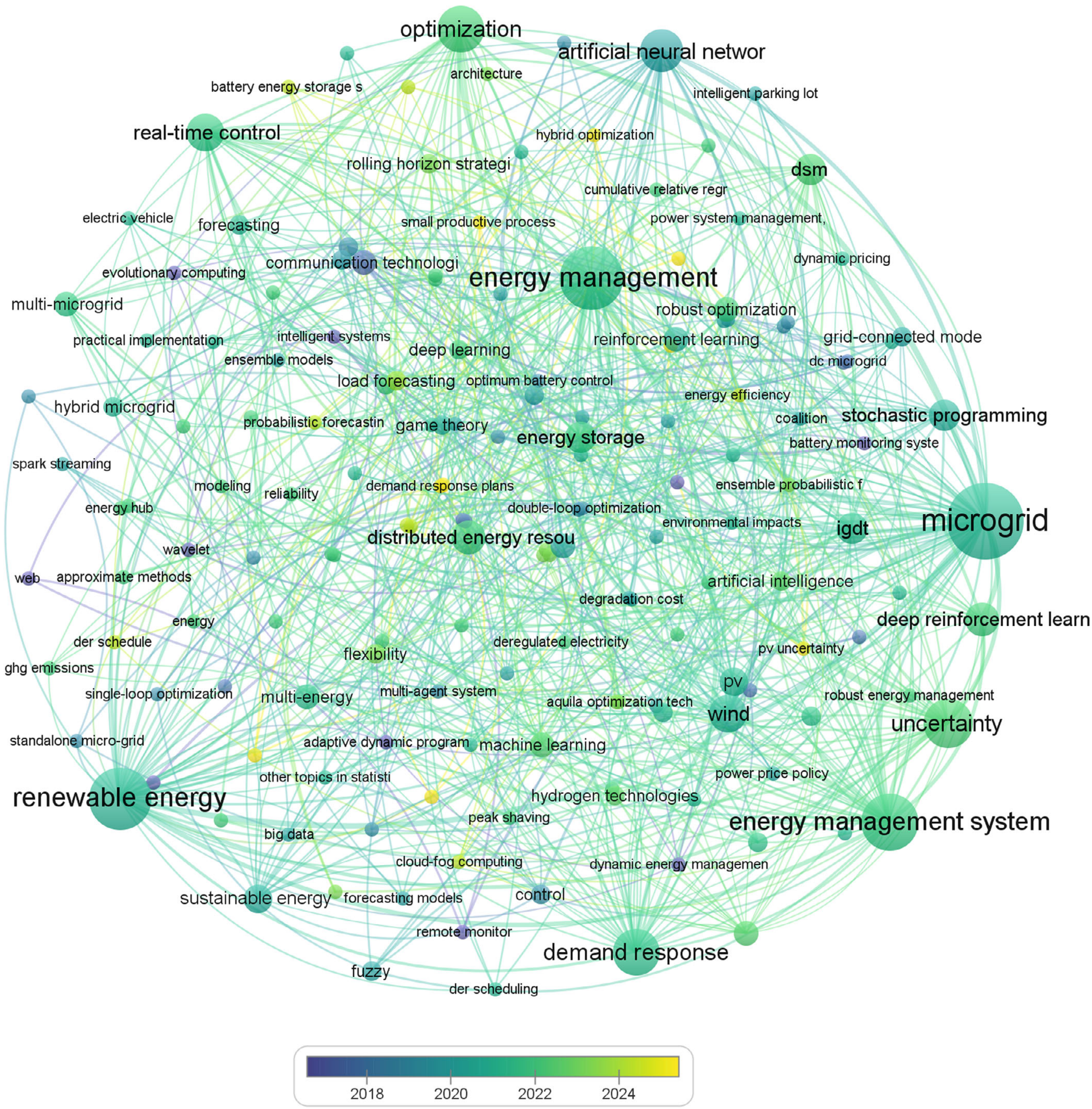

FIGURE 1 | Keyword co-occurrence map of selected publications, generated using VOSviewer (node size indicates keyword frequency, link thickness shows co-occurrence strength and colour represents the average year of publication).

technology, connecting various entities to the internet for data creation, gathering, exchange and utilisation. IoT encompasses a range of technologies, including machine-to-machine and radio frequency identification, that facilitate object intelligence communication [24]. The primary objective of IoT is to create an intelligent environment where everything is interconnected, automating processes with minimal human intervention and enhancing services through comprehensive information fusion. This involves integrating physical and virtual entities with distinct identifiers and attributes, enabling autonomous responses to real-world events and facilitating secure and privacy-conscious internet-based communication. IoT technology has a transformative impact on microgrid EMSs, significantly improving their efficiency by collecting and analysing data from various power sources. This technology allows utilities to perform operational tasks such as optimising load balancing, detecting faults, reducing service costs and restoring services more quickly. Additionally, IoT enables effective management of DRPs, energy collection, sharing and trading, addressing energy conservation and management challenges through a continuous energy supply and power surge prevention system [24].

One of the crucial features of IoT-based microgrid monitoring systems is real-time data analysis. Various sensors collect

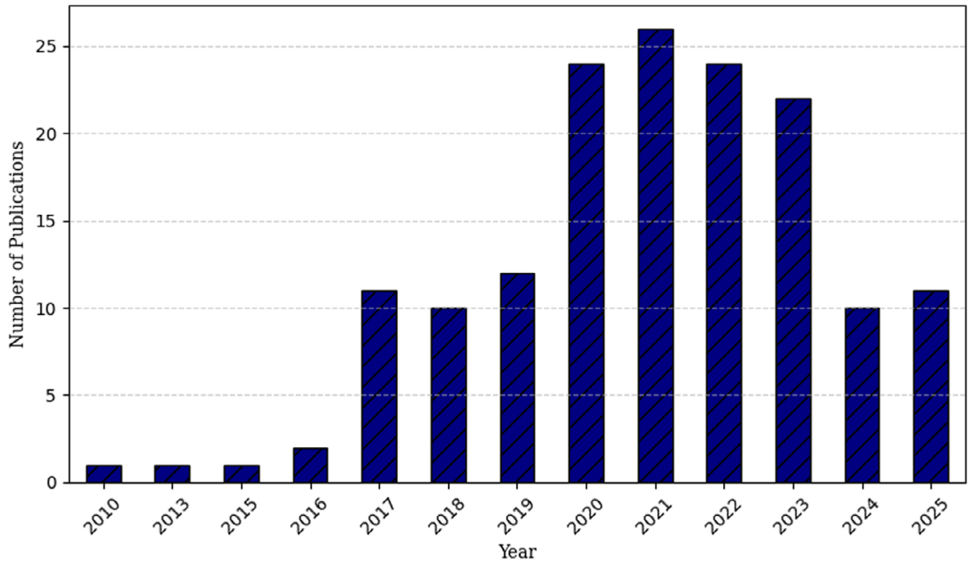

FIGURE 2 | Selected publication trend over the years.

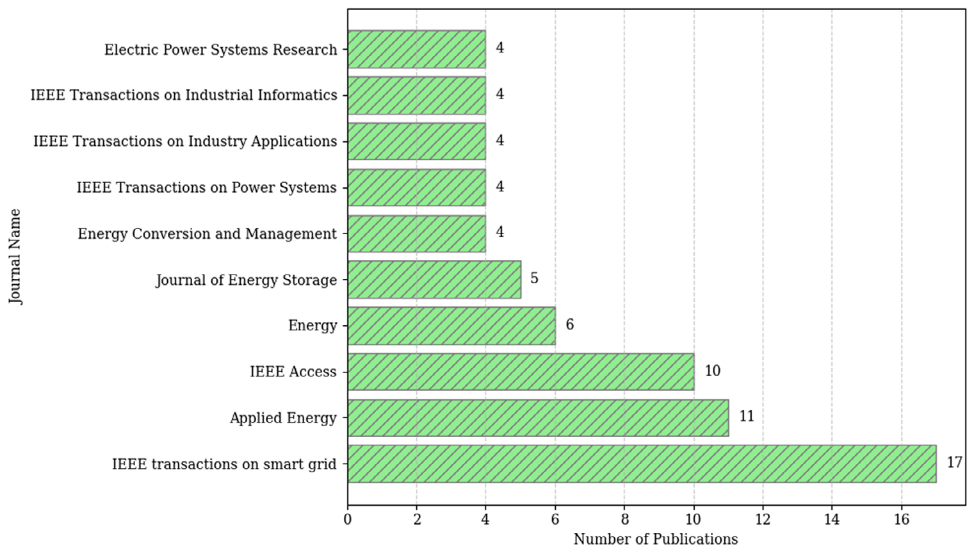

FIGURE 3 | Distribution of publications across the top 10 most frequently cited journals identified in the bibliometric analysis.

current, voltage, power and temperature data, which are then analysed to determine optimal control strategies based on real-time conditions. This data is stored for subsequent analysis to develop predictive control techniques, further enhancing system efficiency and reliability. The integration of IoT technologies into platforms for data collection, processing and visualisation is essential for automated distribution and secure DERs administration, particularly as the adoption of 5G technology progresses [25].

