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Stochastic day-ahead optimal scheduling of multimicrogrids: an alternating direction method of multipliers (ADMM) approach

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Abstract: Multimicrogrid system is a novel notion in modern power systems as a result of developing renewable-based generation units and accordingly microgrids in distribution networks. Their energy management might be challenging due to presence of independent units. Thus, in this paper, a decentralized method for energy management of multimicrogrid systems has been proposed. Decentralized methods can enhance the privacy of users and reduce the burden of calculations. Alternating direction method of multipliers (ADMM) is selected as a decentralized approach which has the capability of breaking problems with complicating constraints in order to facilitate the solving process. Using decentralized approach not only reduces the burden of calculations, but also increases the privacy of entities. Wind turbines as renewable based generators are assumed to participate in this system. To model the uncertainties of these units, chance-constrained programming is employed. Also, due to clean output of hydrogen storage systems and fuel cells, the inclination for using these systems has expanded. Simulations on the test case study demonstrate the applicability and performance of the proposed methodology. Considering the reliability level as 0.9 results in $12,989\$$ in the test case. By considering the reliability level as 0.8, the operational cost becomes $11,712\$$ which shows a reduction of $1277\$$ which is achieved by jeopardizing the system reliability by 10%.

Key words: Stochastic programming, multimicrogrid systems, decentralized optimization, energy management, chance-constrained programming, hydrogen storage system

1. Introduction

Utilization of renewable power generation is growing rapidly in recent years. This might be as a result of policies for reducing greenhouse gases, preventing universal warming, limited fossil fuel resources, and the issues associated with nuclear energy. This leads to arrival of many issues in operating power systems e.g., reliability problems, voltage stability, etc. [1]. One promising solution for the mentioned problems is the development of small scale networks better known as microgrids (MGs). MG is defined as a low voltage network consisting of distributed generators (DG), energy storage units, variety of loads. Two modes of operation are available for MGs known as grid-connected mode, which is for maximizing benefits, and islanded mode which is selected to enhance the reliability in cases of unwanted events [2].

Proper scheduling can enhance the economical aspects of operating MGs. Accordingly, many researches have been conducted in optimal scheduling of MGs. Classical and meta-heuristic approaches have been proposed in the literature for day-ahead energy management of MGs. Authors in [3] have employed modified particle

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swarm optimization (PSO) algorithm for the optimal scheduling in MGs. Rabiee et al. [4] have investigated the effect of proper energy management in environmental issues in both islanded and grid-connected modes utilizing the imperialist competitive algorithm (ICA) as an evolutionary algorithm for solving the optimization problem. A new method for daily energy management of a grid-connected MG with various renewable energy resources including PV system, wind turbine (WT), using a modified bat algorithm (MBA) as the solution approach has been proposed in [5].

One of the main disadvantages of evolutionary algorithms is the lack of optimality in their output answer. Accordingly, many authors have suggested mathematical approaches such as linear programming (LP), mixed integer linear programming (MILP), nonlinear programming (NLP), and mixed integer nonlinear programming (MINLP). Authors in [6] have developed MILP based energy management for MGs considering degradation cost of batteries. In [7], short-term operation scheduling of MGs with multiple-energy carrier networks using MILP model in stochastic framework has been presented. Authors in [8] have proposed an optimization operating approach for a multiobjective problem.

More tendency to use DGs has led to the development of MGs and more presence of them in the distribution systems which leads to arrival of a new notion known as networked MGs or multimicrogrid (MMG) system. Various studies have been dedicated to solving the problems associated with MMG systems e.g., day-ahead scheduling and planning. Authors in [9] have proposed a cooperative multiobjective optimization for daily optimal scheduling of MMG distribution network. Authors in [10] have proposed a novel hierarchical approach for daily energy management of MMGs in presence of renewable energy sources.

There are two main methods for solving the energy management problems as centralized and decentralized approaches. In centralized methods, a central controlling unit is responsible for the optimization process. On the other hand, in decentralized methods, local controllers are responsible for the energy management and coordination is done using some methods and the overall optimization is achieved. Decentralized methods are convenient in systems with multiple owners which makes it a perfect choice for MMG systems. In this method, the privacy of the owner of each entity is considered as one of the priorities.

Authors in [11] have proposed a decentralized method based on the classical symmetrical assignment problem. Also, Wang et al. [12] have proposed a privacy-preserving day-ahead scheduling approach for an MG developing distributed algorithm for solving the problem. A distributed optimal energy management strategy for MGs has been proposed by authors in [13]. Authors in [14] have presented an implementation of a decentralized multiagent based energy management system for an MMG network with the fault tolerance feature.

