energies

Article

Integrated Optimal Energy Management of Multi-Microgrid Network Considering Energy Performance Index: Global Chance-Constrained Programming Framework

Mohammad Hemmati *, Navid Bayati and Thomas Ebel

Center for Industrial Electronics, University of Southern Denmark, 6400 Sønderborg, Denmark; navid@sdu.dk (N.B.); ebel@sdu.dk (T.E.)
* Correspondence: hemmati@sdu.dk

Abstract: Distributed generation (DG) sources play a special role in the operation of active energy networks. The microgrid (MG) is known as a suitable substrate for the development and installation of DGs. However, the future of energy distribution networks will consist of more interconnected and complex MGs, called multi-microgrid (MMG) networks. Therefore, energy management in such an energy system is a major challenge for distribution network operators. This paper presents a new energy management method for the MMG network in the presence of battery storage, renewable sources, and demand response (DR) programs. To show the performance of each connected MG's inefficient utilization of its available generation capacity, an index called unused power capacity (UPC) is defined, which indicates the availability and individual performance of each MG. The uncertainties associated with load and the power output of wind and solar sources are handled by employing the chance-constrained programming (CCP) optimization framework in the MMG energy management model. The proposed CCP ensures the safe operation of the system at the desired confidence level by involving various uncertainties in the problem while optimizing operating costs under Mixed-Integer Linear Programming (MILP). The proposed energy management model is assessed on a sample network concerning DC power flow limitations. The procured power of each MG and power exchanges at the distribution network level are investigated and discussed.

Keywords: energy management; optimization; chance-constrained; multi-microgrid; demand response; renewable energy; confidence level

check for updates

Citation: Hemmati, M.; Bayati, N.; Ebel, T. Integrated Optimal Energy Management of Multi-Microgrid Network Considering Energy Performance Index: Global Chance-Constrained Programming Framework. *Energies* **2024**, *17*, 4367. https://doi.org/10.3390/en17174367

Academic Editors: Dimitrios A. Tsiamitros and Dimitrios Stimoniaris

Received: 7 August 2024
Revised: 26 August 2024
Accepted: 30 August 2024
Published: 1 September 2024

1. Introduction

The emergence of new players in the electrical distribution network, such as distributed generation (DG), demand response programs (DPRs), energy storage systems, etc., leads to the transition from passive networks to active networks [1]. A microgrid (MG) as an active network is a collection of dispersed energy supplies and interconnected loads that function as a coordinated entity concerning the upstream grid. The global MG market size was estimated at USD 76.88 billion in 2023 and is projected to grow up to 17.1% by the end of 2030 [2]. This rapid integration requires the identification of leading requirements and challenges. Hence, in this section, the main motivation of the research, the literature review, and gaps, as well as the main contributions of this study, are introduced separately.

1.1. Background and Motivation

The substantial need to benefit from a distribution network with high reliability and flexibility and the related issues of distribution systems is always one of the critical challenges for energy producers. Expanding the system with DGs is one of the solutions for resolving such challenges. An MG can be characterized as an active power network that employs distributed energy resources to supply backup or off-grid power to meet the demands of local electricity consumers [3,4]. MGs provide a suitable opportunity to facilitate the installation of DGs for several purposes such as power loss minimization, reliability improvement, cost minimization, etc. Additionally, MGs yield service reliability enhancement, emission reduction, and power quality improvement for end-users by exploiting demand response (DR) and energy storage technology [5].

Along with the aforementioned benefits for MGs, the rapid growth of renewable resources with a probabilistic nature causes various challenges in the optimal operation of such networks; if these are not effectively managed, the security and reliability of the network will be compromised [6]. The importance of these challenges multiplies with the growing interest in MG development and installation for various purposes, such as improving reliability, reducing costs, reducing pollution, and digitalization, which grounds a new trend in the future of distribution networks, where each area of the network operates in a decentralized manner in the form of a multi-microgrid (MMG) grid. The MMG network consists of more than one MG connected to the grid operating together to serve the local community more efficiently [7]. Hence, energy management in such a distribution network with a high penetration of uncertain/intermittent energy resources is necessary to improve the system's efficiency and economic benefits.

1.2. Literature Review

Many researchers have addressed the problem of MG energy management using aging optimization techniques and meta-heuristic methods [8–23]. In [8], the risk-based operation of the islanded MG to enhance the energy management model by using the cloud and a big data framework was developed. Furthermore, the authors of [9] adopted a multi-layer ant colony optimization approach to schedule MG day-ahead energy scheduling. Although metaheuristic approaches are known to be strong in identifying solutions to complicated optimization problems, the final solution cannot be decisively claimed to be globally optimal. As a result, mathematical techniques are proper candidates for solving energy management problems in most cases [10]. In [11], optimal energy management has been proposed for the multi-energy type MGs, whose model has been formulated as a multi-objective scenario-based stochastic problem.

The most critical research gap in the corresponding literature relates to considering the related uncertainties in the problem's formulation, as well as flexible emerging technologies' integration into MG operation, such as energy storage and DR. The electrical power systems have already been affected by uncertainties resulting from the load and renewable energy variations. Consequently, the uncertainty sources must be included in the MG systems' energy management model where deterministic methods cannot be utilized. The factual accuracy of the daily power output of renewable sources is low and has already been approved in [12]; hence, the researchers must consider the uncertainty in the problems of day-ahead energy management. It should be noted that probabilistic methods are conventional approaches to addressing day-ahead energy management problems [13]. In a conducted study [14], a stochastic framework was suggested for optimal hybrid AC-DC MGs alongside renewable energy sources. Ref. [15] proposed a new energy strategy trading approach for multi-sector MGs by utilizing a stochastic game model based on recourse. Furthermore, the researchers have presented a data-driven charging method for electric vehicles in MG [16]. In this research, electric vehicles' behaviors and demand levels have been taken into account as uncertainty sources, which are managed to employ conditional value at risk. In another study [17], an enhanced energy management framework for optimal MG operation in the presence of emission constraints has been provided; nevertheless, as a weak point similar to that of the study mentioned above, the network constraints have not been modeled. In [18], the optimal scheduling of hybrid AC-DC reconfigurable MGs has been studied; the proposed strategy has been formulated as a multi-objective problem to minimize the cost and emission rate using a heuristic method. The multi-objective energy management of islanded MG incorporated with high solar power integration was developed by [19]. This paper focused on renewable source control to manage voltage without considering load management. Short-term MG energy management with online optimization was studied by [20]. This paper only focused on battery management online services for MG applications. The role of the Internet of Things, digital twins, and the high penetration of renewable energy in MG management was evaluated by [21]. This paper developed the net-zero concept for smart MG based on the communication infrastructure. Fuzzy-based multi-objective energy management of MG integrated with a battery storage system was studied by [22]. Both economic and environmental objectives are addressed with the slime mold algorithm. As expected, the solution is not completely optimal.

Renewable energy sources like wind, PV systems, and load changes introduce uncertainty into the energy management problem of MMG systems, making it more difficult and complex. In [23], the CCP approach was developed in the unit commitment problem under the high-level uncertainty of the wind power and load demand. The authors of this study used the Benders decomposition to relax the complex optimization problem. The CCP framework has been developed by [24] to coordinate, pre-contingency, the reserve and energy operation of a virtual power plant in the presence of renewable energy. The proposed model was evaluated on 33 and 95 IEEE test systems, and the numerical results reveal that while the confidence level of the system increased, the energy and reserve costs increased, consequently. The generation expansion planning of the power system in the presence of flexible emerging resources under the distributionally robust chance-constrained method was evaluated by [25]. The proposed model improved the reliability of the system, while the investment cost grew notably. In [26], a hybrid CCP multi-objective strategy of multi-carrier MG integrated with energy storage and carbon recycling technology was developed. The numerical results show a 50% reduction in carbon emission, while the total cost increased by 2.5%. The cooperation of a hybrid MG in the hydrogen, heat, and electricity sectors to co-optimize energy and reserve schemes under the chance-constrained approach was developed by [27]. Authors in [28] proposed a chance-constrained performance strategy for smart distribution systems, considering virtual power lines under the second-order cone programming OPF challenge. This study focused on the technical challenges in the power system, and the numerical results show the efficiency of the model in terms of power loss and voltage regulation, ignoring the economic term. Ref. [29] proposed the distributionally robust chance-constrained operation of a hybrid MG integrated with large-scale battery storage and renewable energy. The results of this research show the performance of the proposed model in terms of reliability, operation cost, and computational complexity. Some studies have addressed this issue by using Monte-Carlo simulations and a robust CCP approach to deal with the uncertainties [3]. However, these studies only focused on a single MG and ignored the network constraints. Therefore, more research is needed to schedule the MMG systems in the presence of flexible resources, while considering the security limitations. In [30], a distributionally robust approximation approach for MG operation considering chance constraint was studied. This paper only analyzed the risk of the profit in MG, and no confidence level was considered under the chance constraint. In [31], a comprehensive review of the most recent mathematical formulation for applications of smart technologies in future microgrids was developed. To this end, the standard of communication in smart microgrids, the Internet of Things, cybersecurity, and big data, are discussed.

On the other hand, the rapid growth of MG penetration into the distribution network generates a new concept called MMG systems. In this regard, many distribution system sections become active MGs. The investigation of the energy management of such systems has gained researchers' interest, so numerous studies have been conducted to tackle the emerging issues caused by MMG systems development [32]. A robust strategy in MMG energy management based on peer-to-peer trading has been developed [33]. In this paper, we have developed a robust model to handle the demand and renewable energy output. Ref. [34] presented a framework to schedule MMG systems by exploiting a hybrid stochastic–robust approach in which day-ahead and real-time energy prices have been considered in the energy management process. In one study, the authors introduced an energy management strategy for MMG systems to address contingency issues along the

MMG lines using contingency probability [35]. In the study conducted in [36], the authors propose a novel approach for managing the energy of distribution networks with MMG, incorporating demand response programs and accounting for uncertainties in renewable energy sources, loads, and prices. They modeled energy management as a problem with multiple objectives and solved it using the NSGA-II meta-heuristic method. In the research carried out in [37], joint methods have been proposed to perform energy scheduling in the MMG network. A new measure of performance/success for the energy distribution process has been constructed in this research while taking into account uncertainties and factors caused by load, wind, and PV systems. Moreover, the authors in [38] have presented a distributed energy management method for the joint operation of MMG systems that includes both heat and power systems. Flexible energy technologies such as DR, transactive energy, and supercapacitor storage are integrated into MMG under the stochastic framework [39]. Although this paper outlines a flexible schematic of MMG, the network constraints have been ignored. In [40], a comprehensive machine learning approach is applied to forecast CO2 emissions in energy systems. This paper compares various machine learning approaches, including linear regression and neural networks.

1.3. Contributions and Research Gaps

The corresponding literature features the evaluation of various aspects of MGs and MMG systems' performance and functions, carried out by different methods. Table 1 lists the most closely related methodologies presented so far in the operation and modeling of MGs and MMG functions. According to the research conducted in the field, it can be perceived that MMG systems energy management is a demanding research subject. Moreover, it is deduced that energy management is a primary tool contributing to the system's reliable and economic operation.

Table 1. The main technologies and novelties of the current study compared to the related works.