Numerous studies have explored different aspects of IoT integration in microgrid monitoring. Authors in [26] investigated a hybrid communication platform for M-EMS, demonstrating its ability to operate in both central and decentralised modes to reduce operating expenses despite communication delays. The study in [27] emphasised the benefits, challenges and risks of deploying IoT in intelligent microgrids, highlighting essential processes and procedures for control and protection. Researchers in [28, 29] developed remote IoT-based energy monitoring platforms for companies, integrating various technologies for central and decentralised administration, which are aimed at optimising and conserving energy, reducing energy wastage and providing valuable insights into energy consumption patterns. References [21, 30] presented real-time monitoring systems utilising web server technology, where Ethernet network modules, sensors and microcontrollers are employed for data acquisition and wireless transmission. An IoT-based battery monitoring system has been devised by the authors in [18] specifically to oversee the operational and performance aspects of batteries within microgrids. This system is comprised of a communication channel facilitating bidirectional data exchange between intelligent electronic devices, a data acquisition algorithm for collecting relevant information and an HMI for user interaction and control, integrating with a cloud system for data storage and management.

2.3 | Cloud-Based Systems

The cloud system emerges as an ideal partner for data storage, especially in IoT applications. Functioning as a third-party database, the cloud system facilitates data transfer over internet gateways. Its advantages include expansive data storage capabilities, high reliability, cost-effectiveness and excellent scalability, capable of accommodating increasing workloads. Industries benefit from cloud systems by reducing costs associated with data storage facilities and maintenance, while also gaining the ability to process and analyse data accurately from anywhere, owing to the vast data repository stored in the cloud. This accessibility enables faster decision-making processes.

Cloud computing offers an advanced approach to microgrid monitoring by facilitating seamless communication between power sources and monitoring platforms. In this setup, measurement units send data directly to the cloud for real-time processing and analysis, significantly enhancing data transmission quality and the administration of IoT services. The study by [31] highlights the effectiveness of using remote cloud servers and cloud computing platforms for real-time grid power system monitoring and control. These solutions improve response times, control efficiency and user authentication security while providing a cost-effective means to meet microgrid computational needs. Authors in [32] further emphasise the benefits of cloud-based remote monitoring units and platforms like Thingspeak, which facilitate real-time data visualisation and analysis, crucial for optimal energy management.

3 | Forecasting for M-EMS Applications

The forecasting module stands as a crucial component within the M-EMS, furnishing essential data for the optimisation stage to ensure a consistent and refined power profile. This module is tasked with delivering projected profiles of influential variables that guide the optimal decisions of M-EMS, encompassing factors like electricity market prices, renewable energy source power generation, load demand and weather information, among others [33–36]. A precise forecasting methodology for both generation and consumption is paramount in maintaining a consistent power balance. It guarantees that the system can meet demand while also having sufficient reserves to accommodate unexpected deviations. Accurate forecasted data can then be leveraged to fine-tune microgrid operations by reducing the reliance on backup generators [2].

In power sector forecasting, time scales vary to meet specific planning and operational needs. Long-term load forecasting, spanning one to 20 years, guides strategic planning and infrastructure development. Medium-term load forecasting, spanning a week to a year, aids in maintenance scheduling, fuel procurement and revenue assessment. Short-term load forecasting (STLF), ranging from an hour to a week, is vital for daily operations, aiding in generation and transmission scheduling by M-EMS, while ultra STLF (USTLF), minutes to an hour ahead, supports real-time decision-making or control, allowing immediate adjustments to fluctuations to maintain system stability [37]. The granularity of the forecasting aligns with the specific timescale of energy management, ranging from a few days to intervals as short as five minutes [1].

3.1 | Deterministic Forecasting Approach

Deterministic forecasting involves predicting future outcomes with a single-point estimate, typically based on historical data and deterministic models. In energy forecasting, deterministic methods aim to provide accurate point forecasts of variables such as load demand, generation output of renewable sources and electricity market prices. Various categories of deterministic methods are employed for forecasting, including time series analysis, regression analysis and machine learning (ML) techniques. Time series analysis utilises historical data to identify patterns and trends, which are then extrapolated to forecast future values. The seasonal autoregressive integrated moving average, as a time series forecasting technique, is utilised for M-EMS [38]. Regression analysis establishes relationships between variables such as time, weather conditions and economic indices to predict future outcomes. ANNs and support vector machines, among other ML methods, learn patterns from historical data to make accurate predictions. In recent years, however, neural network-based forecasting methods, particularly those utilising long short-term memory (LSTM) techniques, have garnered significant attention. More specifically, LSTM comprises recurrently connected memory blocks to forecast variables in M-EMS applications [39]. Each block is equipped with three multiplicative units: the input gate, output gate and forget gate. The input gate is responsible for storing either new information or past states of the network. The forget gate filters out irrelevant and redundant information from previous iterations. The output gate extracts crucial information from the memory. This mechanism ensures that only pertinent information is retained within the network, while unnecessary data is discarded [40, 41]. Moreover, hybrid forecasting models have been developed to leverage the strengths of various methods [42].

Deterministic forecasting methods are assessed for accuracy using diverse metrics such as R-squared score (R2), mean absolute error (MAE), mean absolute percentage error, mean square error (MSE), root mean square error (RMSE) and mean biased error (MBE), among others [42]. Nevertheless, the forecasting module is prone to errors and may not be entirely accurate. These errors are perceived as uncertainties within the M-EMS that should be addressed effectively, as discussed in the next section. However, uncertainties may arise from monitoring and data collection inaccuracies, highlighting the necessity for probabilistic forecasting. Unlike deterministic forecasting, which assumes certainty in the raw data, probabilistic forecasting incorporates methods to account for inherent uncertainties.

3.2 | Probabilistic Forecasting Approach

In addition to deterministic forecasting, probabilistic forecasting is another approach to data prediction. Table 2 presents key studies employing deterministic and probabilistic forecasting methods, highlighting the forecasted parameters, accuracy evaluation metrics and their applications in M-EMS. In deterministic forecasting, the goal is to predict a single value for a future

TABLE 2 | Key studies on forecasting for M-EMS applications.

Ref. no.	Forecasting approach	Forecasting core method	Forecasted parameter(s)	Accuracy evaluation metrics	M-EMS application
[43]	Deterministic	CNN-LSTM	Load demand	MAE, MSE, RMSE	Small-scale residential microgrid
[44]	Probabilistic	Regression trees	Solar power	MAE, RMSE, MBE, CRPS	Building EMS
[45]	Deterministic	LSTM	Wind power	N/A	Grid-connected microgrid
[46]	Deterministic	LSTM	Wind and Solar power, Load demand	MSE, R2	Islanded AC/DC microgrid
[47]	Probabilistic	Seq2Seq-LSTM, Seq2Seq-GRU	Wind and Solar power	CPRS, PICP, MPIW	Renewable-based microgrid
[48]	Probabilistic	Seq2Seq-LSTM, GBR	Wind and solar power, market price	MAE, RMSE, R2, CRPS	Renewable-based microgrid
[49]	Deterministic	Polynomial ANN	Wind speed, Solar radiation	N/A	Multi-energy, Grid-connected microgrid
[50]	Deterministic	LSTM	Load demand	MSE	Home EMS (HEMS)

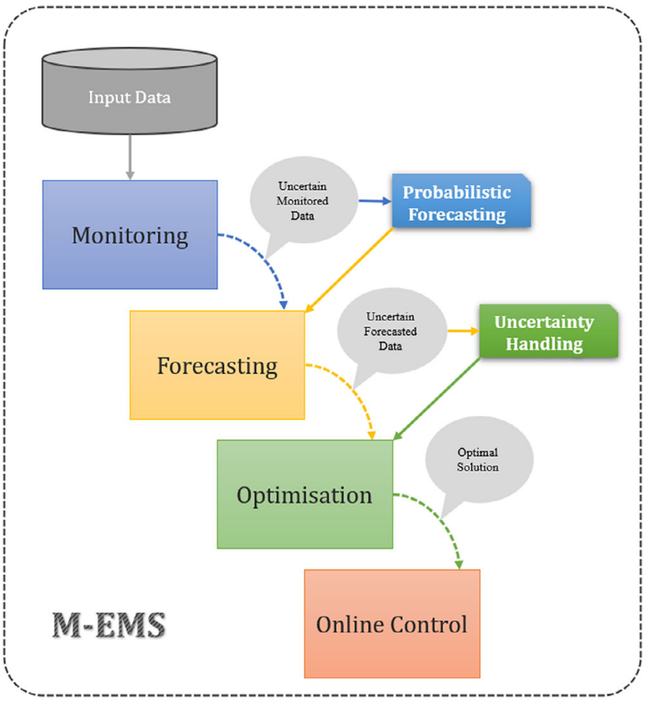

FIGURE 4 | The role of probabilistic forecasting and uncertainty-handling in dealing with propagated uncertainties in M-EMS.