High penetration of renewable in modern power systems has caused entrance of uncertainty in the power systems. Accordingly, to balance the demand and generation amounts, energy storage systems such as batteries, hydrogen storage systems, etc., are required. Many researches have been done investigating the presence of energy storage units in the operation of MGs. Authors in [15] have proposed an algorithm for optimal scheduling of residential battery storage in presence of PV units aiming at maximizing the daily operational savings and minimizing large voltage swings. In [16], a novel optimal day-ahead scheduling for islanded MGs aiming at minimizing cost of operation has been proposed which models the spinning reserves provided by battery storage. Authors in [17] have proposed an analysis for battery storage lifetime characteristics to estimate the battery storage lifetime which can be used for the economic scheduling of a grid-connected MG.

Reliability of engineering systems should remain high in order to provide the costumers in a satisfactory way. Authors in [18] have proposed the theoretical basis and a new technique for detection of failures in pipes by acoustic means. Likewise in [19], the main objective is showing the efficiency and robustness of the artificial immune system. In [20], Monte Carlo simulation technique is used to analyze the fuzzy reliability of systems having complexity. In [21], a new meditative fuzzy ranking technique as the fuzzy extension in decision making is presented. As mentioned earlier, power systems are integrated with uncertainties due to entrance of renewable based power generators. The output power of these sources relies on stochastic environmental conditions such as wind speed and solar irradiance. Consequently, power system problems are transforming into stochastic ones. There are some main methods for modeling the uncertainty, such as scenario-based methods, point-estimation methods and chance-constrained programming (CCP) method. The last one may have some advantages over the other methods. Some of the advantages are enhancement of the security of the system, reducing calculation burden, etc. It also helps improving the reliability of the system in presence of stochastic parameters. Many researchers have employed CCP in their problem modeling. Authors in [22] have proposed classification of the loads according to the urgency, and establishes their satisfaction models respectively, in the energy management problem. The objective is minimizing the customer's cost and guaranteeing the inhabitants' satisfaction and the uncertainties are modelled through CCP. A hierarchical structure for MMG systems considering different uncertainties has been proposed by authors in [23, 24]. CCP has been employed to model the uncertainties of load and renewable generations.

Considering the reviewed literature, various approaches have been investigated in the literature for MGs. Table 1 demonstrates the methodologies in studying the operation of the MGs and MMG systems and the proposed method.

Table 1. Comparison of the proposed method with different studies.

Reference	Uncertainities	Cent/decent	Hydrogen storage	Single/multi-MG	Uncertainty modeling
[6]	✓	Centralized	-	Single MG	CCP
[7]	✓	Centralized	-	Single MG	Scenario-based
[9]	✓	Centralized	-	Multi-MG	Scenario-based
[10]	✓	Centralized	-	Multi-MG	Scenario-based
[11]	-	Decentralized	-	Single MG	-
[12]	-	Decentralized	-	Single MG	-
[15]	-	Centralized	✓	Single MG	-
[23]	✓	Centralized	-	Multi-MG	CCP
[24]	✓	Centralized	-	Multi-MG	CCP
Proposed	✓	Decentralized	✓	Multi-MG	CCP

Considering the references, a research considering a decentralized approach and containing the benefits of the CCP method in the presence of hydrogen storages is lacking. Thus, in this study, an MMG system consisting of three different MGs is assumed and a method for the day-ahead optimal scheduling of the system is presented. In order to enhance the privacy of the entities and easier expansion for adding other MGs to the system, a decentralized approach for solving the problem would be proposed. The presence of WTs causes arrival of uncertainty in the system. Accordingly, CCP is used as a tool for modeling the uncertainty. To sum it up the contributions of this research are as follows:

- Decentralized day-ahead energy management of multimicrogrid distribution networks.
- Modeling the uncertainty of wind power using CCP approach.

- Investigating the effect of various reliability levels in the CCP model on the output schedule of various units.
- Considering hydrogen storage and fuel cells in the structure of the MGs.

The rest of the paper is organized as follows: In Section 2, formulations for each unit and the energy management will be illustrated. In Section 3, day-ahead scheduling using a decentralized approach would be presented. Section 4 contains the simulations and final section is dedicated to the conclusion of the study.

2. Problem modeling and formulation

An MMG system usually consists of some groups of units clustered as MGs and some independent units. A general scheme is shown in Figure 1.

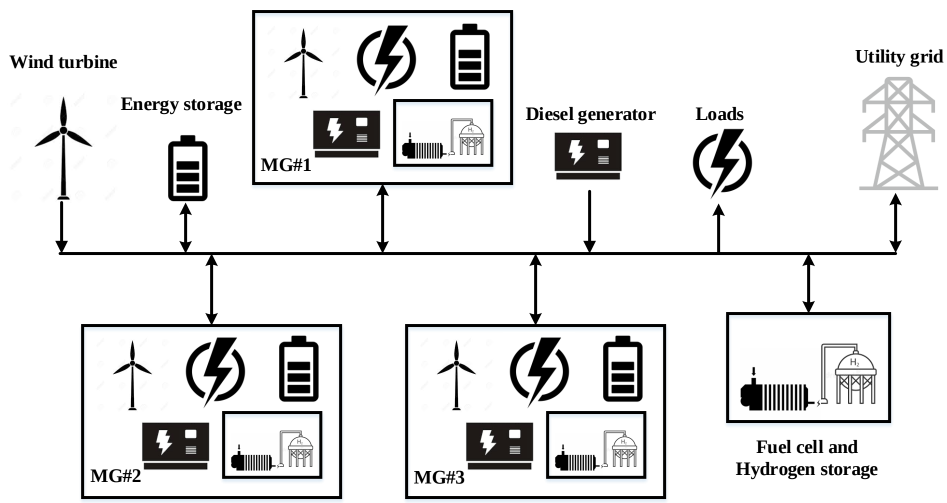

Figure 1. Structure of a typical MMG system.

