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Review

Microgrid Energy Management and Methods for Managing Forecast Uncertainties

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Abstract: The rising demand for electricity, economic benefits, and environmental pressures related to the use of fossil fuels are driving electricity generation mostly from renewable energy sources. One of the main challenges in renewable energy generation is uncertainty involved in forecasting because of the intermittent nature of renewable sources. The demand also varies according to the time of day, the season, the location, the climate, and the availability of resources. Microgrids offer a potential solution for the integration of small-scale renewable energy sources and loads along with energy storage systems and other non-renewable sources. However, intermittent generation and varying demand need to be matched to provide stable power to consumers. Therefore, it is crucial to design an energy management system to effectively manage the energy sources and supply loads for reliable and efficient operation. This paper reviews different techniques proposed in the literature to achieve the objectives of a microgrid energy management system. The benefits of existing energy management systems and their challenges are also discussed. The challenges associated with uncertainties and methods to overcome them are critically reviewed.

Keywords: energy management; forecast uncertainties; microgrids; optimization; renewable energy integrations

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1. Introduction

In the last two decades, the electric power industry strived to increase the electricity generation from renewable energy sources (RES) due to the environmental issues associated with the use of fossil fuels and associated economic benefits. Being proven cost-effective technologies, currently solar PV and wind are the fastest deployed RESs in power generation [1]. However, solar PV power generation is impacted by changing weather conditions and passing cloud cover, while the amount of energy generated by wind varies with wind speed. The intermittent nature of renewable energy resources complicates power system operation and control. These uncertainties introduced to the generation of resources, in addition to the varying electric demand, make energy management more challenging.

The microgrid (MG) concept, schematically illustrated in Figure 1, has become a smart candidate for integrating RESs, as it can be operated as a single controllable system. A microgrid is usually comprised of energy resources, energy storages, and loads and operated within a clearly defined electrical boundary. The energy mix of a microgrid usually includes solar PV and wind as primary sources of renewable energy, and a few non-renewable resources, such as diesel generators, micro turbines, and gas turbines are also used as backup energy resources. Various energy storages, such as batteries, super capacitors, fuel cells, are considered to ensure the availability of power throughout the entire time horizon [2–4].

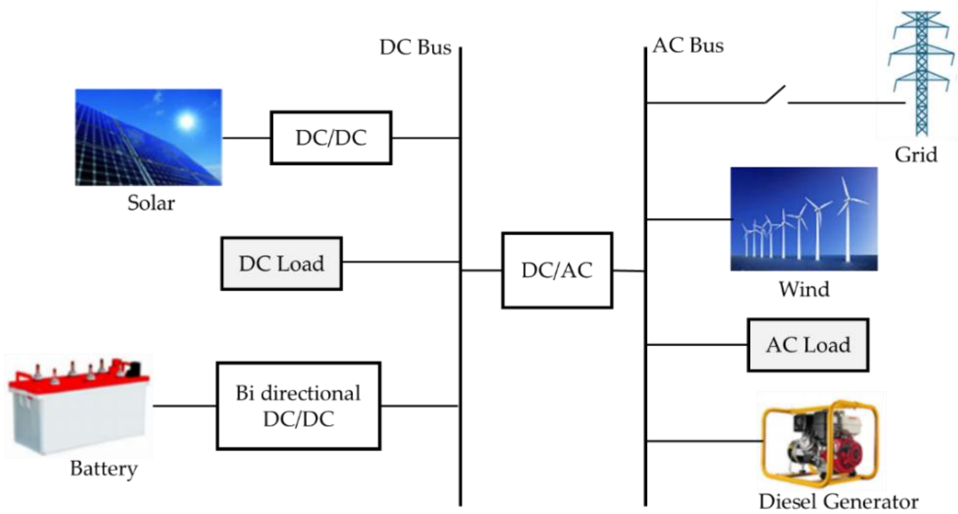

Figure 1. Generalized structure of a microgrid.

A microgrid can be either connected to or isolated from the grid and operate with full controllability. The output power from energy sources must, therefore, meet the requirements of local loads in the islanded mode. In the grid-connected mode, the microgrid shares the energy with the main grid (supply or absorb) via the point of common coupling (PCC). Microgrids can be classified based on voltage, such as AC microgrids, DC microgrids, and hybrid AC/DC microgrids. In AC microgrids, DC generating RES such as solar PV and wind are connected via DC/AC power inverters. The DC microgrid is similar to its AC counterpart, possessing a common DC bus. A hybrid microgrid is a combination of both AC and DC microgrids, offering the best solution for grid integration of RES. Various models and layouts are used to describe the microgrid operations in the literature [5].

A microgrid control system is responsible for ensuring desired voltages, currents, and frequency through proper management and control, including performing economic dispatch, balancing power supply and demand, demand side management, etc., under all modes of microgrid operation. An energy management system (EMS) is usually designed to optimize power generation to meet the demand at the minimum operational cost while maintaining the integrity of the system. Among the various definitions, the IEC 61970 standard has defined EMS as "a computer system comprising a software platform providing basic support services and a set of applications providing the functionality needed for the effective operation of electrical generation and transmission facilities so as to assure adequate security of energy supply at minimum cost" [6]. Microgrid energy management systems (MG EMS) also have the same aforementioned features to provide the required functions to ensure safe and efficient operation. An energy management problem is typically formulated as an optimization problem with the objective of minimizing the total cost of operation over a chosen time horizon (often over 24 h), subjected to operational constraints. The optimization is based on the forecasted load variation. When intermittent generation is involved, a resource forecast is also required to solve the optimization problem. The MG energy management is complicated by forecast uncertainties. The forecast uncertainty, which is the deviation of actual load and renewable generation from their respective forecast values, affects optimum scheduling and raises new challenges in microgrid systems with a high penetration of renewables. Therefore, uncertainty management needs to be incorporated into the energy management problems.

Several comprehensive reviews related to MG EMS can be found in the literature, and they address different aspects of energy management function. The review of microgrid EMS presented in [7] is organized based on four categories: (1) the optimization techniques employed, (2) the type of grid taken into consideration, (3) the mode of operation of the microgrid, and (4) the software used as a platform for solving the EMS problems. Two major categories of microgrid energy management strategies are discussed, including classical and intelligent methods for residential applications in [8]. A comparative and critical analysis of the literature on decision-making strategies and their solution methods for MG EMSs is presented in [6]. A comprehensive description of control and optimization methods to identify the most common and effective methods for MG EMS is highlighted in [9]. In [10], the review is conducted in terms of uncertainty modeling approaches, objective functions, constraints, optimization techniques, and simulation and experiment results for EMSs. However, the uncertainty issues are not comprehensively addressed. Recent techniques to model the uncertainties from renewable energy sources and loads in microgrids are reviewed in [11]. Methods of uncertainty management, parameter modelling, simulation tools, and test system in unit commitment in power systems are discussed in [12]. Methods for uncertainty modelling in power systems, comparison between these methods, strengths, and weaknesses are studied in [13]. A standard classification of uncertainty handling methods is proposed in [14], where the models are compared, and their strengths and weaknesses are investigated.

Proper modelling and managing forecast uncertainties are an important aspect of an efficient and effective energy management system for a microgrid with high penetration of renewables. The main objective of this paper is to present a comparative review of effective energy management methods used in microgrids along with forecast uncertainty management. This study identifies the techniques used for managing forecast uncertainties and modeling those uncertainties in microgrid systems. The paper is organized as follows: the concept of a microgrid energy management system is discussed in Section 2. Energy management problem formulation and solution approaches are discussed in Sections 3 and 4, respectively. Section 5 addresses the potential challenges caused by the uncertainties from forecasted data along with managing methods in MG EMS. Section 6 discusses the application of artificial intelligence (AI) and machine learning (ML) in MG EMS. The paper concludes with future research opportunities related to microgrid energy management under source and load uncertainties.