event or variable. This approach relies on historical data and mathematical models that analyse this data to make predictions. Deterministic forecasting is sufficient when the future is expected to be quite similar to the past and there is minimal uncertainty in the data. However, it falls short when addressing uncertainties and errors in data monitoring, potentially leading to incorrect decisions. Figure 4 conceptually illustrates how probabilistic forecasting and uncertainty-handling methods function in tandem to manage uncertainties within M-EMS operations. Probabilistic forecasting captures uncertainties in monitored data, such as weather conditions that influence demand, generation and market prices and provides a quantified representation of variability. In contrast, uncertainty-handling methods incorporate these probabilistic inputs into optimisation models to mitigate the effects of forecast inaccuracies on operational decisions. Nonetheless, actual operating conditions may deviate from modelled uncertainties due to unforeseen events or equipment failures. Consequently, a real-time control layer is required to capture residual deviations and enable optimal decision-making in dynamically changing environments.

Probabilistic forecasting stands out as an approach that goes beyond single-value predictions, offering a range of potential outcomes with associated probabilities or confidence levels. This is crucial in decision-making scenarios that encounter information gaps, as it adeptly models uncertainties and forecast errors. Stakeholders and operators of microgrids rely on these methods to navigate the uncertainty-surrounding parameters like renewable energy generation, customer consumption patterns and electric vehicle (EV) charging/discharging behaviours. These models help forecasters prioritise critical uncertain factors and empower decision-makers to evaluate various operational and planning decisions, taking into account various scenarios of renewable energy injection and other uncertain variables [40].

Probabilistic forecasting includes a spectrum of techniques, categorised into parametric and non-parametric methods, tailored to the specific nature of the variables at hand. In parametric approaches, established probability density functions (PDFs) are employed to gauge the distributions of response variables. These models include familiar tools like linear regression models, Gaussian and beta distributions and adapted variants of the logit-normal distribution [40, 51]. In contrast, non-parametric methods eliminate the need for predefined PDFs, opting to construct predictive distributions or quantiles/ensembles based on diverse factors or historical data. This category encompasses models such as random forecast, quantile regression forecast like gradient boosting with quantile regression (GBR), kernel density estimation (KDE), short-range ensemble forecast and

ANN-based models like sequence-to-sequence (Seq2Seq) gated recurrent unit (GRU), which can account for autocorrelation and temporal dependencies in data [47, 52–56]. Hybrid techniques like Kalman filters, Gaussian processes and Markov-chain mixture distribution models are also part of the toolkit for probabilistic forecasting, with method selection depending on the nature of the variables, forecasting horizon and data availability. The effectiveness of a probabilistic forecasting model revolves around two key attributes: calibration and sharpness [40]. The accuracy and effectiveness of the probabilistic forecasting models are commonly evaluated using additional metrics specific to probabilistic forecasts, such as the continuous ranked probability score (CRPS), the Brier score, the prediction interval coverage probability (PICP) and the mean prediction interval width (MPIW) [44, 47].

4 | EM Timesframe in an Uncertain Environment

4.1 | Day-Ahead EM vs Real-Time EM

Day-ahead (DA) and real-time energy management represent two distinct approaches within EMSs for microgrids. The former is also known as offline energy management for the next day and the latter is referred to as online energy management. Day-ahead energy management, or offline energy management, focuses on planning decisions and scheduling actions for the following day or a longer period. This is based on forecasts and predictions of energy supply and demand [13, 39]. While day-ahead scheduling may yield the globally optimal solution, slight discrepancies between actual and forecasted values due to inevitable forecast errors can make achieving expected outcomes challenging [10]. Concerning this matter, real-time energy management entails making swift decisions and adjustments based on the immediate operating conditions and available data. Real-time energy management is particularly effective in handling uncertainties linked to RESs and load demand. By doing so, it mitigates the influence of uncertainties on the EMS and simplifies its design [10]; however, this impact persists within the system and needs to be addressed effectively.

The importance of real-time energy management becomes evident when considering the challenges involved in validation, demonstrations and testing. Developing an embedded system for real-time operation is a complex task, where offline simulation outcomes might not be entirely trustworthy due to the unavailability or inadequacy of detailed component models [57]. However, real-time energy management poses several challenges to the system compared with day-ahead energy management:

- **Limited response time:** Real-time decisions require quick response, sometimes within seconds or minutes. This demands highly efficient algorithms and systems capable of processing and acting on data rapidly. Real-time optimisation problems can be more complex due to the need to incorporate numerous variables and constraints while making quick decisions.
- **Data quality and availability:** Real-time management relies heavily on the availability and accuracy of real-time data. Inaccurate or missing data can lead to suboptimal decisions and potentially disrupt the energy system.
- **Very short-time forecasting and errors:** Forecasting RESs, load demand, or market price, which can be highly variable, into real-time operations requires advanced forecasting and control strategies. Real-time management must deal with the immediate and often unpredictable fluctuations in energy demand and supply. This includes sudden changes in weather conditions affecting renewable energy generation, unexpected equipment failures, or rapid changes in consumer behaviour, which pose uncertainty in the system.
- **Dynamic constraints:** Real-time operations may face dynamic operational limits, including equipment constraints and voltage and line flow constraints. These constraints change frequently and need to be continuously monitored and adjusted.
- **Cost considerations:** Real-time decisions may have cost implications due to the need for fast-responding resources. Balancing cost-effectiveness with the need for rapid response is a constant challenge.
- **Safety and reliability:** Real-time decisions directly impact the security and reliability of the energy system. Errors or delays in decision-making can lead to disruptions, blackouts, or even damage to equipment.
- **Regulatory and market constraints:** Real-time operations must adhere to regulatory requirements and market rules. Complying with these constraints while making rapid decisions adds another layer of complexity.
- **Cybersecurity and resilience:** Real-time energy systems are exposed to cyber threats that can potentially disrupt operations. Ensuring the cybersecurity and resilience of the system is crucial.
- **Human-Machine Interaction:** Operators play a critical role in real-time energy management. Ensuring effective training, situational awareness and decision support tools for operators is vital.

Addressing these challenges requires a combination of advanced technology, sophisticated algorithms, robust data infrastructure, skilled operators and a deep understanding of the complexities of real-time energy systems.

4.2 | Electricity Market Interactions

From an uncertainty handling perspective, EMS interact with wholesale electricity markets across various timescales—day-ahead, intraday and real-time—to enhance operational flexibility and grid reliability. In the day-ahead market, the EMS utilises forecasted prices to schedule generation and demand, submitting bids for both energy and reserve capacity to address anticipated supply-demand conditions. Real-time markets, on the other hand, accommodate immediate fluctuations through short-interval trading (e.g., 5–30 min), allowing the EMS to respond dynamically to real-world deviations and to participate in ancillary services like frequency regulation and voltage support, often via demand response aggregators [58, 59]. As illustrated in Figure 5, the intraday market (i.e., intraday adjusting market) bridges these two by enabling continuous adjustments within the day, thereby helping microgrids mitigate forecast errors, avoid

FIGURE 5 | M-EMS uncertainty handling via market interactions.

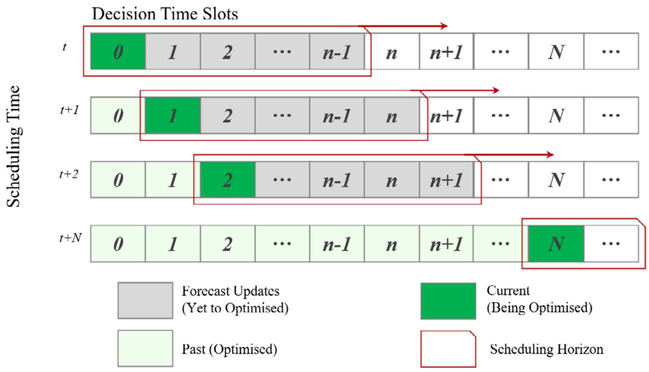

FIGURE 6 | The RTH conceptual diagram.

imbalance penalties and respond to sudden changes in renewable generation or demand [60, 61]. Through participation in these interconnected market structures, the EMS not only ensures local balance and economic efficiency but also strengthens resilience against uncertainties in both load and renewable energy forecasts, supporting a stable and reliable grid [59].