Ref.	Uncertain Parameter			Power Flow	Demand Response	Single/Multi MG	Uncertainty Modelling	Confidence Level and Reliability Index
	Load	PV	Wind					
[17]	-	✓	✓	-	-	Single MG	Scenario-based	-
[29]	✓	✓	✓	✓	✓	Single MG	CCP	Confidence level
[30]	✓	✓	✓	-	-	Single MG	Robust/CCP	-
[33]	✓	✓	✓	-	-	MMG	Robust	Confidence level
[35]	-	-	-	✓	-	MMG	-	-
[38]	✓	✓	✓	-	✓	MMG	Robust	-
[39]	✓	✓	-	-	✓	MMG	Stochastic	-
[41]	-	✓	✓	-	-	Single MG	Scenario-based	-
[42]	-	✓	✓	-	-	Single MG	Scenario-based	-
[43]	-	-	✓	-	-	Single MG	CCP	-
[44]	-	✓	✓	✓	✓	MMG	Scenario-based	-
This work	✓	✓	✓	✓	✓	MMG	CCP	Confidence level and reliability index

In terms of optimization techniques, it should be mentioned that the CCP approach is an appropriate choice for addressing uncertainties in MMG energy management, and with low computational complexity, it facilitates the modeling of uncertain parameters in the problem. The computational burden plays a significant role in hierarchical methods where there are multiple optimization stages. This issue can be effectively overseen by exploiting the features of the CCP method.

The comprehensive literature review mentioned above reveals four main shortcomings ("Sh."), as follows:

Sh.1. Refs. [8–22] focused on the energy management of a single MG without the integration of DR and comprehensive uncertainty modeling. In some cases, energy management is conducted to improve the system's dynamic without involving uncertain parameters;

Sh.2. Refs. [24–31], while developing novel optimization techniques in single-MG management and operation, such as robust optimization, CCP, and machine learning frameworks, to handle the uncertainty, power flow limitation is rarely addressed. This leads to an unrealistic model. Also, the reliability index for energy availability is not provided for MG by these studies;

Sh.3. Refs. [14–16,19–23,30–34] have not considered DR and flexible load as a main component of MG. The DR flexibility service will play a critical role in MMG scheduling, which has been ignored in a wide range of research;

Sh.4. Refs. [32–39] are focused on MMG management and operation. However, the interdependency and energy exchange between neighboring MGs under the coordinated strategy have not been addressed. Also, the reliability index used to improve energy balance in the networked MG incorporated with load and renewable energy uncertainty has been ignored.

To tackle these shortages in previous research, this paper concentrates on the optimal performance of MMG networks integrated with local DG and flexible demand-side management sources, under the CCP framework. For each MG, a new index, namely, unused power capacity (UPC), is defined to provide some useful information about its energy level, individually. The proposed model ensures the safe operation of the MMG network. Each MG serves a local load, which has both responsive and non-responsive users. The DR is implemented for the responsive loads (RLs) to give more flexibility to the entire system. So, the main points of the current work can be listed as follows:

- Proposing the multi-microgrid network infrastructure to provide more flexibility for the distribution network. The interconnected MGs can receive/inject the power from/into the corresponding bus;
- Proposing the chance-constrained programming approach to guarantee the confidence level of the system's operation with high reliability. A model identifies the uncertainty of wind, PV, as well as load demand. Unlike scenario generation-based methods, the CCP guarantees the safety performance of the whole system with a lower burden of calculations;
- Developing the demand response program in individual MG to smooth the load curve, besides improving the flexibility of MMG;
- Introducing a new index named "UPC" for individual MG yields a more efficient energy management strategy at the microgrid and distribution network levels.

1.4. Paper Organization

The rest of this paper is summarized as: The MMG network structure and the problem description are presented in Section 2. Section 3 presents the problem formulation. Also, the CCP method is discussed at the end of this section. The results and case studies are discussed in Section 4. Finally, Section 5 concludes the paper.

2. Multi-Microgrid Structure

Eelectrical distribution systems are evolving towards a grid consisting of small-scale interconnected MGs that exchange power to serve local loads. MGs operate under the supervision and control of a single operator in a distributed manner. In the meantime, MGs can exchange energy with their respective bus (connected to the grid). The term interconnected MGs, the so-called MMG infrastructure, refers to distribution networks consisting of various MGs, as shown in Figure 1.

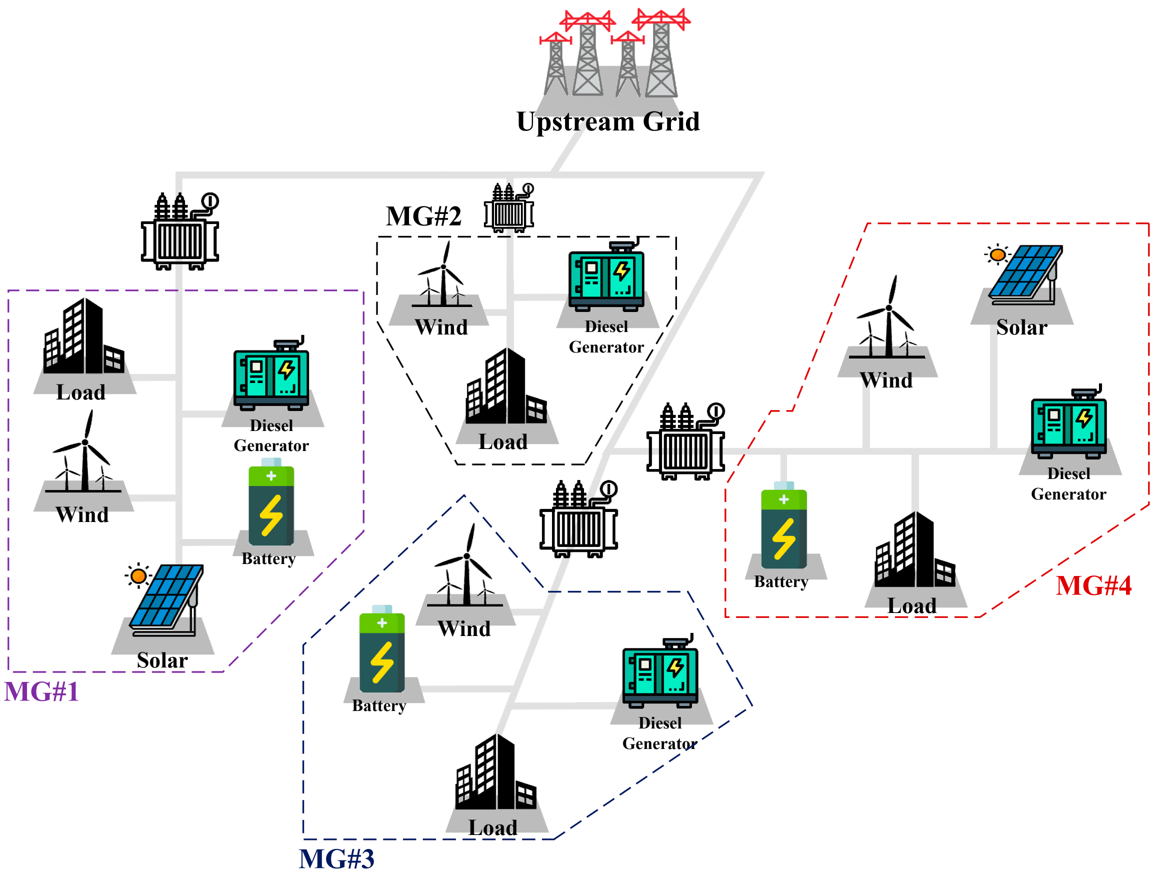

Figure 1. The structure of MMG with multiple types of DGs.

According to Figure 1, each MG is equipped with energy storage systems, renewable sources, loads, and distributed generators. These connected MGs can exchange energy in the neighborhood and manage local loads through local resources in a distributed manner.

For the better management of resources and to address surpluses or shortages of available energy, the status of each MG should be monitored. In this way, the network operator can implement the energy management model with a better view to ensure the reliable performance of the network. Hence, the UPC index is defined to show the level of available energy in an individual MG. The interconnected MGs are operated under the single distribution network operator (DNO) and exchange (sell/purchase) power to/from the common coupling point. Note that the DNO purchases the power from the upstream grid to meet the demands of energy consumers. There are several consumers at the level of the distribution network. To model the uncertain behavior of renewable energy sources and load demands in optimizing MMG operation, we exploit the CCP approach that guarantees a reliable operation with the desired confidence level. The CCP approach, unlike the scenario generation framework, determines the probability of a reliable operation. In other words, the CCP technique involves the uncertainties introduced by multiple sources into the optimization problem, and provides an efficient tool to the system operator to guarantee the whole system's reliable operation.

3. Problem Formulation

The main objective of the proposed scheme for the energy management of the MMG network is to minimize the operation cost related to several components. The objective function is formulated in (1), including six terms. The cost of purchasing power from the upstream grid is defined in the first term. The operation cost of the dispatchable unit, including generation cost and start-up cost, is presented in the second term of (1). In this paper, the linear generation cost is used instead of the quadratic function. The operation cost related to battery degradation cost is shown in the third term of the objective function (1). This degradation cost results from the additional cycling of the battery, which is a key factor affecting the battery's lifespan and performance. To model battery degradation, we utilize the Wöhler curve, which describes the relationship between the depth of discharge and the number of charge–discharge cycles a battery can endure before failure. As the depth of discharge increases, the number of cycles to battery failure decreases exponentially, reflecting the higher wear and tear on the battery when it is subjected to deeper discharges. The parameters of the Wöhler curve, typically denoted as a and b, are specific to the type of battery used, and are obtained based on empirical testing and manufacturer data [45]. The last line of (1) refers to DR cost, wind spillage cost, and PV spillage cost.

$$\min Z = \sum_{t=0}^{NT} \left(\lambda_t^{grid} P_t^{grid} + \sum_{m=1}^{NM} \left[\begin{array}{l} \left(F_C\left(P_{m,t}^{g}\right) + SU_{m,t} \right) + \alpha^b \left[\left(P_{m,t}^{b,ch}\right)^2 + \left(P_{m,t}^{b,dis}\right)^2 \right] + \\ C^{Dr} P_{m,t}^{d,Dr} + C^W P_{m,t}^{w,SP} + C^{PV} P_{m,t}^{PV,SP} \end{array} \right] \right) \tag{1}$$

3.1. Problem Constraints

The strategy proposed for the energy management of MMG is limited by constraints imposed by the operating conditions of grid components, which are described below.