In this section formulations and relations for different entities used in the MMG system will be presented. The elements used in the MGs are diesel generators, WTs, batteries and hydrogen storage systems including hydrogen tanks and fuel cells. The characteristics of each category will be illustrated in the following subsections. Finally, problem formulation for the energy management of an MMG system will be discussed.

2.1. Diesel generator

One of the conventional units used for distributed generation in power systems is diesel generators. Usually the cost function for them is a quadratic function of the produced power as illustrated in (1) [25].

$$Cost_{DG,t} = aP_{DG,t}^2 + bP_{DG,t} + c, \tag{1}$$

where $Cost_{DG}$ and P_{DG} are respective symbols for operational cost and produced power of DG at time t. Also, a, b, and c stand for function coefficients. For operation of diesel generators, there are some limitations for maximum generation capacity and ramp rate which are shown in terms of (2) and (3).

$$0 \leq P_{DG,t} \leq P_{DG,max} \tag{2}$$

$$| P_{DG,t-1} - P_{DG,t} | \leq R_{DG} \times P_{DG,max}, \tag{3}$$

where R_{DG} is the ramp rate of the generator.

2.2. Wind turbines

One of the most promising technologies for utilizing renewable generation in modern power systems is wind turbines (WTs). The first experimental grid-connected WT with a rated capacity of 2 MW was installed in 1979 on Howard Knob Mountain, North Carolina. Nowadays, larger WTs are installed world wide which have the capability of competing with conventional generators in supplying economical and clean power [26].

In WTs, the kinetic energy of the wind is converted into electrical power. The wind speed variations is usually modelled by the Weibull probability distribution function (PDF) as illustrated in terms of Eq. (4). Weibull PDF contains two parameters named as the shape parameter k, and the scale parameter c. The output power of the WT, P_{wt} is a function of wind velocity which is expressed in (5) [27]. The output power is zero before the cut-in speed V_{ci} and after cut-out speed V_{co} which are determined by the manufacturer of the WT. The output power is modelled as a linear function of the wind speed between the V_{ci} and rated speed, V_r and remains constant till reaching the V_{co} [27].

$$f(v) = (\frac{k}{c})(\frac{v}{c})^{k-1} exp-(\frac{v}{c})^k \quad 0 \leq v \leq \infty \tag{4}$$

$$P_{wt} = \begin{cases} 0 & V \leq V_{ci}, \quad V \geq V_{co} \\ \frac{V-V_{ci}}{V_r-V_{ci}} P_{wt,r} & V_{ci} \leq V \leq V_r \\ P_{wt,r} & V^r \leq V \leq V_{co} \end{cases} \tag{5}$$

2.2.1. Uncertainty modeling

Due to presence of WTs, it is required to perform stochastic programming to get realistic results. Monte Carlo simulation (MCS) is one of the usual tools for dealing with the uncertainty, however, the computation time in this approach is high. One of the other methods for handling the uncertainties is the chance-constrained programming (CCP). In this approach, some of the uncertain parameters remain in a predetermined bound. General formulation of CCP approach is presented as (6)

$$min\, f(x) \tag{6}$$

$$s.t. \quad g_i(x) \geq 0 \quad i = 1, ..., n \tag{7}$$

$$Pr[h_j(x, y) \geq 0] \geq \alpha \quad j = 1, ..., m. \tag{8}$$

Two sets of constraints are shown where the first set is associated with deterministic variables and the second set contains stochastic ones, y, which leads to presence of uncertainty in these constraints. In CCP, it is required that the probability of occurrence of these limitations remains in a predetermined value, α, known as reliability level as shown in Eq. (8).