2. Microgrid Energy Management System (MG EMS): The Concept

A microgrid energy management system (MG EMS) performs a variety of functions for the efficient and effective operation of the system. Energy management is an optimization problem with the target of properly scheduling the short-term operation of production by generators, storage, as well as controllable loads, to cover the system demand and minimize the generation costs. The EMS generates a schedule of unit commitment and the optimized output of each source considering the results of the optimization. Figure 2 illustrates the overall outline of the MG EMS.

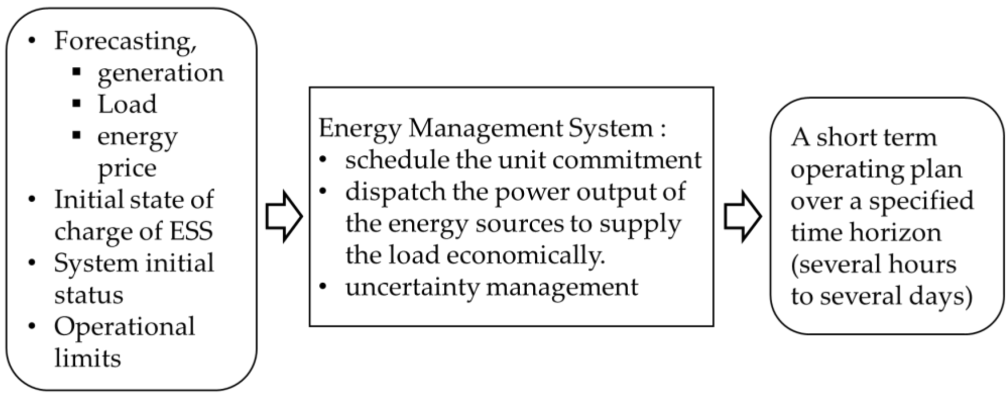

Figure 2. Energy management system outline.

Control Systems Used in EMS

The control system associated with MG EMS can be implemented using centralized, decentralized, and hierarchical control methods [7,15,16]. In centralized control-based EMS, a single central controller that receives all the information, such as RES energy generation, load profile, market price, weather conditions, etc., is used. Based on the inputs, a central controller decides the optimum microgrid energy schedule and then sends these decisions to all local controllers. The basic structure of the centralized control is shown in Figure 3. However, the failure of the central control could cause the entire system to fail. Unlike centralized control-based EMS, in decentralized control shown in Figure 4, a few local connections are needed, and only local measurements are used to make control decisions.

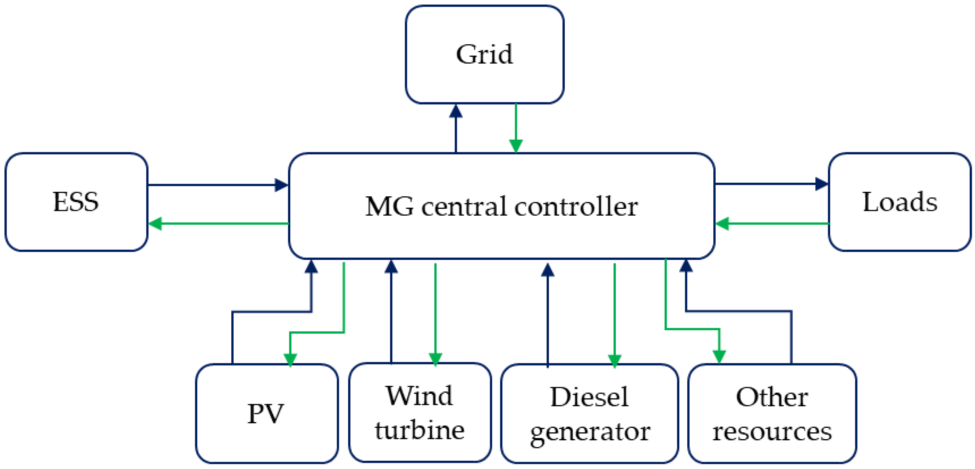

Figure 3. Centralized control structure.

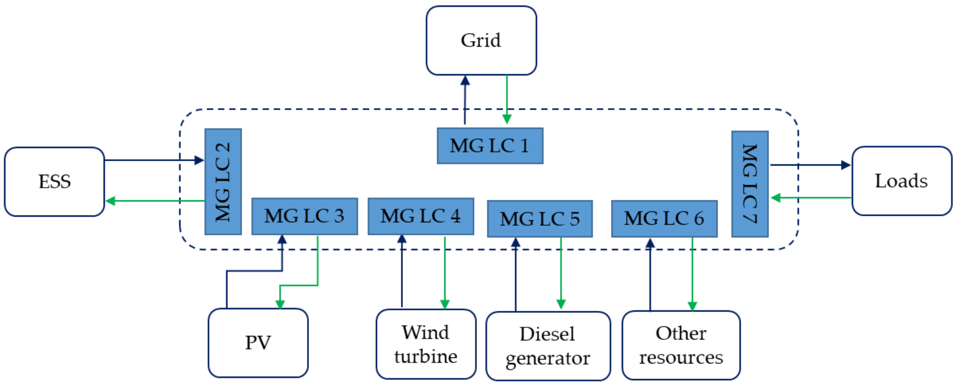

Figure 4. Decentralized control structure.

Hierarchical control approaches are used to provide a compromise between totally centralized and decentralized control structures, and they includes primary, secondary, and tertiary controls. The primary control provides local voltage and current control, as well as power sharing control. It generally follows the instructions of higher-level controllers. The secondary control is responsible for the power management of the system. It is also used for microgrid synchronization to the main grid when switching from islanded to grid connected mode. Tertiary control is used to control the power flow. It can also be used for other objectives, such as islanding detection. The hierarchical control approach is the most widely used conventional method, and its objective is to enhance the efficiency and effectiveness of microgrid operation [17]. However, hierarchical control is challenging with the consideration of the intermittency of RES. Recent studies have extensively focused on hierarchical control approaches to improve the energy management aspects of microgrid systems. A typical hierarchical control scheme is illustrated in Figure 5.

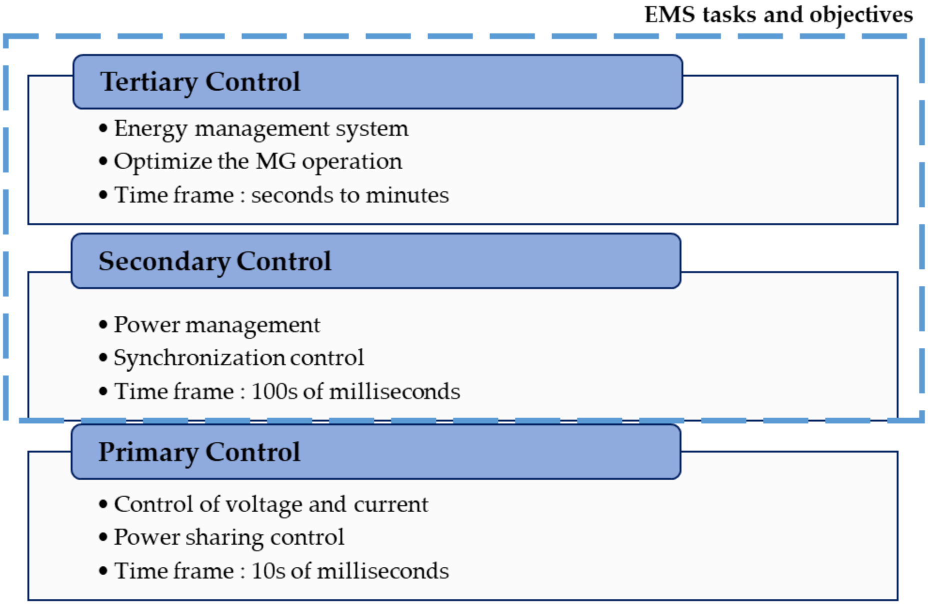

Figure 5. Hierarchical control.