- **Diesel generator constraints**

Constraints (2)–(9) define the limitations of the dispatchable generator. Constraint (2) restricts the generator's power output. Ramp-up and ramp-down limits are specified in (3) and (4), respectively. Equations (5)–(8) pertain to the minimum up- and downtime requirements [46]. Equation (9) formulates the start-up cost. It should be noted that the shut-down cost is ignored in this paper.

$$P_m^{g,\min} I_{m,t}^g \le P_{m,t}^g \le P_m^{g,\max} I_{m,t}^g \tag{2}$$

$$P_{m,t}^g - P_{m,t-1}^g \le R_m^{g,up} \tag{3}$$

$$P_{m,t-1}^g - P_{m,t}^g \le R_m^{g,dn} \tag{4}$$

$$I_{m,t}^g - I_{m,t-1}^g \le I_{m,t+TU_u^g}^g \tag{5}$$

$$TU_u^g = \begin{cases} u & u \le MUT^g \\ 0 & u > MUT^g \end{cases} \tag{6}$$

$$I_{m,t-1}^g - I_m^g \le 1 - I_{m,t+TD_u^g}^g \tag{7}$$

$$TD_u^g = \begin{cases} u & u \le MDT^g \\ 0 & u > MDT^g \end{cases} \tag{8}$$

$$SU_{m,t} = CU_m^g I_{m,t}^g \tag{9}$$

- **Demand response modeling**

As discussed, the demand response program based on the responsive loads is considered in this work. It should be mentioned that this paper only incorporates the shiftable load in the DR program to shift the load from peak hour to off-peak. The equations defining the DR scheme by determining the program's responsive load are given in (10)–(12). However, the shiftable load should be compensated for in other periods. This limit is presented in Equation (13).

$$0 \le Dr_{m,t}^{e,up} \le \gamma^e \times P_{m,t}^d \tag{10}$$

$$0 \le Dr_{,m,t}^{e,dn} \le \gamma^e \times P_{m,t}^d \tag{11}$$

$$\sum_{t'} Dr_{m,t}^{e,up} = \sum_{t'} Dr_{m,t}^{e,dn} \tag{12}$$

$$P_{m,t}^{d,Dr} = P_{m,t}^{d} + Dr_{m,t}^{e,up} - Dr_{m,t}^{e,dn} \tag{13}$$

- **Battery storage constraints**

Battery storage is one of the flexible sources that MG can rely on to meet the consumers' demand. Constraints (14)–(19) show limits on the battery's operating conditions. The limits on the charging and discharging are respectively given in (14) and (15). The energy capacity limits are given in (16)–(18). Hence, to prevent the simultaneous occurrence of charging and discharging operation mode, Equation (19) is used [47].

$$0 \leq P_{m,t}^{b,ch} \leq P_{m}^{b,ch,\max} . X_{m,t}^{b,ch} \tag{14}$$

$$0 \leq P_{m,t}^{b,dis} \leq P_{m}^{b,dis,\max} . X_{m,t}^{b,dis} \tag{15}$$

$$E_{m,t+1}^{b} = E_{m,t}^{b} + \left[\eta^{b,ch} \times P_{m,t}^{b,ch} - \frac{P_{m,t}^{b,dis}}{\eta^{b,dis}} \right] \times \Delta t \tag{16}$$

$$E_{m}^{b,\min} \leq E_{m,t}^{b} \leq E_{m}^{b,\max} \tag{17}$$

$$E_{m,t=0}^{b} = E_{m,t=24}^{b} \tag{18}$$

$$X_{m,t}^{b,ch} + X_{m,t}^{b,dis} \leq 1 \tag{19}$$

- **Network Constraints**

The power flow and power balance constraints must be met in the operation of the MMG network. The power balance constraint is represented by Equation (20). It should be noted that the first term in (20) is only established for the bus exchanging power with the upstream grid. The DC power flow is considered in this paper, as presented in (22). Also, the value of the power that flows through each line is bounded based on (23).

$$P_{t}^{grid} + \sum_{m=1}^{NM} \left(P_{m,t}^{PV} - P_{m,t}^{PV,SP} + P_{m,t}^{w} - P_{m,t}^{w,SP} + P_{m,t}^{g} + P_{m,t}^{b,dis} - P_{m,t}^{b,ch} - P_{m,t}^{d} + P_{m,t}^{d,Dr} \right) \geq \sum P_{p,q,t}^{L} \tag{20}$$

$$P_{p,q,t}^{L} = \beta_{p,q} \left(\theta_{p,t} - \theta_{q,t} \right) \tag{21}$$

$$-P^{L,\max} < P_{p,q,t}^{L} \leq P^{L,\max} \tag{22}$$

- **Wind power modeling**

Wind power is a primary source of uncertainty in the MG operation. The power output of the wind turbine is a function of wind speed. Based on the study carried out in [48], the wind turbine's power output is formulated based on the wind speed (23). Equation (24) defines the upper bound for wind spillage.

$$P_{m,t}^{w} = \begin{cases} 0 & 0 \leq V_t \leq V_{cut-in} \\ (a_1 + a_2 V_t + a_3 V_t^2) P^{w,rated} & V_{cut-in} \leq V_t \leq V_{rated} \\ P^{w,rated} & V_{rated} \leq V_t \leq V_{cut-out} \\ 0 & V_{cut-out} \leq V_t \end{cases} \tag{23}$$

$$P_{m,t}^{w,SP} \leq P_{m,t}^{w} \tag{24}$$

- **PV power modeling**

The output power generated by the PV panel is a function of the irradiation and air temperature formulated by (25) [49]. Similarly to the wind spillage, the PV power spillage is limited based on (26)

$$P_{m,t}^{PV} = \eta^{PV} S^{PV} G_t (1 - 0.005(T_{r,t} - T_{st})) \tag{25}$$

$$P_{m,t}^{PV,SP} \leq P_{m,t}^{PV} \tag{26}$$

- **UPC index**

As discussed in the Introduction section, in this study, we have introduced a new index, named unused power capacity (UPC), showing the available energy level for each MG. This index shows how much surplus or shortage of power in each MG can be exchanged to/from the upstream grid. This index can be calculated by dividing the net load (demanded power) (obtained by subtracting the MG's generations from its consumptions) by the maximum capacity of power generation (27). This value should satisfy the desired UPC (target value), as per Equation (28). The net load (demanded power) is formulated based on the existing component, as defined in (29)–(31).

$$UPC_m = \frac{P_{m,t}^{d,Net}}{\sum P_{m,t}^{g,\max}} \tag{27}$$

$$UPC_m \geq UPC_m^{\text{target}} \tag{28}$$

$$P_{m,t}^{d,Net} = P_{m,t}^{d} - P_{m,t}^{d,Dr} - P_{m,t}^{g} - P_{m,t}^{PV,Net} - P_{m,t}^{w,Net} - P_{m,t}^{b,dis} + P_{m,t}^{b,ch} \tag{29}$$

$$P_{m,t}^{PV,Net} = P_{m,t}^{PV} - P_{m,t}^{PV,SP} \tag{30}$$

$$P_{m,t}^{w,Net} = P_{m,t}^{w} - P_{m,t}^{w,SP} \tag{31}$$

3.2. Chance-Constrained Programming

CCP is a method that manages the uncertainty associated with problems that affect the best solution. CCP considers how the input parameters can vary in the model and makes sure the system has a high chance of safety. As per [50,51], the basic methodology of using CCP to deal with uncertainty can be written as (32)–(34)

$$\min \mathrm{Z} = f(x) \tag{32}$$

$$\begin{gathered} \text{Subject to :} \\ h_k(x) \geq 0 \quad \mathrm{k} \in \Omega_n \end{gathered} \tag{33}$$

$$\Pr\{g_j(x,\xi) \geq 0\} \geq \alpha \quad \mathrm{j} \in \Omega_j \tag{34}$$

Equation (33) shows the fixed limits on the model of a problem that involves finding the best solution. Constraint (34) makes sure that the chance of limits being imposed on variables that can change is higher than α, including a set of limits with variable(s) that can change and a set of random variables. Constraint (34) can be rewritten as (35):

$$\Pr\left\{ \bigcap_{j=1}^{\Omega_j} g_j(x,\xi) \geq 0 \right\} \geq \alpha \tag{35}$$

In the energy management problem of MMG, the power derived from renewable sources (PV and wind) and the electricity demand are uncertain factors that affect the model. Based on (35), for each bus with a connected MG, the power balance limitation can be written in the CCP as (36):

$$\Pr\left\{ \bigcap_{m}^{NM} P_{m,t}^{g} - \sum_{q \in \Omega_p} P_{p,q,t}^{L} \geq P_{m,t}^{d,Net} \right\} \geq \alpha \tag{36}$$

Equation (36) represents the combined likelihood that the generation side, minus the net power flow, meets or exceeds the electricity demand, which must meet or surpass a specified confidence level. Various methods in the literature address the complex constraint defined by Equation (36). However, the standard approach is to model the predicted errors of wind, PV, and load demand using a single probability function. In this study, it is assumed that these uncertainties follow a Gaussian distribution, allowing the net load to be represented as follows:

$$P^{d,net}_{m,t} = P^{\hat{d,net}}_{m,t} + \Delta e_{m,t} \tag{37}$$

where $P^{\hat{d,net}}_{m,t}$ is the actual value of net demand, and $\Delta e_{m,t}$ shows the total forecasted error. The probabilistic distribution function (PDF) of net forecasted error can be guessed by breaking the net error chance into smaller pieces. In [51], a 13-interval approximation has been used. However, in [52], a 5-interval estimate is used to model the predicted error. We assumed that a seven-part estimate of Gaussian distribution could show wind, PV, and load demand prediction errors. In this way, the chance of the left-hand side in Equation (36) is found. More information can be found in [53]. The overall schematic of the proposed CCP for MMG scheduling is shown in Figure 2.

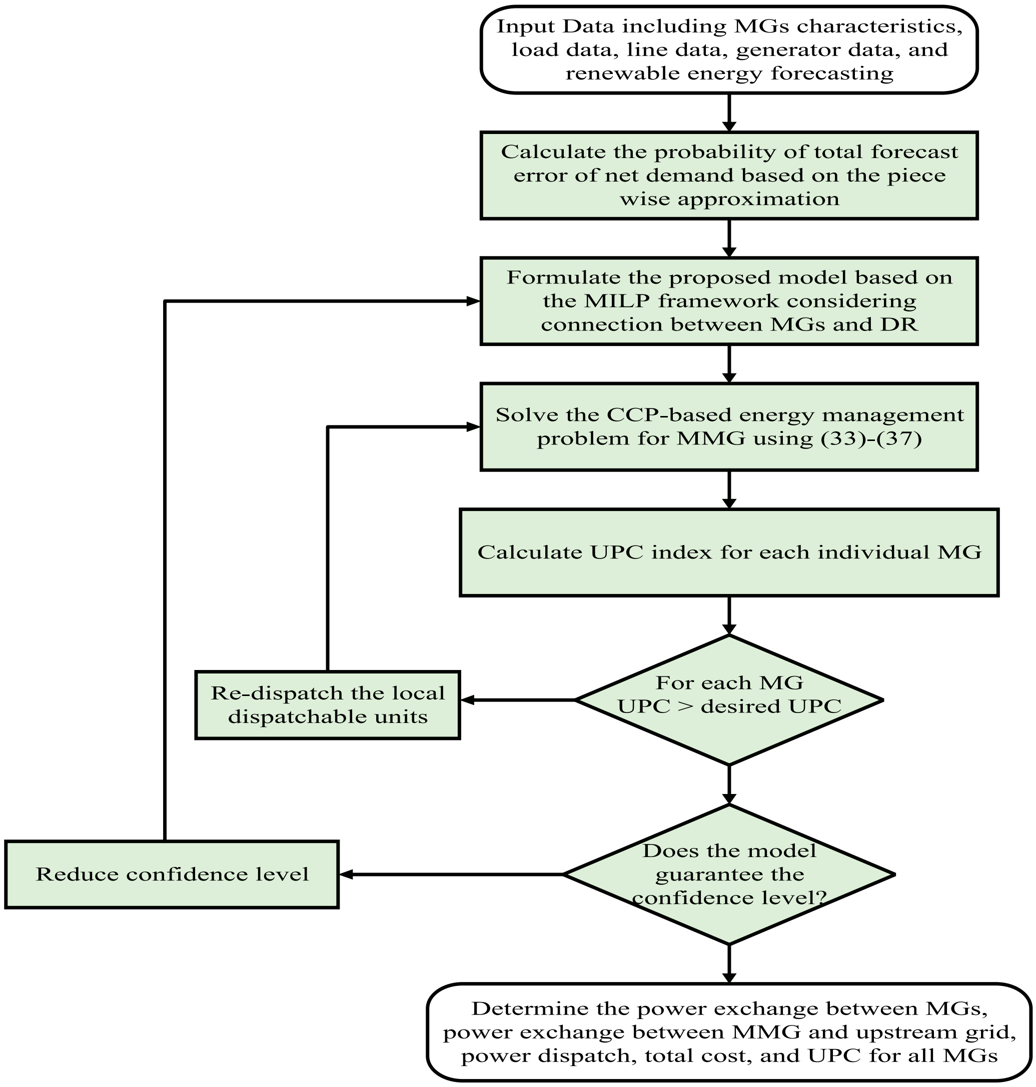

Figure 2. Flowchart of the proposed CCP-based energy management of MMG.