4.3 | Rolling Time Horizon (RTH) and Model Predictive Control (MPC) for RT EM

In energy management optimisation, the RTH method is one of the most widely adopted techniques for real-time decision-making. As illustrated in Figure 6, in this method, the scheduling horizon is divided into discrete intervals and optimisation is performed sequentially for each interval. At each step, the system re-optimises the scheduling problem using the most recent data, implementing only the decision corresponding to the current interval, while future intervals are updated as new information becomes available [39]. In practice, this technique is closely linked with the model-predictive control approach, which is commonly used in the literature for real-time energy management. MPC is emerging as a valuable real-time energy management strategy in microgrid systems. It utilises a feedback mechanism to adapt the initial dispatch solution based on changes in uncertain decision variables. MPC functions within discrete time intervals, solving an open-loop optimal control problem for a selected horizon at each step [62, 63]. This approach leverages models with controllable variables to minimise the deviation between reference and controlled values, determining the optimal action for the subsequent period. MPC benefits from its ability to incorporate constraints and disturbances in forecasted control decisions, making it adaptable to the dynamic performance of the system's components, particularly models for battery charging and discharging [9]. Therefore, MPC is advantageous in handling multivariable systems and reducing the impact of uncertainties. However, it is crucial to carefully select the prediction horizon to balance performance with computational complexity, as larger horizons can lead to increased computational demands. In addition, the effectiveness of MPC is directly influenced by the quality and precision of the predictive model, which poses a challenge when implementing the MPC scheme. For real-time EMS applications, MPC should be implemented in a closed-loop system to continuously receive feedback from the monitoring system and adjust its control actions based on this feedback [64].

4.4 | Real-Time Control for Uncertainty Handling

Several researchers have proposed that during real-time energy management, uncertainty is inherently captured, thus eliminating the necessity for additional uncertainty-capturing methods [65–67]. However, despite the benefits of real-time approaches in mitigating uncertainties, there remains a requirement for employing uncertainty-capturing methods. This need arises from the inherent uncertainties associated with forecasting errors and also the approximation in the system model, which persists even within real-time operations. Therefore, while real-time strategies address some aspects of uncertainty, the utilisation of uncertainty-capturing methods remains crucial for effectively managing and mitigating uncertainties arising from forecast inaccuracies.

5 | Handling Uncertainties in M-EMS

Within M-EMS, addressing uncertainties is particularly crucial. Generally, in uncertain environments, variations in uncertain variables can significantly affect the outcomes of decisions, resulting in actual results that might be better or worse than expected [68]. Various sources of uncertainties in forecasts, including PV and wind turbine (WT) power generation, load and EV demand and electricity prices, are considered in the literature [9]. Solar and wind energy, the most prevalent RESs in microgrid applications, are subject to fluctuations based on factors like weather conditions. This intermittent and unpredictable nature is compounded by consumer load variability, which will be further complicated by including demand response strategies and EV charging. As depicted in Figure 7, uncertainties affecting M-EMSs can be broadly classified into several categories. These include topological parameters related to network configuration, monitoring and forecasting uncertainties (as detailed in Section 3) and modelling inaccuracies arising from simplified or approximate

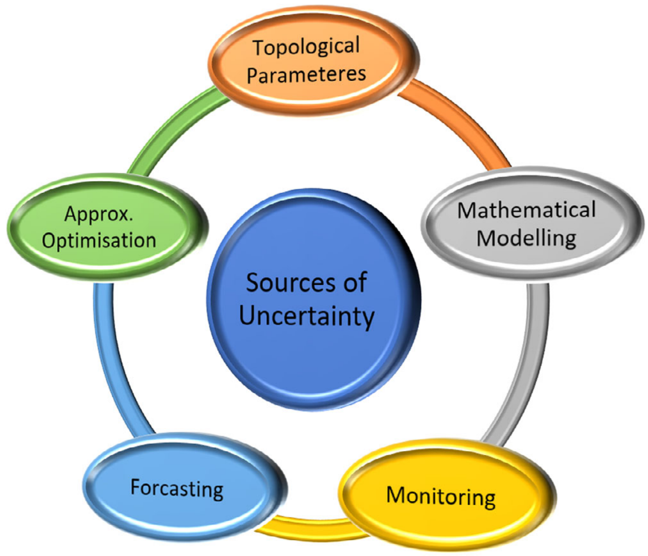

FIGURE 7 | Sources of uncertainty within a microgrid.

optimisation formulations. The subsequent subsections elaborate on these uncertainty sources and their implications for system performance and control strategy design.

This high level of unpredictability creates an environment of operational uncertainties for microgrids. Consequently, effectively managing the uncertainties is a primary challenge. Achieving precise modelling of uncertainties related to parameters and components significantly impacts the operational cost of a microgrid [69]. However, accurately modelling uncertainties is a persistent challenge, leading to the employment of diverse approaches tailored to specific applications. The subsequent subsections delve into pertinent research and varied methodologies for handling uncertainties within M-EMSs.

5.1 | Uncertainty-Capturing Approaches

Various methods are employed to address uncertainties in microgrid energy management. From a technical standpoint, these methods can be broadly classified into two categories: exact or analytical methods and approximate methods [70, 71]. Analytical methods utilise mathematical analysis to derive closed-form expressions describing system behaviour under uncertainties. For instance, sensitivity analysis evaluates how changes in input parameters affect system outputs, while probabilistic analysis assesses the likelihood of different outcomes based on uncertain variables.

In contrast, approximate methods encompass a set of computational techniques used when analytical models are infeasible, typically due to large-scale data or significant uncertainty. These methods focus on deriving near-optimal or practically acceptable solutions rather than exact outcomes. AI-driven methods are commonly considered part of this category. Approximate methods, such as fuzzy logic, simplify complex stochastic processes, making them computationally manageable while preserving the essential characteristics of uncertainty. These methods enable efficient decision-making by providing estimates of system performance and risk under varying operating conditions. Additionally, Monte Carlo simulations (MCSs) generate random samples from probability distributions, such as normal or uniform distributions, to model uncertain parameters like renewable energy generation or load demand. Table 3 presents a variety of techniques and strategies utilised in the literature to handle uncertainties either through real-time energy management or by employing uncertainty-capturing methods. As shown in the table, studies focusing on DA operations typically adopt a 1-hour time resolution, whereas RT energy management is conducted with finer resolutions, sometimes as short as 1 min. Among the approaches used for RT operation, MPC and RL, particularly deep Q-networks (DQNs), are the most prominent solutions. In this context, the strategy refers to the control action implemented by the controller to adapt to actual system conditions, while the technique denotes the modelling approach used to formulate and execute these actions. To mathematically capture uncertainties, mainly in renewable generation and load demand, various methods have been employed across the literature, as reflected in the studies summarised in the table.

5.1.1 | Analytical Approach to Handle EMS Uncertainties

Analytical methods are mathematical techniques used to solve problems by deriving solutions through analytical expressions, equations, or algorithms. Stochastic programming (SP), robust programming (RP), information-gap decision theory (IGDT), chance-constrained programming (CCP) and sensitivity analysis (SA) are addressed in the current study.

5.1.1.1 | Stochastic Programming. SP represents a key methodology employed in devising energy management strategies for microgrids under uncertainty. In this approach, some or all parameters of the optimisation problem are treated as random variables characterised by known probability distributions, which is why it is sometimes referred to as probabilistic optimisation. A major challenge in SP is the need for accurate PDFs for these uncertain parameters. Several techniques are commonly used within the SP framework, including point estimate methods (PEMs), MCS-based methods, scenario-based modelling approaches and approximate analytical techniques [9, 83, 111]. In general, stochastic methods rely on generating numerous scenarios to model uncertainty, often through techniques such as MCS, which can lead to significant computational overhead. MCS effectively captures the randomness of uncertain variables by generating a large number of random samples based on specified probability distributions, providing an effective framework for handling uncertain variables such as PV generation, wind power output and load demand [9, 70]. Although computationally intensive, MCS remains one of the most accurate and widely adopted methods for uncertainty quantification in energy systems. To address the computational challenges of full-scale stochastic simulations, PEMs have been developed as efficient alternatives. PEMs approximate the statistical moments of system outputs by evaluating the system at a limited number of carefully chosen points, offering a balance between computational efficiency and modelling accuracy. They are well-suited for estimating power exchanges and optimal strategies under uncertainty with less computational effort [9, 33].

TABLE 3 | Operation timeframe and uncertainty-capturing methods in the literature.