Table 1 summarizes the features, advantages, and disadvantages of implementing EMS based on different control aspects.

Table 1. Comparison of control methods used in EMS.

	Features	Advantages	Disadvantages
Centralized control	Centralized control has complete knowledge of the entire system and is in charge of ensuring its optimal operation.	It provides wide control over the entire system. Established control approach. Simple architecture. Easy to implement and maintain. It ensures optimal decision.	It requires a high performance computing unit and communication network. The failure of central control could cause the entire system to fail. Computational complexity is high. Low flexibility.
Decentralized control	Functions provided by centralized control are realized in a decentralized way. Local decisions contribute to achieving the goal.	It does not require a high performance computing unit and a high-level connectivity. Easy realization of plug-and-play functionality.	It requires an effective method to ensure corporation among local controllers. Low performance compared to centralized control due to low response time and incomplete information about the total microgrid system installation. High implementation complexity.
Hierarchical control Based methods	Each level provides supervisory control over lower-level systems. Three layers: tertiary, secondary, and primary control layers. The bandwidths of different control levels are separated.	Combining the centralized and decentralized controllers. Higher levels attempt to optimize the microgrid operation. Local controls regulate the voltage and current. It simplifies modelling and analysis of microgrid systems.	Proper coordination of all three layers is required.

3. Microgrid Energy Management: Problem Formulation

Microgrid energy management is used to either minimize or maximize an objective or set of objectives while ensuring the constraints of individual units and the system as a whole. These objectives are quantitative in nature and usually include cost reduction, emission reduction, increased renewable energy integration, etc. The associated constraints include power balance, individual unit ratings, charge and discharge rates of ESS, maximum and minimum limits of the state of charge (SOC) of ESS, power import and export limits, and other technical constraints of the microgrid. Most of the existing literature focuses on microgrid cost minimization in a single-objective format. The considered cost factors are related to fuel, start-up, shut-down, maintenance, degradation, utility purchases, etc. When several objectives are optimized, the optimization framework is formulated in a multi-objective framework. In such cases, each objective is assigned a weighting factor. These weighting factors are usually assigned based on the significance of individual objectives in relation to the final objective function.

Various solving techniques, such as mixed integer linear and non-linear programming (MILP and MINLP) methods, heuristic optimization methods, etc. are used to solve the optimization problem, sometimes together with rule-based and fuzzy logic control methods to simplify the problem. These optimization strategies use various optimization time windows (horizon) on different time scales. A suitable selection is used to improve the energy management system. Recently, the rolling horizon is considered to reduce the impact of uncertainties from the renewable energy output and load forecasting.

The design of an EMS for a microgrid includes the task of the mathematical formulation of objective functions and constraints, selection of the optimization time horizon and the time step, as well as choosing an optimization technique to solve the problem.

The typical mathematical representation of the EMS problem is shown below:

Objective function:

Minimize the total cost of the microgrid operation;

- Operational cost = fuel cost + maintenance cost + startup cost of the thermal unit + shutdown cost of the thermal unit + cost of buying and selling power to the main grid + load shedding penalty cost + losses cost
- Environmental cost = carbon emission + penalties for emissions
- Energy storage cost = charging cost + discharging cost + degradation cost
- Constraints:
- Power balance: load demand at each time must be equal to the summation of power from microgrid resources and receiving/sending power from the main grid.
- Emission constraints: emissions caused by each fossil-fueled thermal generators cannot exceed the maximum limits at each time.
- Capacity limits: each RESs, ESS, and interconnection has a maximum and minimum capacity during the operating mode.
- Limit of ESS: charging and discharging power rates for batteries during operation mode and the operating SOC range must be limited as it may affect battery life time.
- Operating reserve: extra storage and generation capacity
- Generator start/stop limits: the number of generator starts/stops cannot exceed a certain number.
- Ramp rate power limit: the maximum power fluctuation of each unit is defined.

System variables:

- Load profile: the demand forecast varies according to time, geographical location, season, weather, and other factors.
- PV and wind sources: the wind and PV power availability depends on wind speed forecasts and solar irradiation forecasts, respectively. Seasonal and local weather impacts these forecasts, and there is always some uncertainty associated with the forecasts.
- Electricity price: it is related to the price of the buying/selling power to the main grid. Prices may be time-sensitive.

The energy management problem in a microgrid becomes a mono objective when a single cost function is presented. The problem becomes multiple objectives when it simultaneously presents a solution to the competing technical, economic, and environmental problems. The weighting coefficients of each function must be properly defined when multiple objectives, such as operational cost minimization, emission reduction, and other objectives, are taken into account for the optimization problem. Effectively setting the weighting factors of the objective function is still being researched.

In addition to the typical objectives and constraints, there are other elements that needs to be incorporated into the MG EMS. Some such aspects include real-time or time-varying electricity tariffs and demand response, which add further benefits for both energy providers and consumers. From the consumer perspective, consumer comfort and a profitable electricity bill are important considerations. From the energy providers' perspective, efficient load profile reshaping is essential. Techniques such as peak clipping, valley filling, and load shifting can be employed to successfully execute the reshaping of the load profile while considering factors such as cost, dependability, control strategies, targeted customers, and supporting infrastructure [18]. The impact of electric vehicles (EVs) is an emerging factor because the use of EVs is expected to significantly increase in the next decade, causing a major increase in demand and demand pattern. Energy storage available in EV batteries can be used in the MG EMS with proper infrastructure for EV charging. Consumer comfort maximization can be defined as one of the objective functions in the formulation of the MG energy management problem, which includes demand response and EV energy storage. However, it makes optimization tasks computationally complex. The proposed method in [19] ensures customer satisfaction by optimal allocation of demand in a distribution feeder using autonomous decision-making entities.

4. Microgrid Energy Management: Solution Approaches

The selection of EMS methods depends on the microgrid system and the requirements. The solution methods for energy management problems can be classified in various ways. In this paper, those EMS solution methods are classified as shown in Figure 6.

Approaches for solving basic energy management problems

- Mixed Integer Linear and Non Linear Programming (MILP & MINLP)
- Heuristic optimization methods
  - Genetic Algorithm
  - Particle Swarm Optimization
- Rule based control
- Fuzzy logic control

Approaches for Uncertainty Management

- Stochastic optimization
- Robust optimization
- Chance Constrained Programming (CCP)
- Model Predictive Control (MPC)

Figure 6. Classification of microgrid EMS methods.

4.1. *Mixed Integer Linear and Non-Linear Programming Methods*

Mixed integer programming methods deal with optimization problems where variables can be discrete and continuous. Therefore, the methods fit perfectly for applications in microgrid EMS. In mixed integer linear programming (MILP) based EMS, mathematical models of microgrid components are developed using MILP to optimize the cost function. The MILP model considers wind speed and irradiation, loads, and cost parameters of the components. For MILP methods, the objective function and constraints are linear, but for mixed integer non-linear programming (MINLP) methods, they are non-linear. Typically, MINLP models make use of approximations to obtain a linear model. In MINLP models, continuous variables are the power imported/exported at PCC, the power generation from available generators, and the power injection of the ESS. When considering the power flow equation of microgrids, they introduce non-linearity and complexity to the energy management problem and increase the computational burden.