4. Simulation and Results

In this section, the optimal energy management mode for MMG is examined on the test system. For this purpose, the benchmark system of a six-bus distribution network with three interconnected MGs is considered, as shown in Figure 3. All MGs are equipped with a battery, PV panel, wind turbine, and micro-turbine (MT). The characteristics of the grid, including line and bus data, are provided in [54]. Table 2 provides information about each MG's components. Figure 4 shows the load profile for the three involved MGs. It should be noted that only 15% of the load demand in each MG can participate in the DR program. Also, Figure 5 shows the electricity price [55].

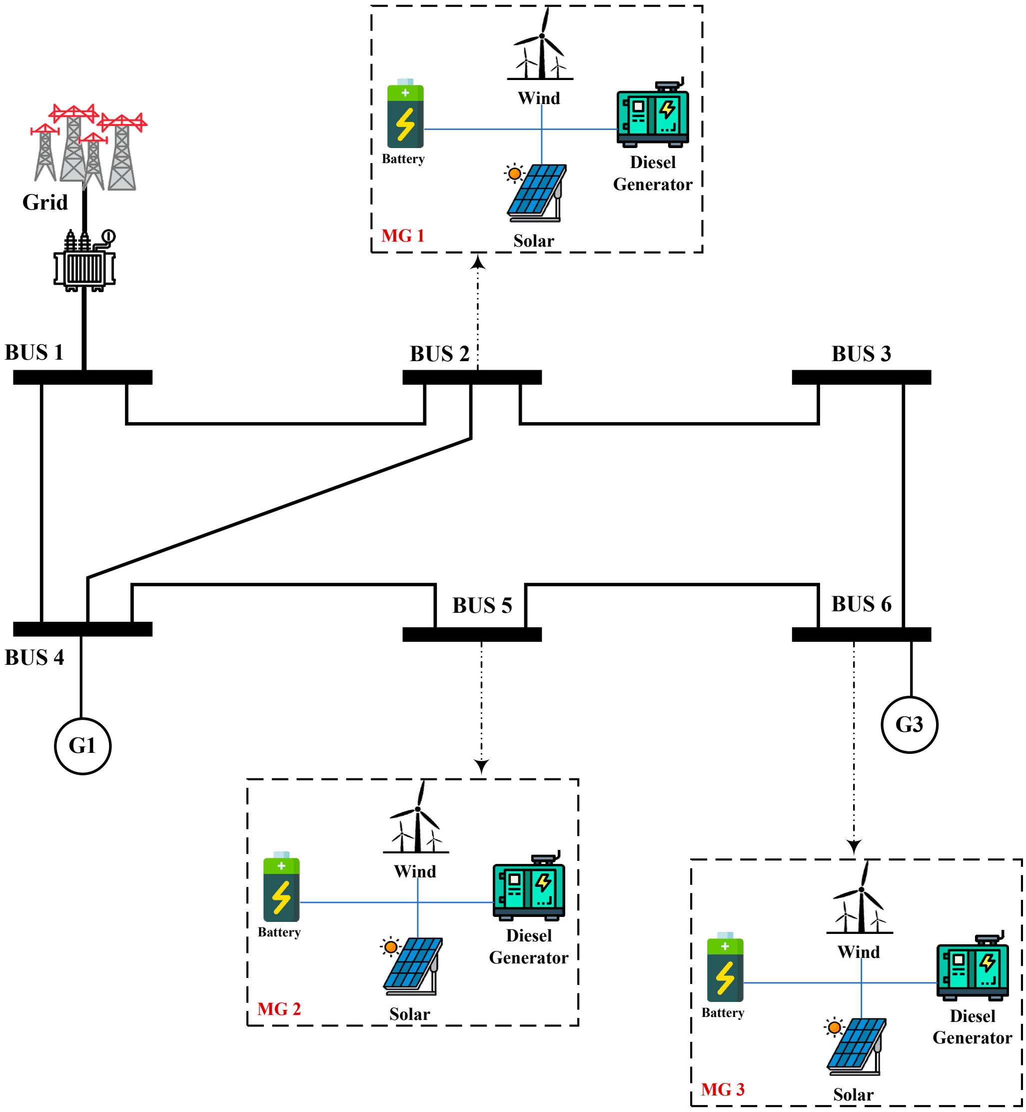

Figure 3. The structure of a 6-bus distribution network with three MGs.

Table 2. Characteristics of the components in each MG [56].

	MG 1	MG 2	MG 3
$P^{g,\min}/P^{g,\max}$ (kW)	0/300	0/300	0/200
MUT^g/MDT^g (h)	2	2	1
$R^{g,dn}/R^{g,up}$ (kW)	40	40	30
π^g ($/kW)	0.12	0.12	0.1
CU^g ($)	10	10	8
$P^{b,dis,\max}/P^{b,ch,\max}$ (kW)	100	50	100
$P^{w,rated}$ (kW)	200	200	150

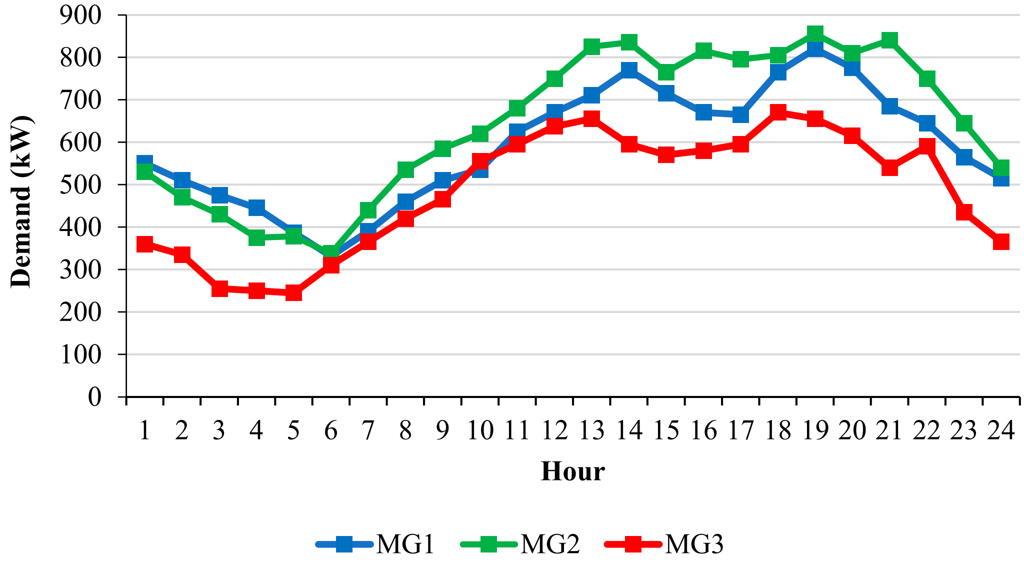

Figure 4. Load demand curve of MGs.

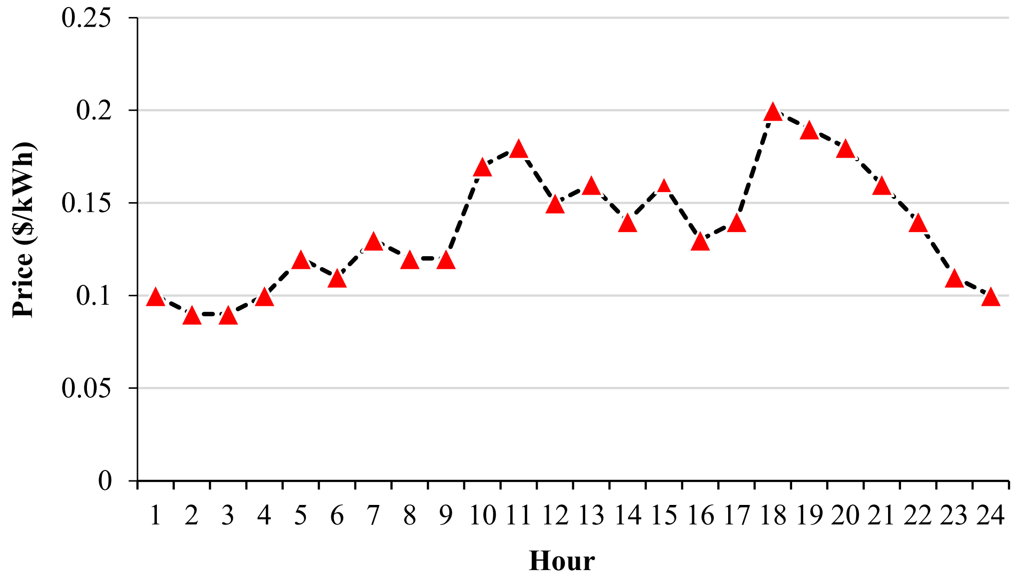

Figure 5. Daily electricity market price.

All required programming is performed in the GAMS software, 46.4.1, in the 64-bit version of Windows and an 8-GB RAM personal computer in the personal computer that the CPLEX solver 22. 1. 0 solves.

There are two generators in the distribution network level connected to buses 4 and 6, with 500 and 400 kW rated power and coefficient costs of 0.08 and 0.15 USD/kW, respectively.

To illustrate the effectiveness of the proposed model, the following study cases are examined:

Case 1—Optimal energy management of the MMG network, while the uncertainty of wind, PV, and load are ignored;

Case 2—CCP-based performance of MMG with $\alpha = 0.98$;

Case 3—CCP-based performance of MMG with $\alpha = 0.95$.

In addition to the provided data, it should be noted that the PV efficiency and standard temperature for all PV units are 30% and 25 °C, respectively. Also, the cut-in, cut-out, and rated wind speeds for wind power output modeling are 3 m/s, 25 m/s, and 12 m/s, respectively.

Although various types of loads can be embedded in each microgrid, this paper assumes that all loads are residential, and the load profiles in all three microgrids follow the consumption pattern of a summer day [56]. The main reason for this is that one of the objectives of this paper is to examine the effects of DR based on load shifting by providing incentives to residential consumers. It is worth mentioning that, since the DC power flow model is used in this paper, only the active load profile is provided for the three microgrids.

4.1. Case 1

Under the deterministic energy management of MMG, the procured powers of MG 1, MG 2, and MG 3 follow Figures 6–8, respectively. For each MG, the DR program shifts the flexible loads from peak hours to off-peak ones, which leads to a smoother load curve. The battery energy storage restricted to energy capacity limits is charged at the initial hours of the day (hours with the lower power price), and then, at peak hours, it is discharged; this procedure is true for all MGs.