		Real-time EM		Timescale		Uncertainty capturing	
Ref. no.	**Year**	**Strategy**	**Technique**	**Time horizon**	**Time resolution**	**Uncertainty-capturing method**	**Uncertain variables**
[72]	2022	BESS ch/dch to maintain load/generation balance	Load shifting mechanism	DA	1 h	N/A	N/A
[73]	2022	N/A	N/A	DA	1 h	RL	N/A
[33]	2021	Control BESS energy level	Battery virtual queue	RT	1 min	3-PEM	N/A
[74]	2021	Minimising the imbalance cost between DA and RT operation	Iterative CPLEX solver	DA/RT	1 h/ 5 mins	Coupling MCS	RES, load, price and EV parameters
[39]	2021	Power exchange with the grid, BESS ch/dch, Industrial load operating point	RTH	DA/RT	1 h	RP	RES, Price
[75]	2019	Load shedding, DER re-dispatch and transition control	Online OPF-based ED	RT	Multi-intervals	N/A	N/A
[65]	2020	Schedule BESSs and flexible loads	Minimising drift-plus-penalty function	RT	5 mins	N/A	N/A
[76]	2022	Active power control, BESS ch/dch	Offline training followed by online training	DA/RT	1 h	RL	PV, WT, load, price
[77]	2016	Active power of DG and BESS SoC	Intelligent-dynamic EMS (I-DEMS)	RT	1 min	N/A	RES
[78]	2023	Any surplus or shortfall in energy is exchanged with the grid according to RT prices	Using a function approximator (NN)	RT	1 h	RL	N/A
[79]	2025	N/A	N/A	DA	1 h	Stochastic planning algorithm	Price, RES, load
[80]	2024	BESS ch/dch, control grid exchange and local generation	DQN	RT	1 h	RL	N/A
[34]	2022	Handle unexpected failures	IGDT-Stochastic programming	DA/RT	1 h	IGDT-SP	PV, WT, load
[69]	2021	N/A	N/A	DA	1 h	RP	RES, Load
[81]	2021	Market price-based adaptive utilisation of ESSs (ToU-based RT EMS)	Enhanced Lyapunov optimisation method	RT	1 h	N/A	N/A
[62]	2020	Managing EVs charging, involving HVAC systems in DR	MPC	DA/RT	1 h	N/A	N/A
[63]	2020	Managing BESS SoC and H2ES SoHC	MPC	RT	1 h	N/A	N/A

(Continues)

TABLE 3 | (Continued)

		Real-time EM		Timescale		Uncertainty capturing	
Ref. no.	**Year**	**Strategy**	**Technique**	**Time horizon**	**Time resolution**	**Uncertainty-capturing method**	**Uncertain variables**
[82]	2020	Minimising PV curtailment and DG utilisation	Receding horizon MPC	RT	1 h	N/A	N/A
[83]	2020	N/A	N/A	DA	1 h	SP	Load, RES, EVs travelling hours, energy tariff
[84]	2019	BESS ch/dch control	RTH	DA/RT	2 h	N/A	N/A
[85]	2022	N/A	N/A	DA	1 h	Interval-based	PV, wind
[70]	2019	N/A	N/A	DA	1 h	Unscented transform	Loads, Price, PV, WT
[86]	2018	N/A	N/A	DA	1 h	2-PEM	PV, WT, load
[87]	2022	N/A	N/A	DA	1 h	RP	PV, load
[88]	2023	N/A	N/A	DA	1 h	RP	RESs
[89]	2020	N/A	N/A	DA	1 h	DRO	N/A
[90]	2023	N/A	N/A	DA	1 h	Affine arithmetic	RES, demand
[35]	2020	Load curtailment	MPC	RT	15 mins	SP	PV, WT, temperature, load
[91]	2021	Reserve allocation	MPC	DA/RT	1 h	N/A	Power variations
[38]	2020	N/A	N/A	DA	5 mins	SP	Prive, PV output, load
[92]	2023	BESS ch/dch	Droop control of secondary control	RT	1 s	N/A	N/A
[93]	2020	N/A	N/A	DA	non-integer hour	N/A	N/A
[94]	2021	Using PEV to address mismatch	Game-theory	DA/RT	30 mins	SP using K-means	RES, load
[67]	2023	Use BESS for critical loads, load curtailment and update the estimation of generation and load	Distributed-MPC	DA/RT	1 h	N/A	RES, load
[95]	2021	EVs' batteries are used to remove the mismatch	Stochastic LO	RT	10 mins	SP	Price, multi-carrier demand, EV behaviour
[66]	2023	Generating price references	MDP	DA/RT	1 h/ 5 mins	N/A	Price
[96]	2023	Update decisions according to intraday RTH	MPC	DA/RT	1 h	N/A	N/A
[97]	2022	Regular recalculation of optimal dispatch and set-points	MPC	DA/RT	5 mins/ 1 s	SP	Output power imbalance
[98]	2020	N/A	N/A	DA	1 h	RP	Power interaction
[99]	2023	N/A	N/A	DA	1 h	DRO	Combined wind, load parameter
[100]	2021	Minimise the deviation between actual and DA solution	Tube-based MPC	DA/RT	5 to 15 mins	RP	RESs

(Continues)

TABLE 3 | (Continued)

Ref. no.	Year	Real-time EM: Strategy	Real-time EM: Technique	Timescale: Time horizon	Timescale: Time resolution	Uncertainty capturing: Uncertainty-capturing method	Uncertainty capturing: Uncertain variables
[101]	2024	Using an ancillary MPC module	Distributed dynamic Tube-MPC	RT	10 mins	DRO	RES, load
[102]	2025	N/A	N/A	DA	1 h	MCS	PV, WT, DG, load
[64]	2021	Gradually correct the deviation caused by a random error in the intraday dispatch	closed-loop MPC-based rolling optimisation	DA/RT	1 h	CC-DRO	RES, Load
[103]	2021	N/A	N/A	DA	1 h	N/A	N/A
[104]	20023	Update scheduling	Aquila optimisation (IAO)	DA/RT	1 h	N/A	N/A
[105]	2019	N/A	N/A	DA	1 h	SP and CVaR	PV, WT, load
[106]	2025	N/A	N/A	DA	1 h	N/A	RESs
[107]	2025	BESS and DG control	DQN	RT	1 h	RL	PV, load
[108]	2025	N/A	N/A	DA	1 h/ 10 mins	Bounded interval-based model	PV
[109]	2025	N/A	N/A	DA	1 h	2-PEM	RESs, load
[110]	2025	N/A	N/A	DA	1 h	Data-driven uncertainty band	PV, WT

5.1.1.2 | Robust Programming. In contrast to SP, RP tackles uncertain parameters without explicit assumptions about their probability distributions. Instead, it operates under the assumption that these uncertain parameters belong to a deterministic set of uncertainties. In a robust optimisation approach, it is presumed that the uncertain parameters are at their most unfavourable or worst conditions [2]. This mathematical technique quantifies and computes robustness, consequently determining optimal values for the variables governing robustness [10]. This approach is especially beneficial in energy management scenarios where there is a scarcity of data, but several sources of uncertainty need to be addressed [2].

Robust optimisation focuses on worst-case scenarios to ensure solution feasibility. The worst-case scenario approach limits random variables to predefined uncertainty ranges with set upper and lower boundaries, calculating prediction intervals for assessing prediction uncertainty [69, 101, 112]. Nevertheless, worst-case outcomes may be overly conservative and unlikely in practice. To bridge this gap, distributionally robust optimisation (DRO) has been introduced. DRO aims to account for uncertainty by considering a range of possible probability distributions rather than relying on a single distribution [64, 89, 99]. By doing so, it strikes a balance between the granularity of stochastic methods and the conservatism of robust optimisation. Within the realm of DRO, moment-based approaches are notable, as they focus on specific statistical moments such as mean, variance, skewness and kurtosis.

5.1.1.3 | IGDT. IGDT is another analytical approach that does not rely on probabilities or fuzzy logic to manage uncertain quantifications. It is particularly useful when dealing with high levels of uncertainty or when sufficient data are not available [113]. This approach aids decision-makers in either maximising or minimising the range of acceptable uncertainties associated with potential failures while ensuring that the forecasted value remains above the specified minimum target. An IGDT model typically comprises three main components: the system model, uncertainty model and performance evaluation [113]. Given the fact that the result might be better or worse than expected, the IGDT technique offers two distinct strategies: the robust or risk-averse and opportunity-seeker or risk-seeker approaches [114]. The risk-averse strategy seeks to maximise the tolerance for uncertain parameters to handle input data deviations while ensuring that the model's results are not worse than the anticipated value. Conversely, in the opportunity-seeker approach, decision variables are set to achieve the expected target value with the smallest possible margin of uncertainty [115, 116].

5.1.1.4 | CCP. Less explored in the existing literature, CCP is employed to enforce security constraints with a specified probability threshold, providing a measure of confidence in meeting these constraints to capture the uncertainties [117–119].

CCP, also known as probabilistic constraints optimisation, offers a mathematical approach to tackling energy management issues in the presence of uncertainties. It introduces chance constraints, which are required to hold with a specified probability. These constraints are formulated to ensure power balance within the microgrid [9, 119]. However, CCP is often reserved for specific cases due to its computational complexity, conservative nature and potential difficulty in guaranteeing constraint satisfaction. Approximate methods, such as the sample average approximation algorithm, are commonly utilised to solve CCP problems [118].