In [20], considering a distribution network with radial structure, power flow of a line (referred to as $S_{ij}(t)$) is expressed using Equation (1), which shows non-linearity.

$$S_{ij}(t) = V_i(t)\ I_{ij}^{*}(t) \tag{1}$$

$$\lceil V_i\,(t)\rceil^2 \times \lceil I_{ij}\,(t)\rceil^2 = {P_{ij}}^2 + {Q_{ij}}^2 \tag{2}$$

Thus, voltage is considered equal to a constant value as voltage changes are very small. With the said assumption, a linear approximation of the current in power flow is calculated using the piecewise linearization method. In a similar manner, nonlinear constraints and equations are converted into linear form to simplify.

Mixed integer linear and non-linear optimizers are often used because of their high efficiency and modelling flexibility. However, complex problems with a large number of variables take a long time to calculate. The MILP and MINLP-based EMS are applied in a variety of ways in the reported literature [21,22].

4.2. Heuristic Optimization Methods

There are many heuristic optimization methods that can be applied to the MG EMS optimization problem. Among them, the genetic algorithm (GA) and particle swarm optimization (PSO) are used frequently to solve energy management optimization problems. Similar techniques, such as the ant colony algorithm [23], Lagrange algorithm [24], crow search algorithm [25], and simulated annealing [26] are also utilized for microgrid energy management.

a. Genetic Algorithm

The genetic algorithm (GA) is a frequently used heuristic optimization method to solve optimization problems, and it has the capacity to optimize multi-dimensional problems. The genetic algorithm is developed through various stages, as shown in Figure 7. The GA repeatedly modifies a population of individual solutions. Individuals can be defined as arrays, trees, or lists of variable values to be optimized. Solutions are typically represented as strings of zeros and ones in binary, but other representations are also available. In a binary implementation of genetic algorithms, GA starts from a population of randomly created individuals. The objective function of every individual in a population will be evaluated and ranked. Selection determines which ones are to be selected from the current population and allowed to reproduce. There are various approaches to implementing selection in GA, such as roulette selection, tournament selection, stochastic universal selection, and Boltzmann selection. Frequently used genetic operators are crossover and mutation. Crossover is a recombination operator by swapping the values between two strings to create new solutions from the existing population. There are various crossover methods, such as uniform crossover, arithmetic crossover, permutation encoding crossover, value encoding crossover, tree encoding crossover etc., being applied based on the application [27]. A new population is full of individuals after selection and crossover. Some are formed by crossover, while others are directly copied. Mutation is the change of a small amount or the replacement of a value with a new one in order to ensure genetic variability among the population. The probability of a mutation is typically 1 to 2%.

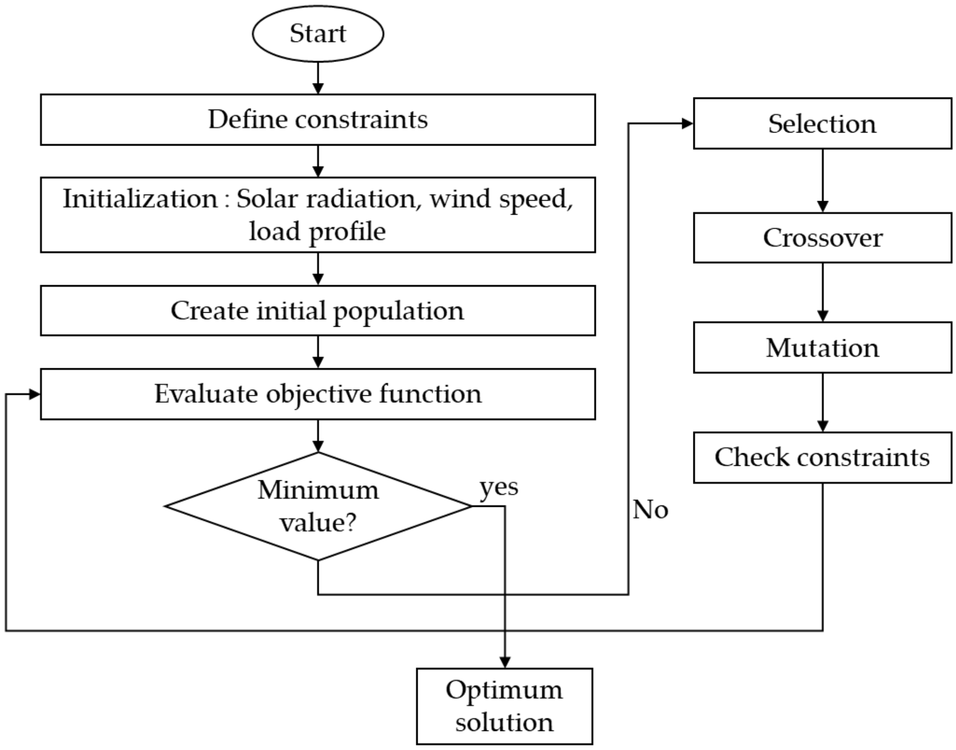

Figure 7. Basic GA algorithm for MG EMS.

In order to solve the optimization problem for MG EMS, GA considers the system variables, constraints, parameters, and the objective function, as shown in Figure 7. The GA is developed to schedule the generators, battery storage systems, and controllable loads. The total running cost, microgrid emission, and other objectives are optimized while satisfying all equality and inequality requirements using a suitable ON or OFF state. The GA optimizes with continuous or discrete variables, and it can also optimize variables in an extremely complex problem. It can handle a large number of variables. However, the challenges associated with GA are the long calculation time involved and the possibility of ending up with one or more solutions. Each run could produce a different result. In the case of EMS in microgrids, it is challenging to find the optimal solution through GA.

b. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based heuristic optimization technique and can be deployed in a wide range of microgrid-related applications. Particles use both the personal best solution and the best solution found by the swarm to collectively move towards the optimum. Figure 8 illustrates the typical PSO algorithm used for microgrid energy management applications.

The system starts with a population of random solutions and then updates generation to search for an optimum solution. It can handle a wide range of problems while achieving a set of goals, such as minimizing energy costs and reducing emissions. It is feasible to update the PSO objective function at a smaller interval. In PSO methods, it is important to define parameters such as population size, maximum number of iterations, etc. The initial particles are selected randomly between the minimum and maximum values of the variables. Each particle is evaluated using the objective function to find the best solution. The performance of PSO depends on the selection of suitable PSO parameters and stopping criteria. The main advantage of PSO-based EMS is its fast convergence time, which is essential for real-time energy management applications. The PSO is also used by many researchers to solve microgrid optimal sizing problems [28,29].