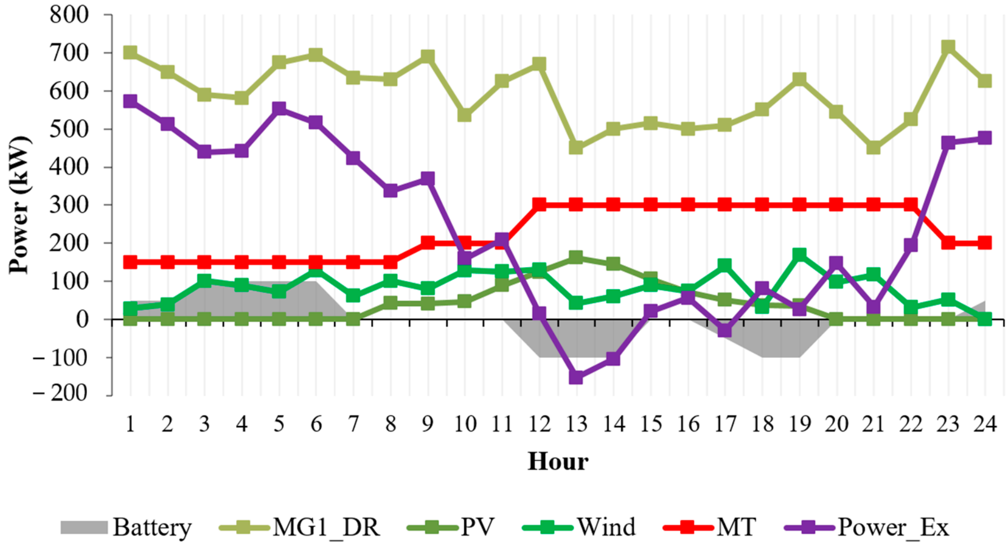

Figure 6. The procured power of MG 1 in case 1.

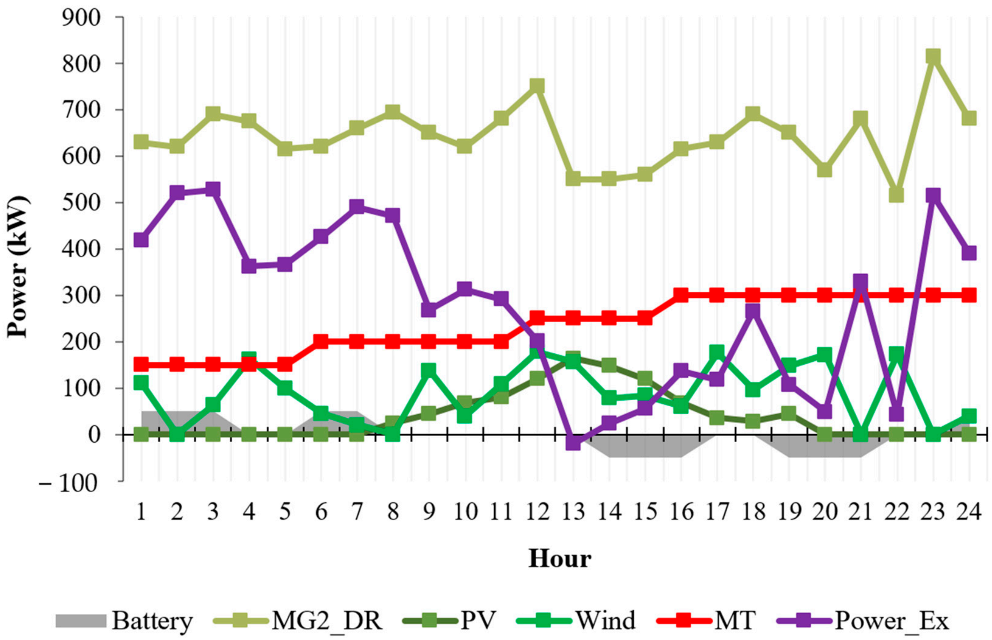

Figure 7. The procured power of MG 2 in case 1.

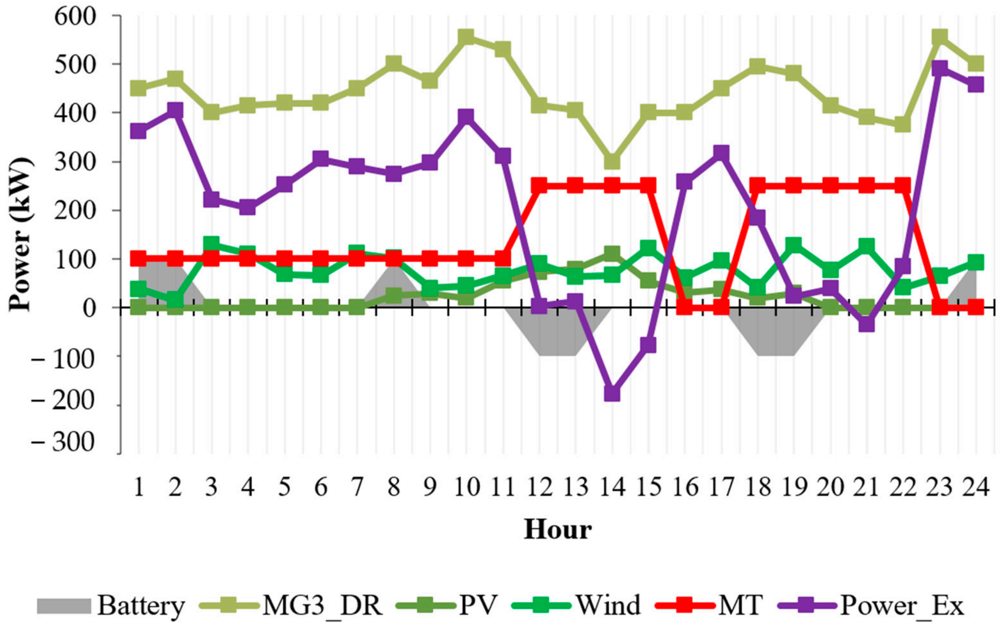

Figure 8. The procured power of MG 3 in case 1.

In MG2, the MT operates with a maximum capacity at hours 16–24. The 50 kW battery is charged at hours 1–3 and 6–7 to provide more flexibility at 14–16 and 20–21. At hour 13, MG 2 injects the surplus power back into the distribution network (see Figure 7).

Figure 8 shows the power dispatch in MG 3. MG 3 injects more power into the distribution network compared with other MGs. According to Figure 8, at hours 14–15 and 21, the surplus power is back into the corresponding bus, which provides a suitable opportunity for the operator to reduce the dependency of the distribution network on the power market, especially at peak (power price) hours. MT in MG 3 is only operated with the maximum capacity at hours 12–16 and 18–22. Also, during hours 16–17, MT turns off.

Figure 9 illustrates the optimal power dispatch of the distribution network for case 1, including power exchanges with the MGs, power purchased from the electricity market, and the hourly dispatch of G1 and G2.

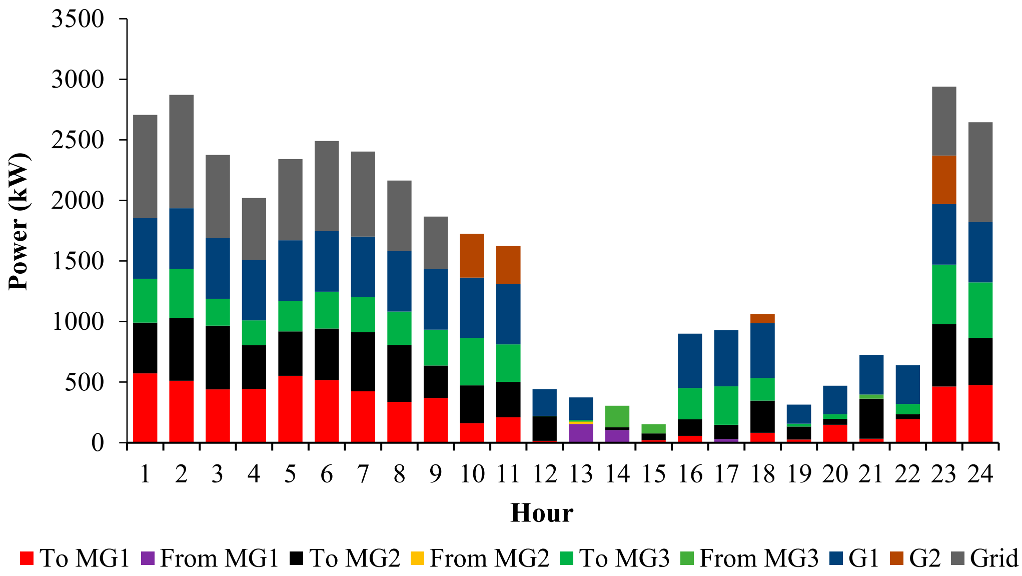

Figure 9. The power purchased and power exchanged schedule of the distribution network, besides G1 and G2, in case 1.

The total operation cost under the deterministic model is USD 5794.67. Moreover, the UPC indexes for MG1, MG2, and MG3 are, respectively, 0.613, 0.759, and 0.766. This means that MG 1 does not use its production capacity optimally, because, as mentioned, a higher value of this index (closer to 1) indicates a more efficient utilization of the available production capacity.

In this case, the reliable operation of the system is not guaranteed. In the next study cases, the energy management of the MMG is analyzed considering the confidence level of the system.

4.2. Case 2

In this case, the CCP-based energy management of the MMG network with $\alpha = 0.98$ is analyzed. The proposed CCP approach involves the uncertainty of wind, PV, and load in the energy management model. Considering the CCP approach, it is stated that the power balance constraint is not violated with a probability of 0.98. Ensuring this requires more use of controllable resources to cover variations in renewable resources and load consumption. The load curve of MGs after implementing DR for case 2 is shown in Figure 10. Compared to case 1, the operator shifts MGs' load more (from peak hours to off-peak intervals) to abide by the power balance constraint. Figure 11 shows the resource scheduling of each MG in case 2 with uncertainty handled by the CCP approach.

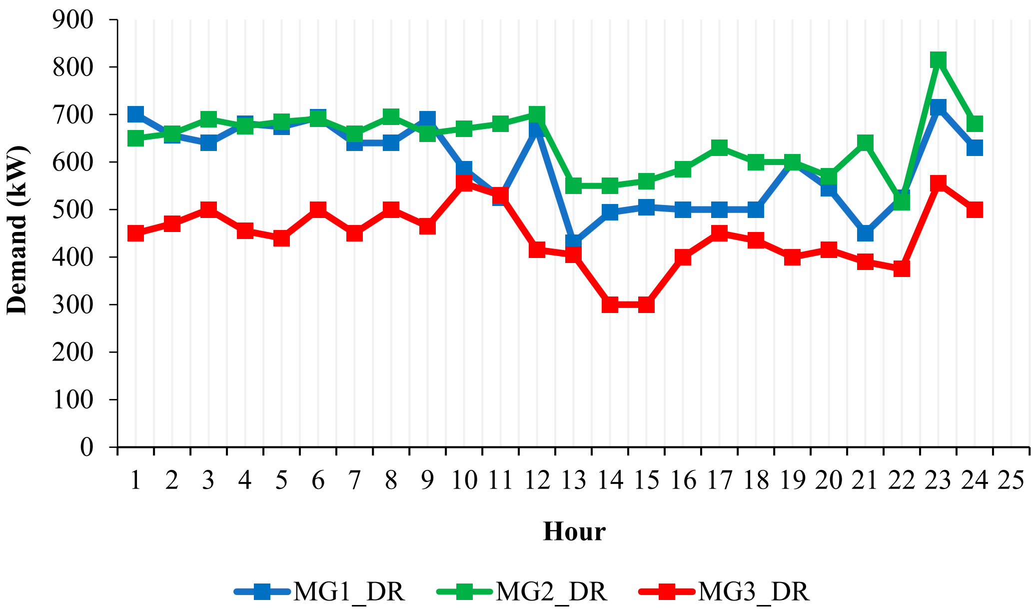

Figure 10. Effects of DR on the load curve of MGs in case 2.