Presence of nondeterministic constraints can add extra difficulty to the solving procedure of the optimization problems. Thus, some deterministic equivalents have been proposed in [28]. Assuming that h_j to be linear, and considering y in one side of the relation, the chance constraint can be rewritten as:

$$Pr[y \leq \sum_i a_i x_i] \geq \alpha \tag{9}$$

Assuming that Φ to be the cumulative distribution function of y, (9) can be expressed as follows which is the deterministic equivalent of the chance constraint. Φ^{-1} can be calculated using numerical methods and Monte Carlo simulations [24].

$$\sum_i a_i x_i \geq \Phi^{-1}(\alpha) \tag{10}$$

2.3. Battery storage

Energy storage devices are one of the essential units in modern power systems. They provide the power balance which can be violated due to the uncertainty of renewable DGs. In this section, battery storage modeling will be presented. The following equations show the operational constraints of battery storage.

$$-P_{b,max} \leq P_{b,t} \leq P_{b,max} \tag{11}$$

$$SC_t = SC_{t-1} + \frac{P_{b,t}}{P_{b,max}} \tag{12}$$

$$0 \leq SC_t \leq 1 \tag{13}$$

$$SC_{t_0} = SC_{init}, \tag{14}$$

where $P_{b,t}$ is the battery storage power which has a negative value while discharging and a positive value while charging mode. SC and $P_{b,max}$ are respective representatives for state of charge and maximum power capacity of the battery storage. Eq. (11) represents the maximum battery charging/discharging capacity and Eqs. (12)–(14) show the state of charge relations in the energy storage.

2.4. Hydrogen storage units and fuel cells

In recent years, the use of hydrogen storage systems in energy systems has expanded. In this system, when the power generation of DGs exceeds the demand level, the excess power is used to activate the electrolysis to the produce hydrogen gas and store it in pressurised tanks. Fuel cells can use this stored hydrogen to generate electricity at times with shortage in supplying the demanded load. The operational constraints of hydrogen storage and fuel cell are as follows:

$$0 \leq P_{El,t} \leq P_{El,max} \tag{15}$$

$$N_{El,H_2,t} = \frac{P_{El,t}}{LHV_{H_2}} \tag{16}$$

$$0 \leq P_{FC,t} \leq P_{FC,max} \tag{17}$$

$$N_{FC,H_2,t} = \frac{P_{FC,t}}{LHV_{H_2}} \tag{18}$$

$$p_{H_2,t} = p_{H_2,t-1} + \frac{R.T_{H_2}}{V_{H_2}}(N_{El,H_2,t} - N_{FC,H_2,t}) \tag{19}$$

$$0 \leq p_{H_2,t} \leq p_{H_2,max} \tag{20}$$

$$p_{H_2,t_0} = p_{H_2,init}. \tag{21}$$

P_{El} / P_{FC} stands for power used/generated by electrolysis/fuel cell. N is a positive value indicating the H_2 gas moles generated by electrolysis or used by fuel cell. Also, LHV, R, T, V and finally p are the symbols indicating the lower heating value of H_2, ideal gas constant, temperature, volume and pressure of the tank, respectively. Eqs. (15) and (17) show power limitations for the electrolysis and fuel cell. Also, amount of generated/consumed moles of H_2 by electrolysis/fuel cell are calculated through Eqs. (16) and (18). Relationships for gas pressure in hydrogen tanks and the amount of H_2 moles are shown in (19)–(21).

2.5. Day-ahead scheduling

One of the main tasks of the system operator is economical and reliable operational control of the system which could be obtained though optimal day-ahead scheduling. The aim is to minimize the operational costs while meeting the constraints. The overall formulation of the energy management process in form of a centralized approach is presented as below:

$$\min: \; objective\ function = \sum_{t}\sum_{MG} Cost_{MG_t} + Cost_{DN,t} + \lambda_t \times P_{UG,t} \tag{22}$$

$$Subject\ to: (2), (3), (11) - (21) \quad \forall utility,\ \forall t$$

$$\sum_{i=1}^{n} P_{DG,i,t} + \sum_{i=1}^{n} P_{FC,i,t} + \sum_{i=1}^{n} P_{WT,i,t} + P_{UG,t} = \sum_{i=1}^{n} P_{b,i,t} + \sum_{i=1}^{n} P_{El,i,t} + \sum_{i=1}^{n} P_{l,i,t} \quad \forall t \tag{23}$$

Eq. (23) demonstrates the power balance equation which obliges the equality of generation and consumption. P_{UG} is the amount of traded power with the upper network and λ_t is the price of electricity at time t.

Presence of WT generation in (23) causes entrance of uncertainty. Thus it transforms into a probabilistic constraint which can be treated as a CCP problem as rewritten in (24).

$$Pr[\sum_{i=1}^{n} P_{WT,i,t} \geq \sum_{i=1}^{n} P_{b,i,t} + \sum_{i=1}^{n} P_{El,i,t} + \sum_{i=1}^{n} P_{l,i,t} - \sum_{i=1}^{n} P_{DG,i,t} - \sum_{i=1}^{n} P_{FC,i,t} + P_{UG,t}] \geq \alpha \quad \forall t \tag{24}$$