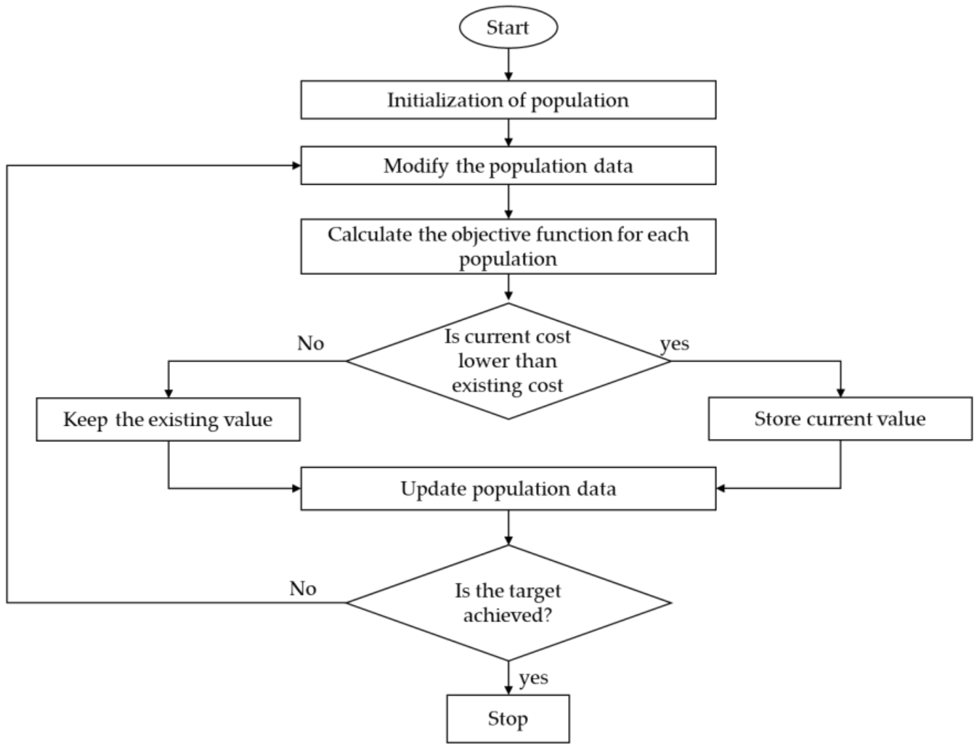

Figure 8. Typical PSO algorithm.

4.3. Rule-Based Methods

With the rule-based methods, the inter-dependability of the resources of the microgrid are defined using predefined logical rules. If-then-else rules are applied for assigning values to binary decision variables used in the optimization procedure of the microgrid operation. Load, PV generation, and wind generation values are not affected by values from the present or the past. However, changes in battery storage have an impact on future schedules. Rule-based algorithms can also be used to develop a method for BESS scheduling to determine the optimal charge/discharge of the battery. Such methods use the energy generated by RESs and the battery SOC level to determine whether the battery energy storage system (BESS) should be charged or discharged. Rules also ensure that SOC is kept under allowable levels while performing perfect dispatch. The analysis takes into account a variety of operational modes. For example, in the case of islanded microgrids, if the output power from renewable resources (solar and wind) is higher than the power demand, the excess power will be used to charge the battery storage up to its maximum capacity. If the generation is higher than the demand and the battery is at its maximum capacity, the remaining power will be discarded to a dump load. Similarly, rules are developed for the optimum operation of microgrid systems. The rule-based method is easy to execute on various storage types once the essential rules have been established [30,31]. The rule-based method allows for a significant reduction in computational complexity.

4.4. Fuzzy Logic Control Methods

Figure 9 shows the block diagram of a fuzzy logic system. The fuzzy logic controller (FLC) contains mainly three parts: the fuzzifier, the fuzzy interface, and the defuzzifier. The fuzzifer converts the input into a linguistic variable, and this process is referred to as fuzzification. The defuzzifier returns the output by converting from linguistic variable, and the process is called defuzzification. The interface system is a rule-based system. Fuzzy controllers do not require complex mathematical modelling.

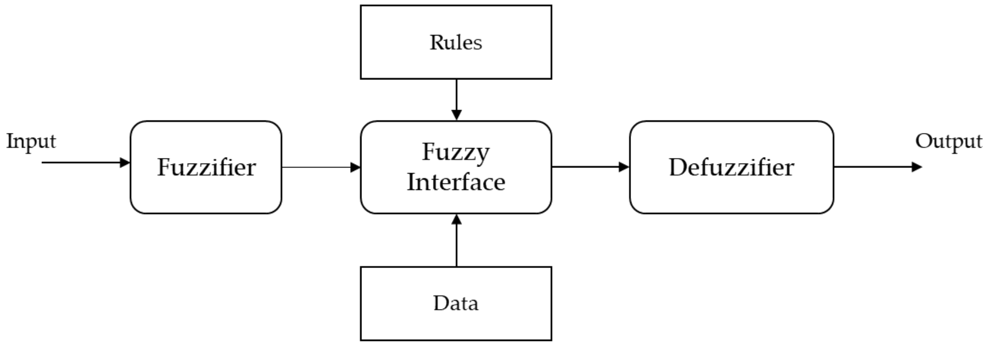

Figure 9. Fuzzy logic system.

Fuzzy logic-based energy management is used for various objectives. Fuzzy logic controller generates the output whether the battery should be charged or discharged, as well as the charging or discharging rates. The fuzzy logic control is designed to meet energy demands and maintain the SOC of the energy storage level within predefined margins while attempting to optimize the utilization cost and lifetime of the ESS [32]. The fuzzy controller is also used to find the status of the power received or supplied from the grid. An optimal fuzzy-based EMS for a residential grid-connected microgrid is used to minimize grid fluctuation and to preserve the storage system lifetime in [33].

In microgrid operations, hybridization of fuzzy logic with other methods such as GA and PSO are used. The problem of energy flow management system optimization in a microgrid is investigated using a fuzzy-GA paradigm in [34]. A hybrid approach combining a fuzzy approach and a neural network is used in EMS presented in [35].

The advantages and disadvantages of the energy management solution approaches discussed above are summarized in Table 2.

Table 2. Advantages and disadvantages of optimization techniques.

Techniques	Advantages	Disadvantages
Mixed integer linear and non-linear programming methods	Availability of efficient software packages. Most flexible modelling. Optimal solution.	Computational complexity.
Generic algorithm	Possibility to use complex formulation. It can handle many objectives and constraints. Widely used in many fields.	GA is unable to ensure mathematical optimality in its output.
Particle swarm optimization (PSO)	It has fast convergence time. Commonly used in the sizing of distributed generators. It can handle a wide range of problems while achieving a set of goals.	PSO is unable to ensure mathematical optimality in its output.
Rule-based methods	The approach allows for a significant reduction in computational complexity. The method is easy to execute on various storage types once the essential rules have been established.	Solution could be a sub-optimal solution.
Fuzzy logic control methods	Gain more flexibility. It can be easily incorporated with other methods.	Solution could be a sub-optimal solution. High-quality processing unit is required.

5. Uncertainties in Microgrid Energy Management

Power generation from the RESs offers an intermittent and uncertain power supply. Solar and wind are the most popular and widely used resources among all the renewable energy resources used in microgrid applications. However, the intermittent nature of solar and wind energy is always a challenge. Solar energy is only available during the day, and it also varies with other factors such as cloud movements and shadow. Wind patterns change according to the weather. Consumer loads connected to the grid are also continuously varying, and these variations can become more complex with the introduction of demand response and EV charging. The high intermittency leads to an uncertain operational environment for microgrids. Therefore, one of the main challenges is to handle the uncertainty of renewable energy generation and power demand.