Hence, in contrast to case 1, here, all three MTs generate more power at most time points. Also, the amount of power injected into all three MGs at the corresponding bus is here increased compared to the first case. To manage the breaking of the electricity balance limit and ensure the desired confidence level in the system's operation, more power is supplied to all three MGs. This, in turn, increases operating costs. It is worth noting that in case 2 with $\alpha = 0.98$, the battery covers load fluctuations better.

The information on the operation of the distribution network in case 2, including the power exchanges with connected MGs, the optimal scheduling of the generators, and the amount of power purchased from the electricity market, is shown in Figure 12. Ensuring the system's safety operation with $\alpha = 0.98$ necessitates the distribution network buy more power to support changes brought about by uncertain parameters.

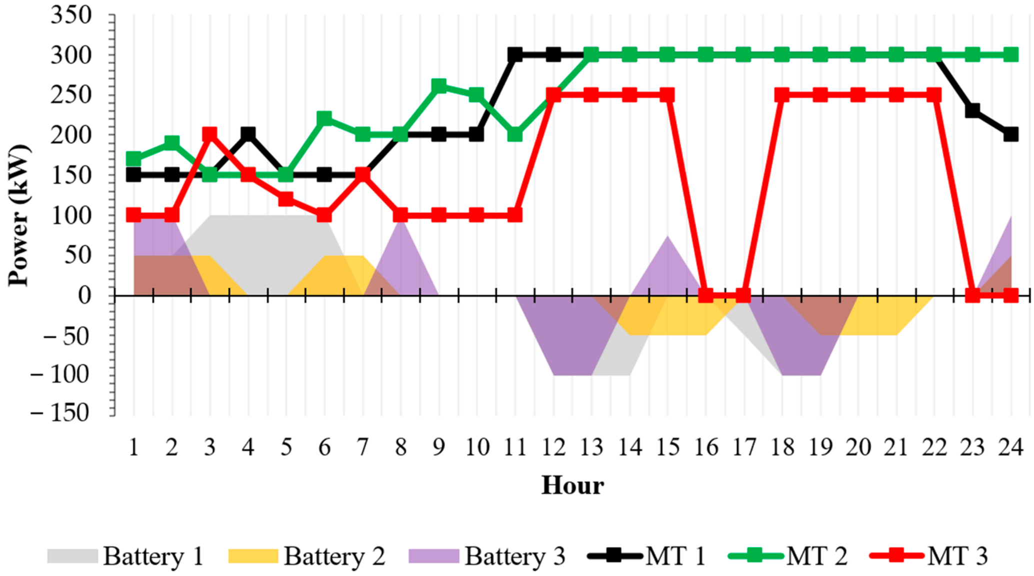

Figure 11. The procured power of MGs in case 2.

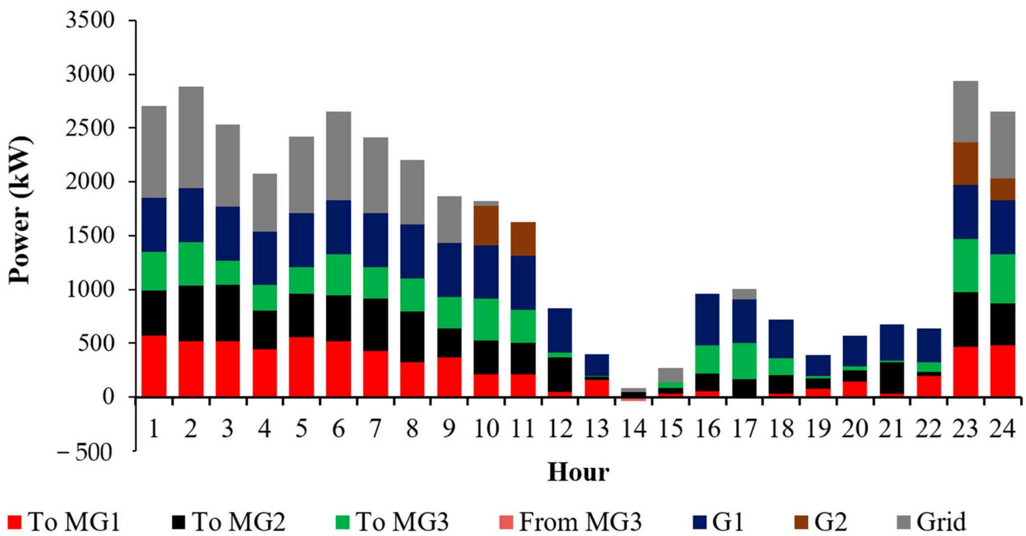

Figure 12. The distribution network's procured power in case 2.

As shown in Figure 12, during low-power-price hours, the operator purchased more electricity from the upstream grid. Besides this, G1 and G2 generators have been committed for more hours to provide power to consumers. Although the optimal distribution network and MGs operation when applying the CCP approach (α = 0.98) increase the operation costs, by utilizing the proposed method, reliable network operation is guaranteed, and the status of the UPC index for all MGs improves as well.

The cost of each MG and distribution network, along with problem-solving time and the amount of UPC index, in all three study cases are given in Table 3 (at the end of this section). According to Table 3, the total operating cost in this case is USD 6520.05. This means that with only an 11% increase in system operation costs, reliable network performance with a probability of 0.98 is guaranteed. Also, in this case, the UPC index improved for all MGs, which confirms that when applying the proposed method, the generation capacity of all three MGs can be used more efficiently.

Table 3. Comparison of major results for three study cases.

	Cost (USD)				UPC_1	UPC_2	UPC_3	Time-Solving (S)
	MG1	MG2	MG3	Distribution Network				
Case 1	1700.45	1158.63	1215.09	1720.5	0.613	0.759	0.766	38
Case 2	1918.37	1294.11	1377.24	1930.33	0.802	0.794	0.809	79
Case 3	1875.61	1194.07	1288.64	1797.26	0.783	0.77	0.703	75

4.3. Case 3

The proposed model employing the CCP approach with α= 0.95 is investigated in case 3. Reducing α means reducing the confidence level, yielding less reliable network operation (compared to case 2) as a result. In other words, to guarantee the system's performance with α = 0.95, compared to α = 0.98, the generating units are scheduled in such a way that the power balance constraint is satisfied with a probability of 0.95. The results of this case, including the impact of DR, the resource scheduling of each MG, and the distribution network, are shown in Figures 13–15, respectively. Comparing Figure 13 with Figure 10 shows that in case 3 (with a lower confidence level), the operator shifts less load at peak intervals based on the DR program. Figure 14 also shows that the power output and power exchanges between MGs and the corresponding busses are more negligible than those of case 2, and greater than those of case 1.

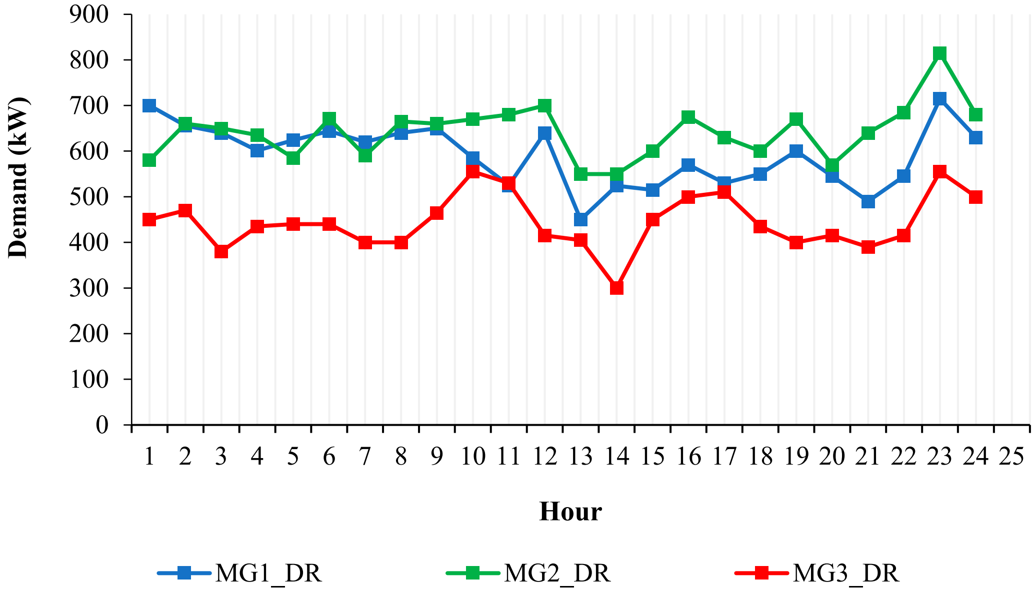

Figure 13. Effects of DR on the load curve of MGs in case 3.

The optimal operation of G1 and G2, besides the power purchased from the grid presented in Figure 15, reveals that MG3 exports more power to the distribution network at hours 13 and 14. Also, G1 and G2 are less committed in case 3. In comparison with case 2, G2 is only committed at hours 10, 11, and 23.

The total cost in case 3 is USD 6155.58. According to Table 3, the computational time, in this case, is approximately equal to that of the second case. However, the computational complexity of case 2 and case 3 (applying the CCP approach) is more than that of the deterministic case. Furthermore, in case 3, the UPC index is improved only for the first and second MGs. The reason behind this is the tendency of MG3 to import electricity instead of using the internal generation capacity of G3. This case also shows that with just a 5% rise in operating costs, system performance is ensured, with a chance of 0.95 in any situation.

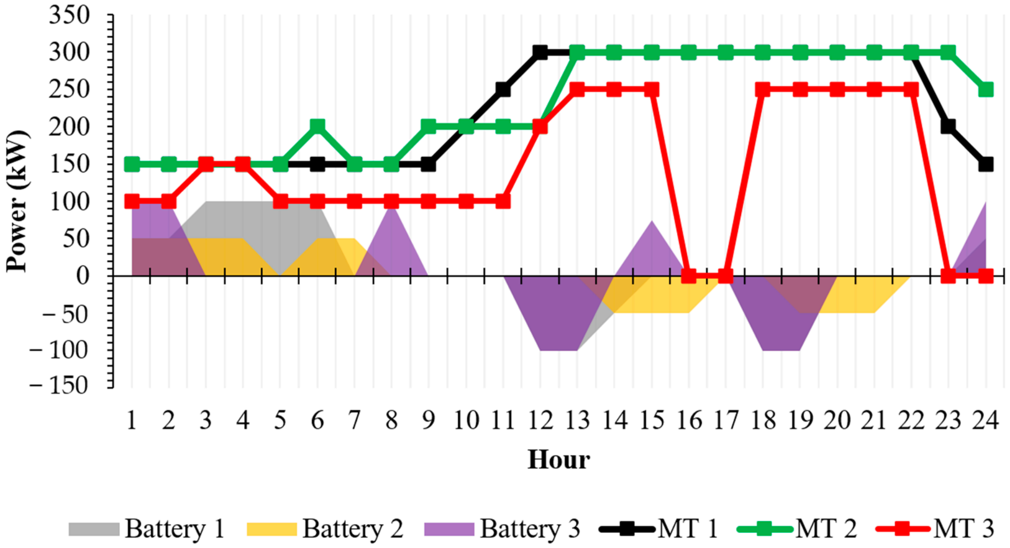

Figure 14. The procured power of MGs in case 3.