Because of the presence of uncertainty in the constraints, the existing solution tools are infeasible for solving the CCP model as in (24). Thus it is required that the probabilistic constraints are transformed into deterministic equivalents efficient solving. Using (10), deterministic equivalent of (24) can be written as below:

$$\sum_{i=1}^{n} P_{b,i,t} + \sum_{i=1}^{n} P_{El,i,t} + \sum_{i=1}^{n} P_{l,i,t} - \sum_{i=1}^{n} P_{DG,i,t} - \sum_{i=1}^{n} P_{FC,i,t} + P_{UG,t} = \Phi^{-1}(1-\alpha) \; \forall t \tag{25}$$

3. Decentralized day-ahead scheduling

In such approaches, the central controlling unit is responsible for the optimization process and based on the price and demand levels, it defines the reference values for DGs and power tradings. In decentralized approaches, local controllers perform optimizations in a competitive environment which makes them appropriate for MMG systems. Furthermore, in these approaches, one of the priorities in the optimization procedure is the privacy of the owners. Also, due to distribution of calculations to various local centers, the burden of calculations decreases and accordingly there is a reduction on computational needs. Moreover, it is easier in decentralised methods to expand the system without any specific changes in the central controller [29].

The formulation presented in the previous section has been modelled based on a centralized method. The DN operator tries to minimize the overall cost of the system including its own units and the units of the MGs. Also, by development of MGs, the energy management optimization might get a large set of variables and suffers from complexity and accordingly solving approaches may need more than the normal time and effort. Thus, it is preferable to use decomposition techniques to translate the problem into a new one which is much easier to solve and less time-taking. This can be obtained using decentralized methods such as Lagrangian relaxation [30], Benders decomposition [31], Dantzig–Wolfe decomposition [32], augmented Lagrangian relaxation [33], auxiliary problem principle [34], alternating direction method of multipliers (ADMM) [35]. Some are used for problems with complicating variable, while others are selected to deal with problems containing complicating constraints.

The general structure of the optimization problem determines the type of decomposition technique that can be applied. In the presented formulation in the section 2, the only constraint that relates all MGs and the DN is (25). Relaxing this constraint, separates the problem into some sub-problems which can be solved by the entities. Usually, augmented Lagrangian relaxation is used for solving optimization problems with complicating constraints. The ADMM is one of the popular approaches for decentralized optimization in the literature. In this method, distributed agents are considered that exchange information among each other and perform local optimizations to solve the overall problem. The robustness of the augmented Lagrangian relaxation and the method of multipliers are combined in ADMM.

This section provides a brief description of the ADMM approach (for more details please refer to [36]). ADMM is applicable to optimization problems with complicating constraint in the below form:

$$\min_{x,y} objective\ function = f(x) + g(y) \tag{26}$$

$$Subject\ to:\ h(x,y) = 0 \tag{27}$$

$$p_i(x) \geq 0 \quad \forall i \tag{28}$$

$$q_j(y) \geq 0 \quad \forall j \tag{29}$$

In above formulation, (27) is considered as the complicating constraint and by relaxing that, the problem could be composed to sub-problems containing, only x or y as the variable. The ADMM is based on the augmented Lagrangian function as follows:

$$L_\gamma = f(x) + g(y) + \eta \cdot h(x,y) + \frac{\gamma}{2} \left\| h(x,y) \right\|^2. \tag{30}$$

The augmented Lagrangian function is composed of two penalty terms. The first one is obtained from the multiplication of the complicating constraint and the respective decision variable. The second one defines the impact of the remaining imbalance of the complicating constraint weighted with a penalty factor. By reaching the optimum point, the penalty terms become zero [37].

The variables are solved in an iterative manner as the following steps:

$$x^{v+1} := \underset{x}{argmin}\ L_\gamma(x, y^v, \eta^v) \tag{31}$$

$$y^{v+1} := \underset{y}{argmin}\ L_\gamma(x^{v+1}, y, \eta^v) \tag{32}$$

$$\eta^{v+1} := \eta^v + \gamma \cdot h(x^{v+1}, y^{v+1}). \tag{33}$$

Considering the fact that x and y in (31) and (32) are updated independently, it can be called a decentralized optimization. Also, it is proved that if $f(x)$ and $g(y)$ are convex, it is guaranteed that the objective value of (26) converges to its minimum and the constraint residual under to zero.

Using ADMM procedure, (25), can be relaxed in the optimization problem leading to a decentralized manner for daily scheduling of MMGs, which is desirable by the MG owners in the system. The problem can be decomposed into subproblems with the number of MGs and other independent entities. The algorithm for the application of ADMM is shown in Figure 2.