In this regard, it is important to properly model the uncertainties in the parameters and components. Researchers consider a variety of sources of uncertainty, such as wind power, load demand, electricity prices, PV generation, EV demand, etc. [36]. In MG EMS, the uncertainty from renewable energy sources and load demand are important factors. To address uncertainty management, modelling the uncertainty of renewable sources and load becomes the consequential issue. Accurate modelling has a high effect on the operational cost of a microgrid. Modelling uncertainty is always a challenge; hence, several approaches are employed to model these uncertainties with respect to their applications. This section provides an overview of all recent uncertainty modeling approaches used by an EMS.

a. Monte Carlo Simulation (MCS)

The MCS is used to calculate the probabilities of various outcomes in a process that is difficult to forecast because it contains random variables. This method can accurately handle the uncertainty variable. For each input parameter, a sample is generated using its probability density function (PDF), and the sample generation process is repeated for many iterations. Therefore, the method is computationally complex. Most of the studies are focused on developing uncertainty models for PV, wind power, and load demand [12].

b. Worst Case Scenario Method

Even though it is not a new concept, the worst-case scenario approach is frequently used in recent studies. The worst-case scenario approach restricts the range of the random variables to a set of predetermined uncertainty with defined upper and lower boundaries. Prediction intervals (PIs) are calculated to evaluate the measure of prediction uncertainty. Upper and lower limits are used to define PIs [11].

c. Point Estimate Method (PEM)

The PEM is one of the approximate methods with a low computation burden. The method focuses the statistical data of a random variable on a specific number (K) of points in order to create a connection between input and output variables. Solar radiation and wind speed are treated as two random variables, and the function is developed using power flow equations in [37]. In [38], PEM is used to determine power exchanges between MGs and evaluates the optimal solutions in terms of accuracy and computational effort.

d. Fuzzy Method

Each uncertain parameter can be assigned a degree of membership based on fuzzy theory by using membership functions. After a suitable fuzzy membership function is applied to each parameter, the defuzzification will be carried out. The fuzzy method is used to model the uncertainty in forecasting day-head demand in [39]. Although uncertainty is handled in fuzzy systems, the issue of randomness is not properly accounted for. Approaches, such as probabilistic fuzzy systems, have been introduced for overcoming this issue [18].

e. Autoregressive Moving Average

It is another model used in recent days to model uncertainties from load demand and wind power. The autoregressive moving average model is a combination of auto regression and moving average. This method can be used to forecast future estimates of a variable if historical data of the variable with uncertainty is presented by a time series, such as load demand, wind, etc. A significant amount of historical data, as well as data mining and analysis, are required for developing proper autoregressive models, and the predictions with these models are valid only over a short horizon [11].

Other methods, such as kernel density estimation, hyper-heuristics, and two stage scheduling strategy, are also used to model these uncertainties. Each model has its own advantages and disadvantages that determine its application.

There are various approaches that could be used to deal with different sources of uncertainty. Generally, optimization under uncertainties can be broadly categorized as stochastic programming [40,41], robust optimization [42,43], and other methods, such as model predictive control and chance constrained programming. These methods are implemented as either a single-layered or multi-layered framework.

5.1. Stochastic Optimization

In stochastic programming methods, uncertain parameters are described using probabilistic distributions. Stochastic optimization, which is based on statistical data, is widely used for energy scheduling under uncertainty due to its effective performance in the case of uncertainties [44]. Stochastic programming can be classified into four main methods, including the three-point estimating technique, the Monte Carlo simulation-based method (MCS), the scenario-based modelling approach, and the approximate analytical method. The scenario-based modelling approach is utilized to handle the uncertainties from wind in [45–47].

However, there are significant limitations to stochastic optimization in some situations, such as the large presence of uncertain data, dependence between uncertain parameters, and a lack of historical data. The computational complexity of the model also increases along with its scale. Stochastic programming methods may lead to an infeasible solution due to the constrained violation [12].

5.2. Robust Optimization (RO)

Robust optimization (RO) is an interval-based approach, and RO methods do not require prior knowledge of the probability distribution of the uncertain parameter. The RO method addresses data uncertainty by considering a single worst-case scenario over an uncertainty set, and it can improve the performance of MG EMS even under the lack of full information on the nature of uncertainty. The typical extreme cases in real-world applications can be included in the uncertainty set in the RO methods. Robust optimization has significantly reduced the computational complexity compared with stochastic approaches [48]. The RO method has received attention for being able to handle the uncertainty optimization problem. However, complexities in deriving the uncertainty set can lead to a computationally intractable solution. Additionally, focusing on the worst-case scenario can lead to a more conservative resource-handling option degrading the benefits achievable through an optimized solution.

A two-stage robust optimization approach is proposed for the islanded microgrid system to reduce the uncertainty impacts from energy sources and loads in [49]. Uncertain parameters were used to classify decision variables for two stages: (1) the day ahead stage decision (pre-scheduling) and (2) the real-time stage decision (rescheduling). This approach is moderately effective in reducing the impact of uncertain factors.

5.3. Chance Constrained Programming (CCP)

The chance constrained programming (CCP) approach is also used to solve energy management problems under uncertainties. It is a mathematical program containing chance constraints which only needs to be satisfied with a probability. The requirement for power balance in the microgrid is formulated as chance constraints. Approximated methods have been commonly employed to solve the CCP. In general, CCP is employed only for special cases due to being computationally challenging, conservative, or incapable of guaranteeing the satisfaction of chance constraints [50].

5.4. Model Predictive Control

The traditional deterministic frameworks have a feedback mechanism to adjust the initial dispatch solution to compensate for variations in the uncertain decision variables. Among them, model predictive control (MPC) is gaining considerable attention in microgrid systems as a promising control scheme with several advantages, such as the possibility of incorporating optimization techniques and the ability to integrate the constraints and disturbances in forecasted control decisions. The MPC is a discrete time control scheme in which each time step solves an open-loop optimal control problem for a chosen control horizon. Figure 10 illustrates the block diagram of a typical MPC structure.

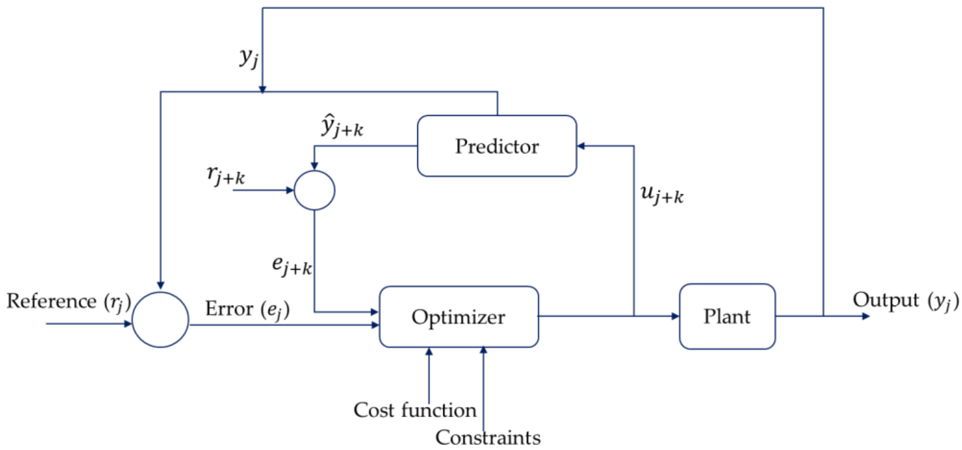

Figure 10. Basic structure of MPC.

Model predictive control is usually implemented by developing a model with relevant and controllable variables and then minimizing a cost function between reference values and candidate values of controlled variables. The minimal difference to actuate the next period is chosen. The general MPC-based optimization process is shown in Figure 11.

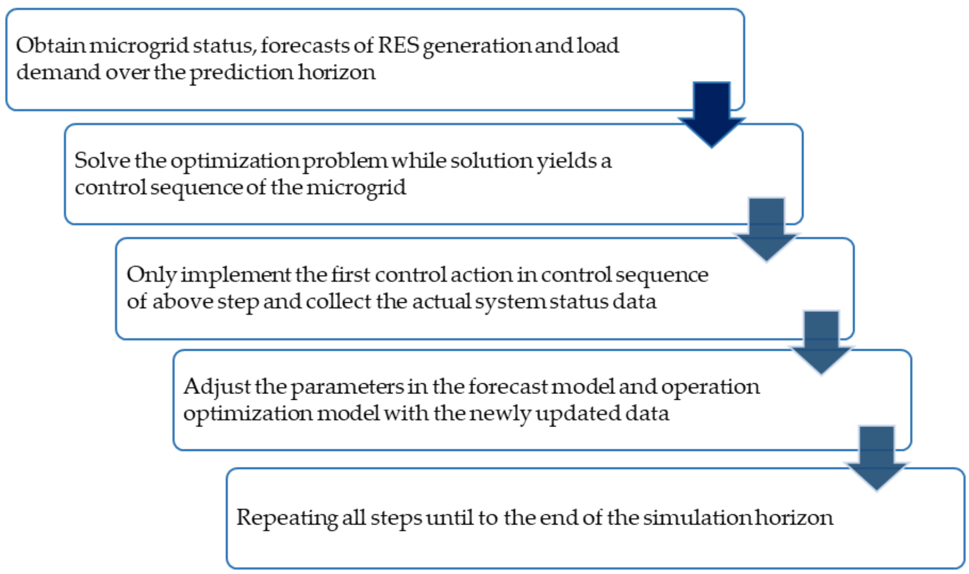

Figure 11. MPC-based optimization process.