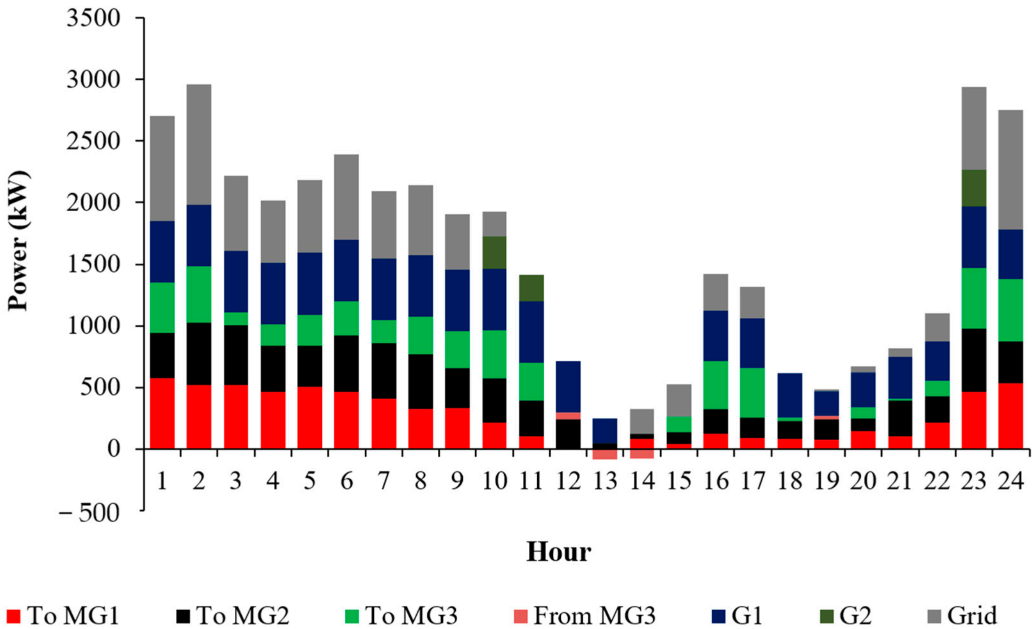

Figure 15. Distribution network procured in case 3.

5. Conclusions

The optimal energy management of a multi-microgrid (MMG) network, considering battery storage, renewable-based energy sources (wind and solar), and demand response programs based on the shiftable load, has been elaborated in this paper. A new performance index named unused power capacity (UPC) was introduced to show the efficient operation of the individual MG in terms of using its generation capacity. Hence, the proposed model improved the UPC of each MG while minimizing the operation cost. The chance-constrained programming (CCP) approach was developed to involve variations in solar, wind, and load in the energy management model, with the desired confidence level. Employing the CCP approach, the power balance limit was defined via the intended confidence level, which guarantees the reliable operation of the system. The proposed model was examined on the test system with three interconnected MGs. The effects of each technology in MGs, besides the optimal resource scheduling and power exchange between MGs and the distribution network, were studied for deterministic and uncertain cases.

The numerical results reveal that under CCP-based energy management, reliable network performance is guaranteed with a probability of 0.98, imposing an 11% increase in the cost.

Future Works

Future research will explore several avenues to enhance the energy management of multi-microgrid networks. One promising direction is the integration of machine learning techniques and smart technologies to further refine and optimize energy management strategies. Advanced machine learning models, such as reinforcement learning and deep learning algorithms, could be utilized to improve forecasting accuracy and adapt to real-time changes in renewable generation and load demands. Furthermore, future studies will investigate the application of a bi-level optimization framework for energy management, where multiple operators manage distinct microgrids and distribution networks. This approach will address the coordination challenges among different entities and seek to balance individual and collective objectives within the network.

These advancements aim to push the boundaries of current energy management practices, leading to more sustainable, efficient, and resilient multi-microgrid systems.

Author Contributions: Conceptualization, methodology, software, validation, writing—original draft preparation, M.H.; supervision, N.B.; writing—editing, T.E. All authors have read and agreed to the published version of the manuscript.

Funding: Authors acknowledge the support of the MARGIN project funded by the DANIDA Fellowship Centre and the Ministry of Foreign Affairs of Denmark to aid in research in growth and transition countries under grant no. 21-M06-AAU.

Data Availability Statement: All data have been provided in the main text.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

Index	
t	Index of time
m	Index for microgrid
g	Index for generator
L	Index for line
u	Index of minimum on/off time limits from 1 to max$\{MUT^g, MDT^g\}$
b	Index for battery
d	Index for load
p/q	Bus nodes
w	Index for wind turbine
Parameter	
NT	Number of time span
NM	Number of microgrids
Ω_p	Set of buses
λ_t^{grid}	Market price
F	Objective function
MDT^g	Minimum down time of generator
MUT^g	Minimum up time of generator
$R_m^{g,dn}$	Ramp down of generator
$R_m^{g,up}$	Ramp up of generator
C^{LS}	Load shedding cost
C^W	Wind spillage cost
C^{PV}	PV spillage cost
$\beta_{p,q}$	Susceptance of line
η^{PV}	PV panel efficiency
S^{PV}	Surface of PV panel
G_t	Solar irradiation
$T_{r,t}$	Air temperature

T_s	Standard temperature
UPC_m^{target}	Target UPC index
$\eta^{b,ch}/\eta^{b,dis}$	Charging/discharging efficiency
Δt	Time period (1 hour in this work)
$E_m^{b,\min}/E_m^{b,\max}$	Minimum/maximum capacity of battery
$P^{L,\max}$	Maximum power flows in line
$P_m^{b,ch,\max}$	Maximum power charged of battery
$P_m^{b,dis,\max}$	Maximum power discharged of battery
$P_m^{g,\min}/P_m^{g,\max}$	Min/max power output of generator
γ^e	Load factor for participating in DR
Variable	
P_t^{grid}	Power exchange with upstream grid
$P_{m,t}^g$	Power output of generator in microgrid m
$SU_{m,t}$	Start-up cost
TD_u^g	Number of continuous times that the generator must be turned off
TU_u^g	Number of continuous times that the generator must be turned on
$P_{m,t}^{d,Dr}$	Value of load participate in DR
$P_{m,t}^{LS}$	Load shedding value
$P_{m,t}^{w,SP}$	Value of wind spillage in microgrid m
$P_{m,t}^{PV}$	Value of PV power output in microgrid m
$P_{m,t}^{b,dis}, P_{m,t}^{b,ch}$	Power discharging, charging of battery in microgrid m
$P_{m,t}^d$	Value of load demand in microgrid m
$P_{m,t}^w$	Power output of wind turbine in microgrid m
$P_{m,t}^{dr}$	Value of demand response in microgrid m
P_t^L	Power flow in line
$\theta_{p,t}$	Magnitude of bus angel
$X_{m,t}^{b,ch}/X_{m,t}^{b,dis}$	Binary variable for charging/discharging mode
$E_{m,t}^b$	Energy capacity of battery in microgrid m
$P_{m,t}^{PV,SP}$	Value of PV power spillage
UPC_m	Unused power capacity in microgrid m
$P_{m,t}^{d,Net}$	Net load demand
$I_{m,t}^g$	Binary variable for generator operation

References

1. Dahane, A.S.; Sharma, R.B. Hybrid AC-DC microgrid coordinated control strategies: A systematic review and future prospect. *Renew. Energy Focus* **2024**, *49*, 100553. [CrossRef]
2. The Insight Partners. Microgrid Technology Market. *Trends and Outlook for 2031*. 2024. Available online: https://www.theinsightpartners.com/reports/microgrid-technology-market (accessed on 26 August 2024).
3. Wang, H.; Xing, H.; Luo, Y.; Zhang, W. Optimal scheduling of micro-energy grid with integrated demand response based on chance-constrained programming. *Int. J. Electr. Power Energy Syst.* **2023**, *144*, 108602. [CrossRef]
4. Ahmethodzic, L.; Music, M. Comprehensive review of trends in microgrid control. *Renew. Energy Focus* **2021**, *38*, 84–96. [CrossRef]
5. Costa, V.B.; e Silva, T.L.; Morais, L.B.; Bonatto, B.D.; Zambroni, A.C.; Guedes, P.A.; Ribeiro, P.F. Economic analysis of industrial energy storage systems in Brazil: A stochastic optimization approach. *Sustain. Energy Grids Netw.* **2023**, *33*, 100968. [CrossRef]
6. Abisoye, B.O.; Sun, Y.; Zenghui, W. A survey of artificial intelligence methods for renewable energy forecasting: Methodologies and insights. *Renew. Energy Focus* **2023**, *48*, 100529. [CrossRef]
7. Rodriguez, M.; Arcos-Aviles, D.; Guinjoan, F. Simple fuzzy logic-based energy management for power exchange in isolated multi-microgrid systems: A case study in a remote community in the Amazon region of Ecuador. *Appl. Energy* **2024**, *357*, 122522. [CrossRef]
8. Wu, Y.; Hu, M.; Liao, M.; Liu, F.; Xu, C. Risk assessment of renewable energy-based island microgrid using the HFLTS-cloud model method. *J. Clean. Prod.* **2020**, *284*, 125362. [CrossRef]
9. Marzband, M.; Parhizi, N.; Adabi, J. Optimal energy management for stand-alone microgrids based on multi-period imperialist competition algorithm considering uncertainties: Experimental validation. *Int. Trans. Electr. Energy Syst.* **2016**, *26*, 1358–1372. [CrossRef]
10. Vaish, J.; Tiwari, A.K.; Siddiqui, K.M. Optimization of micro grid with distributed energy resources using physics based meta heuristic techniques. *IET Renew. Power Gener.* 2023. [CrossRef]