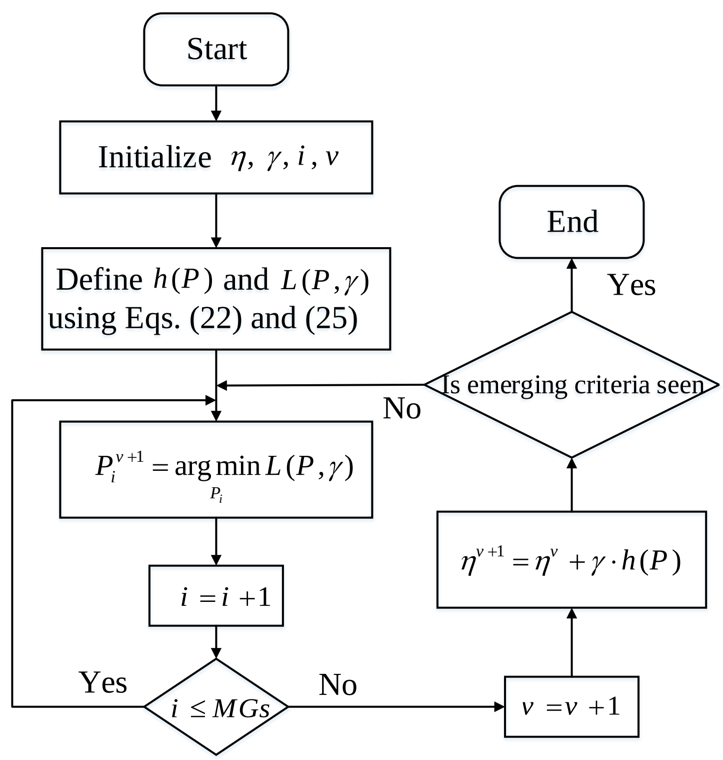

Figure 2. Flowchart of applying ADMM.

4. Simulations

In this section simulation results for a test system using the proposed decentralized method are provided. GAMS software has been chosen for the simulations using a computer with Core i7 CPU and 8 gigabytes of RAM under Windows 10. The test system consists of three independent MGs and some entities such as WTs, batteries, fuel cells, hydrogen storage systems, diesel generators and loads. In other words, the DN contains dispatchable units as fuel cells and diesel generators and a WT as renewable based DG. Likewise, MGs consist of dispatchable and renewable energy based units. The system structure has been depicted in 1. Two different case studies with various reliability parameters in CCP process has been selected to see its effect on the output results of energy management. The characteristics of entities are tabulated in Table 2. Also, Figure 3 shows the electricity price signals and the load curve of the system during 24-h horizon.

Table 2. The characteristics of the entities.

Entity	MG#1	MG#2	MG#3	DN
Diesel Gen (MW)	1	1	1.5	2
Diesel Gen Coeff: a (\$/MW^2)	10	12	10	10
Diesel Gen Coeff: b (\$/MW)	70	75	65	70
Diesel Gen Coeff: c (\$)	100	80	100	100
Diesel Gen Ramp Rate (%)	30	30	30	30
Maximum demand (MW)	1	1	1.5	2.5
WT Power (MW)	0.5	1	1	1.5
Battery storage converter cap (MW)	0.25	0.5	0.5	1
Battery storage cap (MWh)	0.5	1	1	2
Fuel Cell (MW)	0.5	0.25	0.5	0.75
Electrolysis Power (MW)	0.5	0.25	0.5	0.75
Maximum H_2 Tank Pressure (bar)	5	1	5	10
H_2 Tank Volume (m^3)	1.5	1	1.5	3

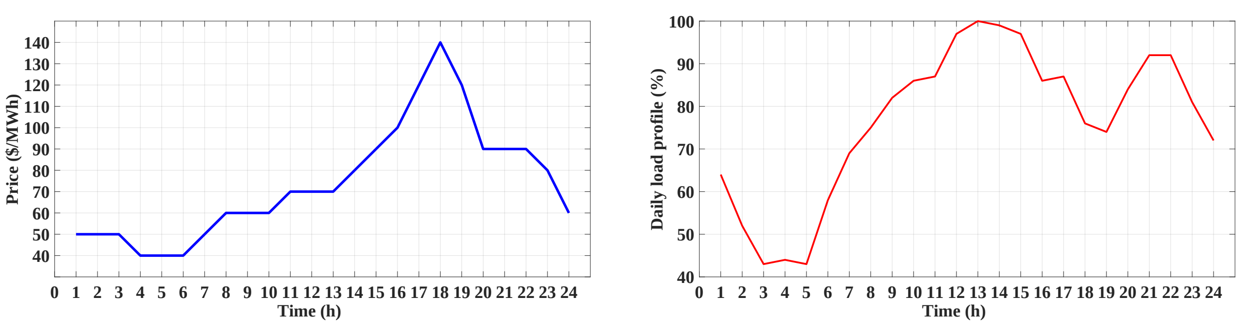

Figure 3. (a): Electricity price signals during 24-h horizon, (b): Daily load profile percentage.

4.1. Case 1

In this case study it is assumed that the reliability level in CCP approach is set to 0.9. This means that we expect that the schedules of the system are defined in a way that probability of violating Eq. (23) is less than

10%. By relaxing (25), the problem is decomposed into four subproblems, and each MG and the DN performs the energy management independently and accordingly they can benefit from the advantages of decentralized approach.