The MPC framework models for microgrids have advantages, as they use the dynamic behavior of microgrid components, particularly the battery charge and discharge models [51]. Typical control methods are no longer effective against fluctuations, but MPC has received more attention due to its flexibility to include constraints and non-linearity [52]. Another advantage of MPC over other control techniques is its simple expansion to the multivariable case. The MPC method can provide a receding prediction horizon with a feedback mechanism that also effectively reduces the impacts of uncertainties [53]. Model predictive control is typically used for MG EMS with a prediction horizon of 24 h, considering the daily periodicity of generation and load profiles. The performance of MPC is affected by the selection of the prediction horizon. One of the main drawbacks of MPC is that computational complexity increases with a larger prediction horizon [54]. With significant development in recent years, MPC with its variations is used at different levels.

A model predictive control-based energy management is proposed in [55] to provide an economically optimal operation, and the system is represented by a linear invariant discrete time model. In this study, the minimization of the cost of energy consumed from the main grid is considered to be an optimization objective. When renewable generation is insufficient to supply demand, the battery will start supplying the load. If this energy also becomes insufficient, EMS has to acquire energy from the main grid. Another economic MPC is proposed in order to achieve optimal economic performance in terms of the operational cost of a microgrid in [56].

A MPC rolling horizon approach for the optimal operation of a microgrid for residential network is proposed in [57]. The MPC problem is formulated using a MILP model used to optimize the total cost of the microgrid. The objective of the problem is to minimize the total cost for the DER system over the prediction horizon. Heat and electricity storage terms are additionally included in the objective function. The overall planning and performance could have been improved if the uncertainty on solar irradiance and energy demands was considered in the modelling of the network.

The conventional MPC approach, with techniques such as robust optimization and stochastic optimization methods, directly incorporate uncertainty in the optimization models to achieve effective and efficient operation of microgrids.

Stochastic MPC methods are used to take uncertainty due to the stochastic behavior of renewable energy generation and demand into consideration. A two-stage stochastic programming-based MPC strategy for microgrid energy management under uncertainties is proposed in [45]. Stochastic programming is used for the inclusion of uncertainties in the optimization model. The MPC can effectively compensate for the disturbances in load profile and power delivered from renewable sources that are connected to the AC microgrid through a feedback mechanism. The cost of the microgrid is commonly formulated using start-up/shut down costs, the fuel cost of diesel generators, the degradation cost of a battery, and the power purchase cost from the utility grid. Here, uncertainties of solar PV, wind, and load are also considered in the formulation of microgrid cost. In the first stage, decisions are made before the actual realization of available uncertainty. In the second stage, correction decisions are made after a particular realization.

Sliding mode control (SMC) is a reliable control technique that can address uncertainties. The combination of MPC and SMC can be applied for the effective and efficient operation of microgrids. A suboptimal second-order SMC is designed as a low-level controller to track the power references generated by a high-level MPC component for EMS [58]. Nonlinear MPC is implemented using nonlinear models that include non-linear constraints on the state and control variables, as well as the cost functions. The nonlinear MPC type control is implemented for energy management of the batteries and load shedding purposes in [59].

The reviewed literature shows successful applications of using MPC for handling uncertainties related to microgrid energy management.

Researchers in this field have been motivated by recent developments in machine learning techniques to work on more realistic predictive strategies. The MPC is formulated based on the predictions generated by the predictive model and possible desired targets. The MPC performance is directly impacted by the modelling quality and accuracy of the predictive model. This is one of the challenges when using the MPC scheme. When the MPC strategy is used, the prediction method must be considered. Various methods, such as physics-based models, the Markov chain, neural networks, the Kalman filter, etc., can be used for prediction. For example, in terms of Markov chain prediction, the future value depends on the current value and the transition probabilistic matrix, which is calculated based on a historical statistical data set. In real-time operation, actual measurements are continuously updated. To predict load demands and renewable outputs, online learning Markov chain prediction can be used. However, quite often, a physics-based model is needed for repetitively predicting the MG system behavior. It constitutes high computational complexity, depending on the type and complexity of the models used.

In MPC-based energy management problems, the design, arrangement, and allocation of all the control objectives, along with the proper constraints, can reduce the computational burden. Furthermore, the MPC-based energy management problem formulation can be simplified by using methods such as fuzzy logic control, rule-based methods, PSO, etc.

The MPC optimization problems are resolved by moving the time horizon window ahead. Once new predictions are available, the optimization problems can then be recalculated and resolved. The time horizon is often determined according to multiple factors. One of the most challenging aspects of MPC is that it needs to deal with short sampling times for the power electronic technology, and it also needs long-time horizons to improve the robustness and accuracy of the model. Combining short and long-time horizons at different stages is an approach used to obtain better system performance. Receding time horizon methods are also found in recent research because they aid in dealing with uncertainty and achieving effective performance [60].

Scalability is crucial to address the changing requirements when moving from industrial plants to very large-scale systems with operational and managerial independence. Distributed model predictive control (DMPC) [61] attempts to address this issue through the development of multi-level, multi-scale models. The goal is to avoid redesigning the overall energy management system (EMS) when the additional sources and storage are connected. In DMPC, the power of each energy source is optimized using an individual subsystem-based MPC to make the plug-and-play property easier to achieve and to reduce the computational load [60].

DMPC could be a suitable strategy for large-scale systems to solve the resulting economic optimization problem. Many researchers are focusing on using stochastic and distributed model predictive control techniques to optimize large-scale microgrid systems [59]. Another study, in [62], proposes fully distributed water-filling distributed algorithms that scale to large-scale situations. A decentralized charging control is formulated for large populations of plug-in EVs [63]. Approaches used to handle uncertainties in microgrid system are summarized in Table 3.

Table 3. Approaches used to handle uncertainties in microgrid system.

Proposed Approach	Modelling Uncertainty	Uncertainty Handling	Scalability Handling Possibility
Optimal probabilistic energy management in a typical microgrid based on robust optimization and point estimate method [37]	Uncertainties of wind, solar, and load are used.	PEM and RO are used. The data determined from PEM are used in the PSO-based energy management algorithm. RO generates and transfers the load demand scenarios to the PSO algorithm.	The proposed algorithm is used in order to perform an optimal operation on a low voltage (LV) MG, including renewables and conventional DGs, as well as a battery bank.
Two-stage stochastic programming based MPC strategy for microgrid energy management under uncertainties [45]	Load, PV, and wind uncertainties are used.	Two stage scheduling strategy is used. The first stage makes a decision before the actual reality of the uncertainty becomes available, and the second stage makes a correction decision to compensate for infeasibilities from the first stage.	The proposed method combines the advantages of both two-stage SP and MPC.
A two-stage robust optimization method based on the expected scenario for islanded microgrid energy management [50]	Uncertainties of wind, solar, and load are considered.	Two stage scheduling strategy is used. Prescheduling stage and rescheduling stage are applied to reduce the impact of uncertain factors.	To manage various constraints during the optimization process and ensure the feasibility of individuals in the evolving population, a constraint-handling technique is developed.