5.1.1.5 | Sensitivity Analysis. SA, as a post-analysis method, involves varying input parameters to see how sensitive the output is to changes in those parameters. SA is particularly useful for topological uncertainties [120]. It helps identify which parameters have the most influence on the results to handle the associated uncertainties. Topological parameters encompass the structural characteristics of a microgrid that influence the effectiveness of EMSs. These include the microgrid's configuration as AC, DC, or hybrid, its operational mode and its potential interactions with neighbouring microgrids or the main grid. Additionally, the control architecture of the microgrid, which significantly affects M-EMS strategies, is considered a topological parameter.

5.1.2 | AI Solutions for EMS Uncertainties

In recent years, artificial intelligence (AI) has emerged as a powerful enabler for tackling the complexity and variability inherent in EMSs. The digitalisation of EMS, driven by AI, is transforming the way microgrids are controlled and optimised, enhancing operational efficiency, responsiveness and real-time decision-making. Beyond its established role in forecasting applications discussed in Section 3, AI has gained increasing attention for its ability to manage uncertainties and optimise system performance under dynamic operating conditions by providing scalable, adaptive and intelligent solutions. However, limitations related to data availability and the lack of interpretability still remain. This section categorises and examines state-of-the-art AI methodologies employed for uncertainty management in EMS, highlighting their functionalities, advantages and limitations.

5.1.2.1 | Deep Learning (DL) Models. DL methods, including neural networks, have shown significant promise in learning patterns from historical data to support predictive and prescriptive analytics in EMS [39, 78, 121]. Neural networks, in particular, are effective in modelling nonlinear relationships and handling high-dimensional data, making them suitable for load forecasting, renewable energy prediction and fault detection. While DL models offer high accuracy and scalability, they often require large datasets and high computational resources for training. These techniques are integral to intelligent EMS designs, providing adaptive and data-driven decision support under uncertainty.

5.1.2.2 | Reinforcement Learning (RL). RL, particularly in its deep RL form [73], has been increasingly adopted to solve sequential decision-making problems in EMS. In this paradigm, an agent learns to make decisions through interactions with its environment by maximising long-term rewards without requiring an explicit model of system dynamics. RL is well-suited for real-time control and adaptive management in dynamic, uncertain settings such as microgrids with high penetration of renewables [66, 76, 122]. It enables autonomous learning and optimisation without relying on predefined models, which is crucial for systems operating in volatile conditions. The Markov decision process (MDP) framework plays a fundamental role in applying RL to energy management problems. In this context, MDP models the decision-making environment where the EMS transitions between different operational states based on control actions under uncertainty. Each action taken influences future states and yields a corresponding reward. RL algorithms, particularly value-based and policy-based methods, use MDP formulations to learn optimal energy management strategies [123–125].

5.1.2.3 | Fuzzy Logic-Based Approaches. Fuzzy logic falls within the domain of computational intelligence, which is considered a subfield of AI, especially in the context of neuro-fuzzy systems, where it is combined with neural networks to enhance learning and adaptability. While it does not inherently involve learning as ML does, fuzzy methods can be enhanced by ML techniques (e.g. fuzzy RL). Fuzzy logic provides a rule-based framework that mimics human reasoning by handling imprecision and ambiguity in input data. It is particularly effective in situations where sharp boundaries are hard to define, making it suitable for modelling uncertain parameters in microgrid operations. These methods assign degrees of membership based on fuzzy theory [112, 126, 127]. It is useful for modelling uncertainties in forecasted variables but may not fully account for randomness. Fuzzy systems are commonly used to support decision-making in energy scheduling and load balancing when system dynamics are not fully known or are highly variable. The fuzzy method is an example of an approximate method that, considering the literature, has limited applications for uncertainty capturing in M-EMS.

The suitability of uncertainty-handling techniques in M-EMS depends on data availability, computational resources and the operational conditions. As summarised in Table 4, which highlights the strengths and weaknesses of the main methods in capturing the uncertainties, analytical methods such as MCS and SO are most suitable when the system under study exhibits high complexity, non-linear dynamics and multiple sources of uncertainty. MCS excels in probabilistic assessment and scenario generation, making it ideal for detailed reliability and risk analyses. SO is particularly effective when uncertainty distributions are well-characterised, allowing for uncertainty-aware optimisation over expected scenarios. RO and IGDT are better suited for environments with deep uncertainty where probability distributions are difficult to estimate or highly variable, such as emerging microgrids with limited historical data or rapidly changing renewable profiles. RO provides computationally efficient, conservative solutions that ensure system feasibility under worst-case conditions, whereas IGDT focuses on minimising potential regret, making it valuable in strategic planning where extreme events could have severe operational or financial consequences.

On the other hand, PEM and CCP are practical for mid-scale microgrid studies requiring moderate computational effort while

TABLE 4 | The strengths and weaknesses of uncertainty-capturing methods.

Uncertainty-handling technique		Strengths	Weaknesses
Analytical methods	MCS	• Provides a comprehensive assessment of uncertainty by generating multiple scenarios • Suitable for complex systems with non-linearities • Allows for probabilistic analysis • Capable of handling constraints • Rapid dynamic response	• Extensive computation, especially for large-scale problems • Requires an extensive array of simulations to achieve reliable results • May not capture rare events effectively
	SP	• Incorporates probability distributions to model uncertainties effectively • Provides robust solutions under uncertainties • Suitable for modelling complex systems.	• Computationally intensive for large-scale problems • Requires accurate probability distributions • May not capture all sources of uncertainty
	RP	• Provides solutions that are robust against uncertainties • Allows for optimisation under ambiguity • Computationally efficient compared to stochastic programming	• Requires accurate characterisation of uncertainty sets • May lead to conservative solutions • Limited applicability to highly uncertain systems
	PEM	• Straightforward to implement • Require minimal computational resources compared to probabilistic methods • Provide a single solution, making them easy to interpret and communicate to decision-makers	• By providing a single solution, may overlook the inherent uncertainties in input parameters or model assumptions • May lead to suboptimal decisions when uncertainty is not adequately accounted for, particularly in highly uncertain environments • Rely on deterministic input values, making them sensitive to errors or inaccuracies in the input data or assumptions
	IGDT	• Focuses on minimising the regret associated with decision-making under uncertainties • Provides robust decisions in the face of severe uncertainties • Suitable for highly uncertain environments	• Relatively complex to implement • Requires subjective judgments in setting information gaps • Limited applicability to certain decision contexts
	CCP	• Ensures that constraints are satisfied with a high probability • Allows for explicit consideration of uncertainties in optimisation models • Suitable for risk-averse decision-making	• May lead to conservative solutions • Computationally extensive for large-scale problems • Requires accurate estimation of probability distributions
	SA	• Facilitate identifying the most significant parameters and uncertainties within the model • Provides insights into the system's behaviour under varying scenarios.	• Post-implementation analysis • Limited to assessing the impact of individual uncertainties • May not capture complex interactions among uncertainties • Requires multiple simulations

(Continues)

TABLE 4 | (Continued)

Uncertainty-handling technique		Strengths	Weaknesses
AI-driven methods	Fuzzy-based	• Accommodates linguistic variables and expert knowledge • Suitable for systems with vague boundaries	• Lack of mathematical rigour compared to probabilistic methods • Subjective interpretation of fuzzy rules. • Difficulty in defining membership functions
	DL	• Learns complex, non-linear relationships and hidden patterns in uncertain, high-dimensional data • Effective in forecasting tasks • Scalable to large datasets and adaptable to new data through transfer learning	• Requires large volumes of labelled training data, which may not always be available • Prone to overfitting, especially with noisy or sparse uncertainty-related data • Limited transparency and interpretability, making real-time decision-making under uncertainty less explainable
	RL	• Excels in sequential decision-making under dynamic and uncertain environments • Learns optimal policies by interacting with the environment, making it suitable for real-time M-EMS under uncertain conditions • Naturally supports exploration–exploitation trade-offs, which is key when dealing with unknown or partially known uncertainties	• Requires extensive training through simulations or real-world interaction • Highly sensitive to reward design and environment modelling; poor design may lead to suboptimal or unstable policies • Performance may degrade in non-stationary environments unless constantly retrained or adapted

still accounting for uncertainty. PEM is appropriate for rapid assessments and sensitivity studies where input uncertainties are not extreme, while CCP is suitable for risk-averse operational optimisation, such as ensuring power balance or meeting reliability targets under probabilistic constraints. SA complements all these methods by identifying the most influential parameters, guiding model simplification and prioritising data collection. In parallel, AI-driven methods, including fuzzy-based systems, DL and RL, are increasingly relevant for real-time M-EMS applications, especially in highly dynamic, data-rich environments. Fuzzy-based methods excel when expert knowledge and qualitative information dominate, DL is ideal for forecasting tasks under high-dimensional and nonlinear uncertainty and RL is uniquely capable of sequential decision-making, adapting to evolving microgrid conditions in real time, albeit requiring careful training and reward design to ensure reliability and robustness.