Figure 4 illustrates the output schedules of different entities of MMG system and Figure 5 shows the H_2 moles used/generated by fuel cell/electrolysis and also pressure in the hydrogen storage tank. Figure 4 shows diesel unit output, battery storage power, battery storage energy level, fuel cell and electrolysis power of MGs and the DN. The output power of diesel generator in the third MG is zero. The owners of entities are inclined to sell the maximum amount of their excess power to upper network in the hours with higher prices, and they try to buy in the periods with lower prices. For calculating the reveres cumulative distribution function, Monte Carlo simulation is employed. For instance, in MG #1, during peak price hours like hours 17 to 19, it is seen that fuel cell and diesel generator are producing power while at hour 9, electrolysis is generating H_2 to store in the hydrogen tank which is visible in Figure 5. This has happened to the other MGs and the DN as well which shows the independent operation of the entities as a benefit of decentralized approach.

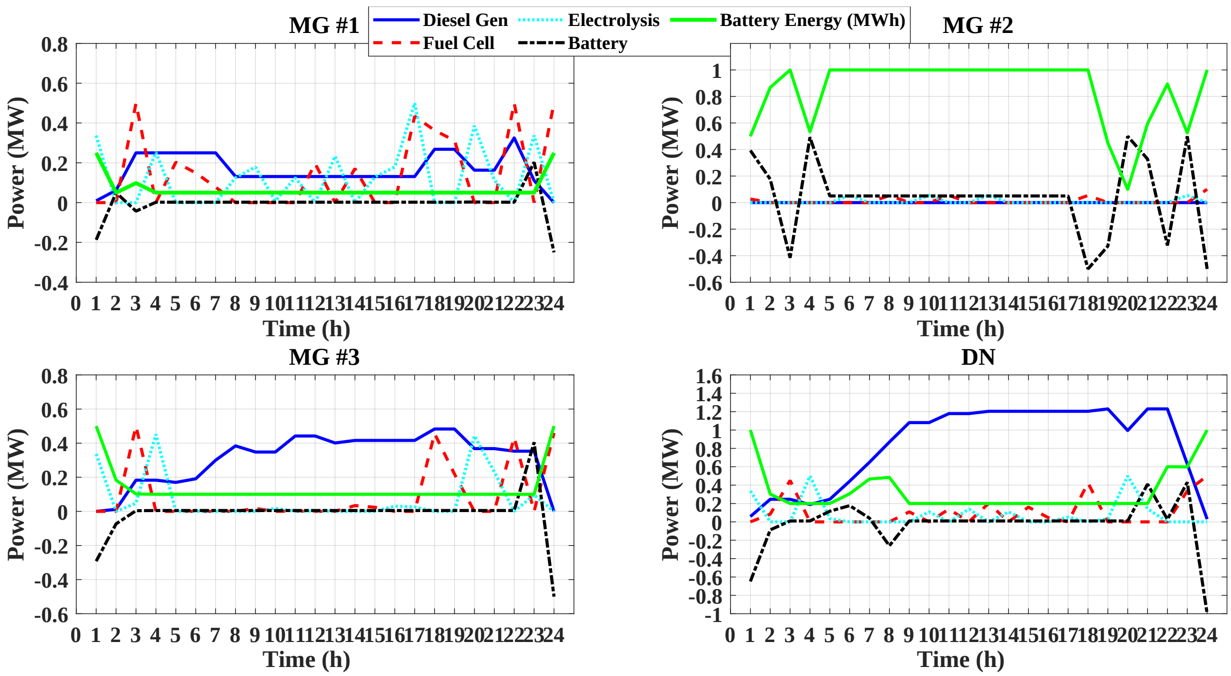

Figure 4. Output schedules of entities during 24-h day-ahead energy management in case 1.

The presence of hydrogen storage system including electrolysis process and fuel cell has facilitated the operation of the system by optimally injecting power and storing H_2. In high price hours, the fuel cell of the entities is consuming H_2 and generating power in order to prevent the system from buying power from upstream network and even selling its excess power to the grid. In lower price hours, by electrolysis of the water, H_2 is stored in the tank.

4.2. Case 2

In this case study the reliability level in CCP approach is set to 0.8 meaning that the probability of violating Eq. (23) is less than 20%.