11. Jirdehi, M.A.; Tabar, V.S.; Hemmati, R.; Siano, P. Multi objective stochasticmicrogrid scheduling incorporating dynamic voltage restorer. *Int. J. Electr. Power Energy Syst.* **2017**, *93*, 316–327. [CrossRef]
12. Mayhorn, E.; Xie, L.; Butler-Purry, K. Multi-time scale coordination of dis-tributed energy resources in isolated power systems. *IEEE Trans. Smart Grid* **2016**, *8*, 998–1005.
13. Şengör, İ.; Erenoğlu, A.K.; Erdinç, O.; Taşçıkaraoğlu, A.; Catalão, J.P. Day-ahead charging operation of electric vehicles with on-site renewable energy resources in a mixed integer linear programming framework. *IET Smart Grid* **2020**, *3*, 367–375. [CrossRef]
14. Papari, B.; Edrington, C.S.; Bhattacharya, I.; Radman, G. Effective energymanagement of hybrid ac–dc microgrids with storage devices. *IEEE Trans. Smart Grid* **2017**, *10*, 193–203. [CrossRef]
15. Chen, X.; Zhai, J.; Jiang, Y.; Ni, C.; Wang, S.; Nimmegeers, P. Decentralized coordination between active distribution network and multi-microgrids through a fast decentralized adjustable robust operation framework. *Sustain. Energy Grids Netw.* **2023**, *34*, 101068. [CrossRef]
16. Li, C.; Liu, C.; Deng, K.; Yu, X.; Huang, T. Data-driven charging strategy ofpevs under transformer aging risk. *IEEE Trans. Control Syst. Technol.* **2017**, *26*, 1386–1399. [CrossRef]
17. Abdollahi, A.; Mahdavinia, A.; Khaloie, H.; Mohammadnejad, M. Energy man-agement of a microgrid with emission limitations under uncertainty. In Proceedings of the CIRED 2018Ljubljana Workshop on Microgrids and Local Energy Communities, CIRED, Ljubljana, Slovenia, 7–8 June 2018; p. 0426.
18. Papari, B.; Edrington, C.S.; Gonsoulin, D. Optimal energy-emission managementin hybrid ac-dc microgrids with vehicle-2-grid technology. *J. Renew. Sustain. Energy* **2019**, *11*, 015902. [CrossRef]
19. Samoon, F.A.; Hussain, I.; Iqbal, S.J. Multi-objective optimal control of renewable energy based autonomous AC microgrid using dandelion optimisation. *Renew. Energy Focus* **2024**, *49*, 100563. [CrossRef]
20. Žnidarec, M.; Šljivac, D.; Knežević, G.; Pandžić, H. Double-layer microgrid energy management system for strategic short-term operation scheduling. *Int. J. Electr. Power Energy Syst.* **2024**, *157*, 109816. [CrossRef]
21. Wu, P.; Mei, X. Microgrids energy management considering net-zero energy concept: The role of renewable energy landscaping design and IoT modeling in digital twin realistic simulator. *Sustain. Energy Technol. Assess.* **2024**, *63*, 103621. [CrossRef]
22. Chakraborty, A.; Ray, S. Economic and environmental factors based multi-objective approach for optimizing energy management in a microgrid. *Renew. Energy* **2024**, *222*, 119920. [CrossRef]
23. Zhang, Y.; Wang, J.; Zeng, B.; Hu, Z. Chance-constrained two-stage unit commitment under uncertain load and wind power output using bilinear benders decomposition. *IEEE Trans. Power Syst.* **2017**, *32*, 3637–3647. [CrossRef]
24. Majumder, S.; Khaparde, S.A.; Agalgaonkar, A.P.; Kulkarni, S.V.; Srivastava, A.K.; Perera, S. Chance-Constrained Pre-Contingency Joint Self- Scheduling of Energy and Reserve in VPP. *IEEE Trans. Power Syst.* **2023**, *39*, 245–260. [CrossRef]
25. Chen, B.; Liu, T.; Liu, X.; He, C.; Nan, L.; Wu, L.; Su, X.; Zhang, J. A Wasserstein Distance-Based Distributionally Robust Chance-Constrained Clustered Generation Expansion Planning Considering Flexible Resource Investments. *IEEE Trans. Power Syst.* **2022**, *38*, 5635–5647. [CrossRef]
26. Xiao, M.; Smaisim, G.F. Joint chance-constrained multi-objective optimal function of multi-energy microgrid containing energy storages and carbon recycling system. *J. Energy Storage* **2022**, *55*, 105842. [CrossRef]
27. Wu, G.; Li, T.; Xu, W.; Xiang, Y.; Su, Y.; Liu, J.; Liu, F. Chance-constrained energy-reserve co-optimization scheduling of wind-photovoltaic-hydrogen integrated energy systems. *Int. J. Hydrogen Energy* **2023**, *48*, 6892–6905. [CrossRef]
28. Lee, D.; Han, C.; Kang, S.; Jang, G. Chance-constrained optimization for active distribution networks with virtual power lines. *Electr. Power Syst. Res.* **2023**, *221*, 109449. [CrossRef]
29. Du, P.; Lei, H.; Ansari, I.S.; Du, J.; Chu, X. Distributionally robust optimization based chance-constrained energy management for hybrid energy powered cellular networks. *Digit. Commun. Netw.* **2023**, *9*, 797–808. [CrossRef]
30. Zhang, C.; Liang, H.; Lai, Y. A distributionally robust energy management of microgrid problem with ambiguous chance constraints and its tractable approximation method. *Renew. Energy Focus* **2024**, *48*, 100542. [CrossRef]
31. Giannelos, S.; Borozan, S.; Aunedi, M.; Zhang, X.; Ameli, H.; Pudjianto, D.; Konstantelos, I.; Strbac, G. Modelling smart grid technologies in optimisation problems for electricity grids. *Energies* **2023**, *16*, 5088. [CrossRef]
32. Hemmati, M.; Ghasemzadeh, S.; Mohammadi-Ivatloo, B. Optimal scheduling of smart reconfigurable neighbour micro-grids. *IET Gener. Transm. Distrib.* **2019**, *13*, 380–389. [CrossRef]
33. Gao, J.; Shao, Z.; Chen, F.; Chen, Y.; Lin, Y.; Deng, H. Distributed robust operation strategy of multi-microgrid based on peer-to-peer multi-energy trading. *IET Energy Syst. Integr.* **2023**, *5*, 376–392. [CrossRef]
34. Misaghian, M.S.; Saffari, M.; Kia, M.; Nazar, M.S.; Heidari, A.; Shafie-khah, M.; Catalão, J.P. Hierarchical framework for optimal operation of multiple micro-grids considering demand response programs. *Electr. Power Syst. Res.* **2018**, *165*, 199–213. [CrossRef]
35. Aghdam, F.H.; Salehi, J.; Ghaemi, S. Contingency based energy managementof multi-microgrid based distribution network. *Sustain. Cities Soc.* **2018**, *41*, 265–274. [CrossRef]
36. Haddadian, H.; Noroozian, R. Multi-microgrid-based operation of active dis-tribution networks considering demand response programs. *IEEE Trans. Sustain. Energy* **2018**, *10*, 1804–1812. [CrossRef]
37. Arefifar, S.A.; Ordonez, M.; Mohamed, Y.A.R.I. Energy management in multi-microgrid systems—Development and assessment. *IEEE Trans. Power Syst.* **2017**, *32*, 910–922.

38. Xu, D.; Zhou, B.; Chan, K.W.; Li, C.; Wu, Q.; Chen, B.; Xia, S. Distributed multi energy coordination of multimicrogrids with biogas-solar-wind renewables. *IEEE Trans. Ind. Inf.* **2018**, *15*, 3254–3266. [CrossRef]
39. Seyednouri, S.; Safari, A.; Quteishat, A.; Younis, M.; Salehi, J.; Najafi, S.; Taghizadegan, N. Stochastic energy management of a multi-microgrid system with battery/ supercapacitor energy storages considering demand response and transactive energy. *Renew. Energy Focus* **2024**, *48*, 100531. [CrossRef]
40. Giannelos, S.; Bellizio, F.; Strbac, G.; Zhang, T. Machine learning approaches for predictions of CO2 emissions in the building sector. *Electr. Power Syst. Res.* **2024**, *235*, 110735. [CrossRef]
41. Shen, J.; Jiang, C.; Liu, Y.; Wang, X. A microgrid energy management systemand risk management under an electricity market environment. *IEEE Access* **2016**, *4*, 2349–2356. [CrossRef]
42. Zhang, Y.; Fu, L.; Zhu, W.; Bao, X.; Liu, C. Robust model predictive controlfor optimal energy management of island microgrids with uncertainties. *Energy* **2018**, *164*, 1229–1241. [CrossRef]
43. Shi, Z.; Liang, H.; Huang, S.; Dinavahi, V. Distributionally robust chance-constrained energy management for islanded microgrids. *IEEE Trans. Smart Grid* **2018**, *10*, 2234–2244. [CrossRef]
44. Papari, B.; Edrington, C.; Vu, T. Stochastic operation of interconnected microgrids. In Proceedings of the 2017 IEEE Power & Energy Society General Meeting, Chicago, IL, USA, 16–20 July 2017; pp. 1–5.
45. Kavousi-Fard, A.; Khodaei, A. Efficient integration of plug-in electric vehicles via reconfigurable microgrids. *Energy* **2016**, *111*, 653–663. [CrossRef]
46. Eghbali, N.; Hakimi, S.M.; Hasankhani, A.; Derakhshan, G.; Abdi, B. Stochastic energy management for a renewable energy based microgrid considering battery, hydrogen storage, and demand response. *Sustain. Energy Grids Netw.* **2022**, *30*, 100652. [CrossRef]
47. Hemmati, M.; Mansour-Saatloo, A.; Ahrabi, M.; Mirzaei, M.A.; Mohammadi-Ivatloo, B.; Zare, K. Evaluating the advantages of electric vehicle parking lots in day-ahead scheduling of wind-based power systems. In *Energy Storage in Energy Markets*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 251–263.
48. Coelho, A.; Iria, J.; Soares, F.; Lopes, J.P. Real-time management of distributed multi-energy resources in multi-energy networks. *Sustain. Energy Grids Netw.* **2023**, *34*, 101022. [CrossRef]
49. Hemmati, M.; Mohammadi-Ivatloo, B.; Abapour, M.; Anvari-Moghaddam, A. Day-ahead profit-based reconfigurable microgrid scheduling considering uncertain renewable generation and load demand in the presence of energy storage. *J. Energy Storage* **2020**, *28*, 101161. [CrossRef]
50. Aghdam, F.H.; Kalantari, N.T.; Mohammadi-Ivatloo, B. A stochastic optimal scheduling of multi-microgrid systems considering emissions: A chance constrained model. *J. Clean. Prod.* **2020**, *275*, 122965. [CrossRef]
51. Hemmati, M.; Mohammadi-Ivatloo, B.; Abapour, M.; Anvari-Moghaddam, A. Optimal Chance-Constrained Scheduling of Reconfigurable Microgrids Considering Islanding Operation Constraints. *IEEE Syst. J.* **2020**, *14*, 5340–5349. [CrossRef]
52. Liu, G.; Starke, M.; Xiao, B.; Zhang, X.; Tomsovic, K. Microgrid optimal scheduling with chance-constrained islanding capability. *Electr. Power Syst. Res.* **2017**, *145*, 197–206. [CrossRef]
53. Odetayo, B.; Kazemi, M.; MacCormack, J.; Rosehart, W.D.; Zareipour, H.; Seifi, A.R. A Chance constrained programming approach to the integrated planning of electric power generation, natural gas network and storage. *IEEE Trans. Power Syst.* **2018**, *33*, 6883–6893. [CrossRef]
54. Aghdam, F.H.; Kalantari, N.T.; Mohammadi-Ivatloo, B. A chance-constrained energy management in multi-microgrid systems considering degradation cost of energy storage elements. *J. Energy Storage* **2020**, *29*, 101416. [CrossRef]
55. Karimi, H.; Jadid, S. Optimal energy management for multi-microgrid considering demand response programs: A stochastic multi-objective framework. *Energy* **2020**, *195*, 116992. [CrossRef]
56. Hemmati, M.; Mohammadi-Ivatloo, B.; Ghasemzadeh, S.; Reihani, E. Risk-based optimal scheduling of reconfigurable smart renewable energy based microgrids. *Int. J. Electr. Power Energy Syst.* **2018**, *101*, 415–428. [CrossRef]