Overall, uncertainty-capturing methods provide a range of strategies to effectively manage system uncertainties, accommodating different levels of computational complexity and risk tolerance. These methods can be deployed in single-layered frameworks for targeted analysis or in multi-layered frameworks to capture complex interactions among uncertainties. Emerging hybrid approaches, which combine analytical methods with AI-driven techniques, such as DL-assisted stochastic optimisation or RL-based robust control, show significant promise. Alternative approaches, including hyper-heuristics, KDE and two-stage scheduling (wait-and-see), are also employed to deal with uncertain variables, each with distinct applications, advantages and limitations [9, 71, 112].

5.2 | Uncertainty Mitigation Within Microgrids

The management of uncertainties within EMS poses multi-faceted challenges across microgrid operations, including security, reliability, stability and economic considerations [8]. While uncertainty-capturing methods deal with mathematical solutions to foresee the impact of uncertainties and associated challenges, there is a range of technical and practical strategies and measures to mitigate these challenges. As the most common option, energy storage technologies have emerged as integral components due to their ability to flexibly transfer power and energy across distinct time and space scales. Advancements in energy storage technologies, such as electrochemical energy storage systems (ESSs) like lithium-ion batteries and vanadium flow batteries [128], have significantly enhanced their applicability and efficiency, making them an ideal option for mitigating uncertainties. Additionally, demand response and regulation strategies have gained prominence [129, 130], particularly in leveraging users' flexibility to manage and mitigate uncertainties arising from fluctuating renewable energy, varying prices and load demands.

Moreover, the introduction of real-time and ancillary service markets, as well as the concept of multi-energy complementarity, enriches the landscape of uncertainty mitigation in microgrids. Tradable energy markets facilitate the coordinated participation of flexible resources in power system operations, thereby promoting renewable energy consumption while ensuring reliability. Furthermore, multi-energy complementarity, achieved through interconnecting multiple energy networks and facilitating flexible energy conversion, offers a promising avenue for mitigating the impact of uncertainties in renewable energy. For example, power-to-gas technology facilitates the conversion of electrical energy into stable high-energy-density gas, facilitating the storage of fluctuating renewable energy in a more stable chemical form [131].

6 | State-Of-The-Art in Uncertainty Handling for M-EMS

The integration of RESs into microgrids introduces significant operational uncertainties that challenge traditional deterministic energy management strategies. To ensure economic efficiency, reliability and resilience, recent research has focused on developing uncertainty-aware EMSs capable of transforming raw data into robust decision-making. A critical review of current studies reveals remarkable methodological progress yet also exposes persistent gaps that limit scalability, practicality and interpretability.

Uncertainty management approaches in EMS are primarily dominated by SP frameworks [73, 74, 105], where random variables such as renewable generation, load and market price are represented by probabilistic scenarios. These models improved scheduling accuracy compared to deterministic counterparts but at the cost of excessive computational burden caused by scenario explosion, particularly when accounting for correlated uncertainties. Despite advancements in scenario reduction and clustering, these methods still struggle to balance precision and tractability, often leading to simplified systems or short-term horizons that limit real-time applicability.

To overcome dependency on known probability distributions, robust optimisation (RO) emerged as a powerful alternative [69, 87, 98]. RO guarantees feasibility under the worst-case realisation of uncertainty by optimising within predefined uncertainty sets. While this approach enhances reliability and ensures constraint satisfaction, it typically produces overly conservative decisions, resulting in higher operational costs and underutilisation of renewable resources. Some studies attempted to tune the uncertainty budget or integrate risk measures such as conditional value-at-risk (CVaR) [64, 105] to mitigate conservatism, but a unified calibration methodology for balancing robustness and cost efficiency remains absent.

A more recent development is DRO, which generalises RO by optimising against a family of probability distributions rather than a single one [64, 89, 99]. DRO formulations based on Wasserstein and moment-based ambiguity sets allow flexible adjustment between risk aversion and empirical realism. However, many DRO studies rely on small historical datasets, making the estimated ambiguity sets statistically fragile. Moreover, their computational complexity remains a concern for large-scale or multi-microgrid (MMG) systems, often requiring decomposition or approximation techniques that compromise accuracy.

In parallel, MPC [62, 67, 100, 101] and Lyapunov-based real-time optimisation [33, 65, 81, 95] methods have gained attention for their adaptability to evolving system conditions. By continuously updating decisions as new data becomes available, these approaches reduce the dependency on forecast accuracy. Yet, they require precise model identification and face difficulties in handling high-dimensional uncertainties or ensuring long-term optimality. Moreover, MPC frameworks that rely on linearised system models may oversimplify nonlinear dynamics inherent to hybrid microgrids, leading to suboptimal control under abrupt renewable fluctuations.

The literature has also seen a growing interest in data-driven and learning-based EMS frameworks. RL and deep neural architectures have shown potential for capturing complex system dynamics without explicit modelling of uncertainty distributions [66, 76, 78]. For example, the real-time RL-based M-EMS proposed for renewable-powered mobile microgrids (i.e. ships) [107] effectively managed uncertainties, reducing fuel consumption by up to 5.43% compared to RO methods. This demonstrates the promise of learning-based strategies in dealing with high-dimensional, non-stationary uncertainties. However, RL approaches face challenges related to training stability, interpretability and safety, as black-box models may violate operational or safety constraints under unseen conditions. Few studies have incorporated formal safety guarantees and the lack of transparency makes it difficult for operators to trust such autonomous systems.

Another important stream of work involves MMG coordination under uncertainty. Distributed and decentralised EMS frameworks based on ADMM [87], consensus algorithms and game theory [100, 101] promote scalability and privacy preservation by enabling local optimisation while maintaining global coordination. The recent multi-objective multi-verse optimiser-based EMS [79] for a four-microgrid system exemplifies this direction, addressing uncertainties in DER output, demand and price while minimising both the cost of energy and loss of power supply probability. Although the algorithm achieved faster convergence than competing algorithms, its reliance on metaheuristic tuning and absence of theoretical convergence guarantees limits its reliability for real-time operation. Moreover, distributed methods often assume ideal communication and synchronisation, neglecting cyber-physical uncertainties such as latency or data integrity issues.

A further limitation across most studies lies in simplified uncertainty characterisation. Some studies assume independent or stationary random variables and neglect temporal correlations or spatial dependencies among renewable outputs. Only a few papers, such as those employing copula-based distributions [83], attempt to capture these dependencies. Furthermore, multi-energy system uncertainties, involving coupled electricity, heating and hydrogen networks, are rarely addressed, despite their growing relevance in integrated energy systems [35, 85, 132]. Current formulations generally treat non-electrical vectors deterministically, missing the complex interactions that influence optimal dispatch.

Another concern is the lack of empirical validation and standardisation. Most EMS models are tested on simplified testbeds or synthetic datasets, without validation using real-world high-resolution data. The reliance on simulated scenarios prevents accurate assessment of robustness under real operational noise and non-stationary behaviour. Comparative analyses are also inconsistent; studies use diverse metrics such as cost reduction, reliability indices, or emission levels, making cross-study evaluation difficult. This heterogeneity underscores the need for open benchmark datasets and standardised evaluation frameworks.

7 | Real-World Deployment of M-EMSs

Numerous papers in the literature have concentrated on the global development and implementation of microgrids, but there is comparatively less information available on M-EMSs. In addition, while many microgrid applications are linked to research or rural electrification projects, detailed reports on industrial microgrids are notably absent from the literature [4]. Most of the studies focus on experimental testbeds, revealing that the majority of existing microgrid testbeds are based on AC systems, with only a few documenting DC systems [133]. For instance, the Illinois Institute of Technology has implemented a DC system for economic dispatching analysis. Additionally, the U.S. Department of Energy is developing a master controller to seamlessly integrate the Bronzeville community microgrid with the Illinois Institute of Technology campus microgrid [8]. To explore microgrids from the perspective of EMS, several researchers have developed testbeds and conducted related evaluations. In particular, authors in [134] presented an experimental hybrid microgrid testing facility focusing on energy management, which combines high-efficiency AC and DC distribution architectures to serve as a research testbed for investigating microgrid systems. A cloud-based real-time EMS for microgrids, integrating IoT, cloud computing and ML, is examined in [135], aiming at enhancing autonomy, scalability and real-time data analysis, tested on a hardware-in-the-loop testbed for economic power dispatch and battery storage management. The testbed for EMSs implemented by the authors in [136] links the multi-agent RL algorithm with price-sensitive responsive load demands. The study assesses the RL algorithm's effectiveness in a laboratory setting for DR management.