Table 3. *Cont.*

Proposed Approach	Modelling Uncertainty	Uncertainty Handling	Scalability Handling Possibility
Optimal operation of a smart residential microgrid based on model predictive control by considering uncertainties and storage impacts [59]	Uncertainties from solar, wind, load, and electricity price are used.	The MILP problem is incorporated into a MPC framework for compensating the potential disturbances.	Stochastic and distributed model predictive control techniques can be used to optimize large-scale microgrid systems.
Distributed MPC for grid-connected microgrid power management [60]	Uncertainty related to the availability wind and load are considered.	The MPC-based EMS is implemented under a distributed framework. Receding horizon methods are used to mitigate uncertainties.	The optimization problem is decomposed into several small-scale nonlinear continuous optimization problems and several integer programming problems.
A two-layer stochastic MPC scheme for microgrids [64]	Uncertainties from wind and PV are considered.	Shrinking-horizon MPC is implemented. A stochastic MPC runs at a higher frequency at the lower layer to compensate for uncertainties and maintain the energy exchange as close as to the desired value over each sampling period.	Stochastic MPC is used with high-level off-line economic optimization.
Stochastic programming and market equilibrium analysis of microgrid energy management systems [65]	Load, PV, and wind uncertainties are used.	Two-stage stochastic programming model is used. In the first stage, the decision for investment in microgrid devices is deter-mined, and energy management strategies are determined in the second stage.	A general algebraic modeling system is designed for solving large-scale, complex optimization problems.
Energy management system for hybrid PV-wind-battery microgrid using convex programming, model predictive and rolling horizon predictive control with experimental validation [66]	Uncertainties from solar, wind, load and electricity price are used.	A rolling horizon predictive controller with a MPC at the lower control layer with a one-minute sampling time reduces the impact of prediction and model uncertainties.	A rolling-horizon predictive controller does not require a complex optimization process.
Analysis of robust optimization for decentralized microgrid energy management under uncertainty [67]	Uncertainty related to the availability wind and load are considered. Prediction intervals are used.	The impact of different levels of uncertainty is evaluated.	Agent-based modelling (ABM) is used to describe the system, with each stakeholder modeled by an individual agent.
Robust optimization for dynamic economic dispatch under wind power uncertainty with different levels of uncertainty budget [68]	Wind uncertainties is used.	A robust optimization method with an adjustable uncertainty budget with different levels is proposed.	Constraint handling technique is also proposed to handle various constraints and ensure the feasibility of individuals in the evolutionary population.
Robust optimization of microgrid based on renewable distributed power generation and load demand uncertainty [69]	Uncertainties of wind, solar, and load are considered.	A two stage scheduling strategy is used. Robust adjustment parameters are optimized to make the microgrid have a reasonable robustness.	The robustness of grid operation is guaranteed by the proposed solution, which is more in line with technical realities and has better practical value.

6. Application of Artificial Intelligence and Machine Learning

The use of machine learning and data-driven techniques for MG energy management is becoming increasingly popular due to the recent development of machine learning (ML) and artificial intelligence (AI), as well as the availability of advanced processing in modern control systems. For example, ML has been introduced as a methodology either for energy management in microgrids or for forecasting weather conditions and loads. A hybrid approach of a nonlinear MPC controller integrating machine learning models is presented in [70]. A two-layer ensemble machine learning technique is used to construct a data-driven multi-model wind forecasting system [71]. Utilizing the statistically different characteristics of each machine learning algorithm is the focus of this two-layer model. Additionally, many of the heuristic optimization techniques used in MG EMSs are considered under the umbrella of AI. The opportunities for ML extend far beyond forecasting, model improvement, and adaption.

7. Conclusions

The literature review highlighted energy management methods, modelling uncertainties, and forecast uncertainty management in microgrids. The microgrid energy management systems are developed considering factors such as the operating mode, control system, intermittent nature of renewable sources, economic and environmental aspects, and other factors. Different approaches can be used to design microgrid energy management. It is necessary to choose proper methods based on the required application. This paper reviewed recent energy management strategies for microgrids. Several EMS methods were discussed, including MILP and MINLP methods, heuristic optimization methods, rule-based methods, fuzzy logic control methods, MPC methods, and others based on numerous studies. The suitable EMS method is determined by the microgrid system and its requirements. The MILP methods deal with optimization problems when variables may be either discrete or continuous. However, it takes a long time to calculate complex problems with a large number of variables. The GA and PSO are frequently used to solve heuristic optimization problems due to convenience in application to multidimensional problems. Finding the optimal solution through GA is difficult. Fast convergence time, which is necessary for real-time energy management applications, is the main advantage of PSO-based EMS. Many researchers also use the PSO to address issues with microgrid optimum sizing. Rule-based methods allow for a significant reduction in computational complexity compared to other methods. Fuzzy logic control methods gain more flexibility, and they can be easily incorporated with other methods.

It has been identified that the uncertainty present in microgrid systems must be considered for proper energy management. Recently, to model the uncertainty, the Monte Carlo simulation, worst case scenario method, point estimate method, fuzzy method, and auto regressive method were used. Few uncertainty modelling techniques depend on the latest data recorded for future projection. Some uses present forecast errors. There is still a lot of scope for the development of new techniques. Many approaches are used in the reviewed research to overcome the uncertainty problem. Generally, uncertainty optimization can be broadly categorized as stochastic programming, robust optimization, and other methods that include MPC. Among those methods, MPC methods have gained more attention, especially in the application of MG EMS because of its ability to manage future behavior as well as the feedback mechanism. The feedback mechanism introduced through the MPC partially compensates for the uncertainty associated with the microgrid system. To adopt future power systems, MPC-based research and development must be established. The MPC has been improved with multi levels and different time horizons, and it has been incorporated into other methods to mitigate uncertainties and to improve performance.

Uncertainty may also result from stochastic electricity price fluctuations and demand response. The MG EMS can be formulated to take into account such other sources of uncertainty; however, when more factors are considered in the formulation of the problem, it becomes more complex. Possible corrective measures to decrease this complexity require more investigations.

The use of machine learning and data-driven techniques for MPC is becoming increasingly popular due to the recent development of machine learning (ML) and artificial intelligence (AI), as well as the availability of advanced processing in modern control systems. There is great potential for applying machine learning (ML) to MG energy management for various tasks to improve solutions and computational efficiency.

This paper highlights the research areas in energy management, considering forecast uncertainty from renewable sources and load in microgrid environment, for further investigation.

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Abbreviations

AC	Alternative Current
AI	Artificial Intelligence
BESS	Battery Energy Storage System
CCP	Change Constrained Programming
DC	Direct Current
DER	Distributed Energy Resources
EMS	Energy Management System
ESS	Energy Storage System
EV	Electric Vehicles
FLC	Fuzzy Logic Controller
GA	Generic Algorithm
IEC	International Electrotechnical Commission
MCS	Monte Carlo Simulation
MG	Microgrid
MG LC	Microgrid Local Controller
MG EMS	Microgrid Energy Management System
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
ML	Machine Learning
MPC	Model Predictive Control
PCC	Point of Common Coupling
PDF	Probability Density function
PEM	Point Estimate Method
PI	Prediction Interval
PSO	Particle Swarm Optimization
PV	Photo Voltaic
RES	Renewable Energy Sources
RO	Robust Optimization
SOC	State of Charge
SOWGP	Sparse Online Warped Gaussian Process

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