7.1 | Technical Barriers

While academic advancements in M-EMSs have been substantial, real-world deployment reveals a series of practical challenges that extend beyond algorithmic optimisation. Industrial and commercial microgrids face persistent barriers associated with cybersecurity, interoperability and regulatory compliance, all of which significantly influence system reliability, scalability and long-term sustainability. From a regulatory standpoint, M-EMS implementation is shaped by diverse interconnection codes, market participation rules and cybersecurity requirements that vary considerably across jurisdictions [137].

Among these challenges, cybersecurity remains one of the most critical concerns, as modern EMSs increasingly rely on cloud connectivity, IoT-based monitoring and distributed control networks. Attacks such as false-data injection, denial-of-service, or unauthorised access can compromise operational decisions and threaten grid stability. To mitigate these risks, commercial M-EMS platforms typically comply with standards such as IEC 62443 and IEC 62351, incorporating features like encrypted communication, secure gateways, authentication mechanisms and local fallback control during network disruptions. Despite these safeguards, uneven standard adoption, the prevalence of legacy devices with weak protection and limited in-house cybersecurity expertise continue to pose vulnerabilities. Consequently, state-of-the-art EMS architectures are trending toward resilient, multi-layered security frameworks designed to maintain partial functionality and system integrity even under cyberattack conditions.

Interoperability presents another major technical challenge. Microgrids often comprise diverse devices and communication protocols, such as Modbus, OPC UA and IEC 61850, resulting in complex integration processes, data latency and potential incompatibility between system components. To address these issues, some EMS vendors have adopted open architectures and standardised communication interfaces that facilitate modular expansion and plug-and-play integration of DERs and storage assets. However, achieving semantic interoperability (i.e., the consistent interpretation and utilisation of shared data across heterogeneous platforms) remains limited. Emerging standards such as IEEE 2030.7 and IEEE 2030.8 aim to define interoperable frameworks for microgrid controllers, yet their widespread adoption is still in progress [138].

7.2 | Commercially Available M-EMSs

In the area of practical EMS development, companies such as ABB, Ageto, Wartsila, Siemens and Schneider have directed their efforts toward advancing EMS technologies. The Ageto ARC EMS optimises on-site energy resources like solar and energy storage, ensuring reliable and clean backup power. It integrates existing industrial generators with these resources. Suitable for both grid-connected and off-grid applications, the ARC system offers intelligent utility rate optimisation, reducing electricity bills through time-of-use shifting, peak shaving and demand response programs. Since 2017, Ageto has deployed over 50 ARC systems worldwide, enabling diverse energy resources to work together efficiently in various settings, from remote Alaskan communities to fire-affected regions in California [139]. Schneider's EMS offers transmission operators enhanced insight into transmission and sub-transmission networks. It can function as a standalone system or integrate seamlessly with an advanced distribution management system. Key features include state estimation, optimal power flow, contingency analysis, optimal topology change, performance indices and voltage stability. These capabilities enable utilities to visualise, operate and optimise their networks. Siemens is also working on EMSs covering smart grid technologies and an IoT platform to gather microgrid data. For instance, this company delivered an M-EMS based on cloud technology at Expo 2015 in Milan, Italy [140]. Table 5 summarises the most relevant features of the aforementioned systems according to the available information on their manufacturers' websites. As outlined, each system has unique strengths depending on the application. ABB and Wärtsilä focus on advanced AI-driven optimisation, Siemens excels in market participation, Schneider Electric emphasises battery storage integration and Ageto provides flexible, equipment-aware solutions.

8 | Conclusion

This review presents a comprehensive assessment of uncertainties in M-EMSs, outlining their origins, impacts and mitigation strategies. Uncertainties arise from diverse sources, ranging from measurement noise and forecasting errors to model approximations and real-time deviations from expected operating

TABLE 5 | Comparative analysis of leading M-EMSs.

Feature	ABB [141]	Ageto [142]	Wärtsilä [143]	Siemens [144]	Schneider Electric [145]
DER integration	Supports various DERs, including renewables and conventional sources	Universal compatibility, integrates diverse energy resources	Integrates storage, renewables and thermal generation	Supports multiple energy sources, including solar, wind and biomass	Fully integrated with battery storage and other DERs
Electricity market participation	Provides market optimisation and participation tools	Focuses on local optimisation rather than direct market participation	Uses AI-driven analytics for market optimisation	Offers market-based optimisation through microgrid management system (MGMS)	Supports demand response and ancillary services
Uncertainty handling capability	Uses predictive analytics and optimisation	Real-time monitoring and control, adapting to dynamic conditions	ML-based forecasting	Forecasting and optimisation for load and generation	Predictive DER management
Real-time performance	Suitable for distributed, fast control; supports seamless islanding, load balancing and fast transitions	Works at second-by-second control granularity	Handles microsecond-level response, low latency and fast frequency response events	Supports real-time switching, islanding and fast transitions	Handles real-time power flow control, switching and island transitions
AI integration	AI-driven optimisation and forecasting	Real-time control and automation	ML for asset optimisation	AI-powered microgrid control	AI-based predictive energy management
Cybersecurity	Focus on availability, safety and cybersecurity	Secure VPN-based remote monitoring	IEC-62443 cybersecurity certification	Complies with IEC-62443 cybersecurity standards	Secure cloud-based management
Digital Twin capability	Supports digital twin-based optimisation	Not explicitly mentioned	Uses digital twin for asset monitoring	Digital twin integration for microgrid simulation	Digital twin-based predictive control
Scalibility	Modular and scalable	Supports scaling across DERs	Multi-GWh scale, fleet-level control, site partitioning and modular expansions	Scalable and integrates into industrial plants with increasing size	Scalable from low-voltage microgrids to large industrial systems via modular architecture
Reliability	Supports seamless islanding, self-healing, redundancy in distributed agents, fallback modes	Operates under challenging conditions (load shedding, fault tolerance)	Handles fast transitions to protect reliability	Stable transitions with IEC standard conformance	Includes fallback modes, redundant control paths, defined switching hierarchy
Ideal use case	Industrial sites, remote communities	Off-grid and grid-tied microgrids	Large-scale hybrid power plants and energy storage systems	Industrial and commercial microgrids	Resilient microgrids, demand charge reduction

conditions. Collectively, these factors influence generation dispatch, load management, energy storage operation and grid interactions across multiple temporal and spatial scales. Hence, a multi-level perspective is crucial, linking data acquisition, forecasting, optimal scheduling and real-time control, since even small discrepancies between predicted and actual conditions can cascade, compromising system performance.

To address these challenges, a broad spectrum of strategies has emerged to anticipate, quantify and mitigate uncertainty. Probabilistic forecasting allows early-stage characterisation of variability, minimising error propagation throughout the control hierarchy. Analytical, stochastic and RO techniques, supplemented by AI-driven and data-centric approaches, have progressively enhanced the adaptability and resilience of M-EMSs. The field has evolved from deterministic optimisation toward hybrid, data-driven and decentralised architectures. Foundational methods such as stochastic and RO have been complemented by DRO and MPC, enabling improved real-time flexibility. More recently, RL and hybrid metaheuristic algorithms have demonstrated significant potential in managing high-dimensional nonlinear systems, though issues of interpretability, constraint satisfaction and computational efficiency remain unresolved.

Despite considerable progress, widespread adoption of uncertainty-aware M-EMSs is still constrained by several practical barriers. The high computational complexity of advanced optimisation and AI-based frameworks limits their real-time feasibility, while the accuracy and reliability of underlying data, particularly from renewable forecasts, load measurements and grid parameters, remain critical determinants of system performance. Furthermore, explainability and transparency are essential to ensure operator confidence, regulatory compliance and secure system operation. Cybersecurity considerations, regulatory heterogeneity and the interoperability of DERs further complicate large-scale deployment. Therefore, future progress will depend on balancing algorithmic sophistication with operational transparency, computational efficiency and system robustness.

Looking ahead, the next generation of M-EMSs will likely emphasise integrated multi-energy management, enhanced demand-side flexibility and inclusion of emerging vectors such as hydrogen. The application of advanced AI, particularly deep RL, is expected to further improve uncertainty handling and autonomous decision-making. The comparative review of commercial M-EMS solutions provided herein offers valuable insights for bridging research and practice. Achieving fully operational, uncertainty-resilient M-EMSs will ultimately require standardised evaluation frameworks, open datasets and hardware-in-the-loop testing to transition from simulation-based studies to real-world robust deployment.

Author Contributions

Farid Moazzen: conceptualisation, data curation, formal analysis, methodology, validation, visualisation, writing – original draft. **MJ Hossain:** project administration, supervision, validation, writing – review and editing. **Li Li:** supervision, validation, writing – review and editing. **Behnam Mohammadi-Ivatloo:** supervision, validation, writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data are available upon reasonable request.

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