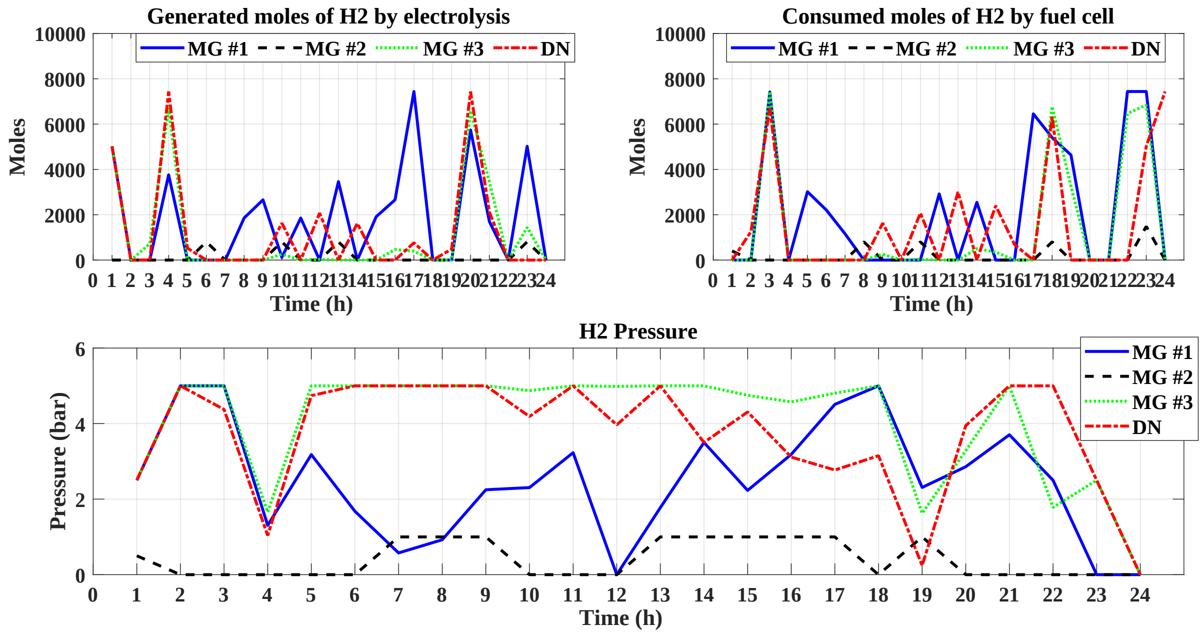

Figure 5. Consumed/generated moles of H_2 by fuel cell/electrolysis and H_2 pressure in tank in case 1.

Figure 6 depicts the output schedules of MMG system and Figure 7 shows the H_2 moles consumption/generation and pressure in the hydrogen storage tank. In this case, by decreasing the reliability level, more dependence is assumed on WT, and accordingly the generation of dispatchable units is decreased. For example, at hour 6, the diesel generator of MG #3 is not generating, while in the previous case, there was power on the output of the respected generator. Likewise, there are other points, indicating less usage of dispatchable units.

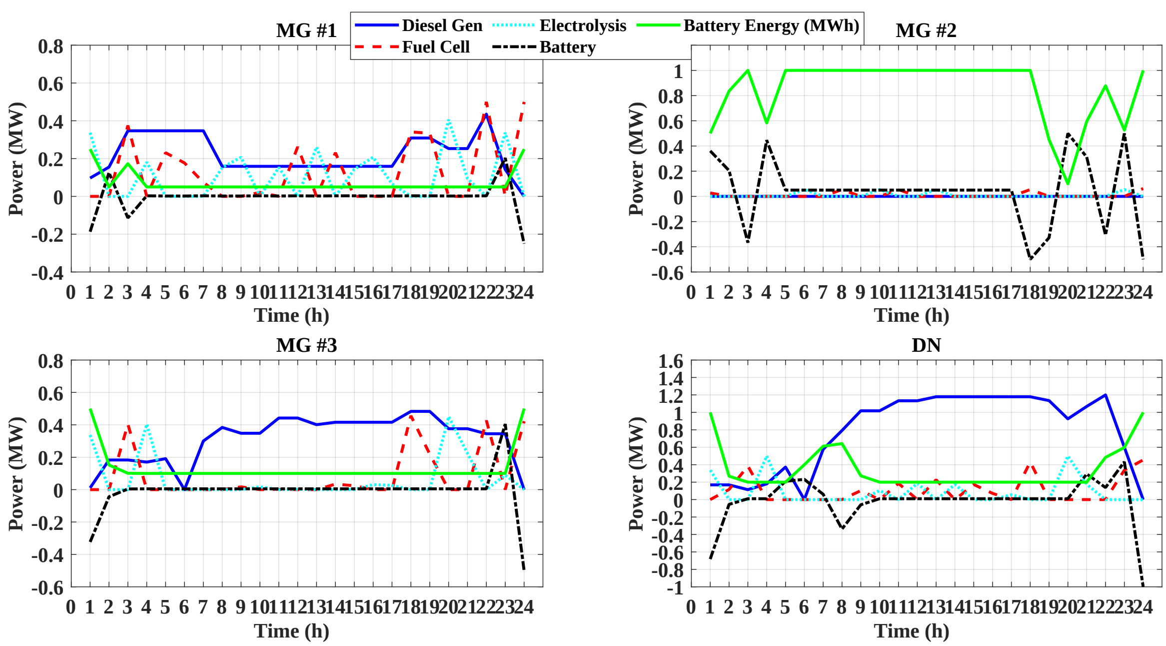

Figure 6. Output schedules of entities during 24-h day-ahead energy management in case 2.

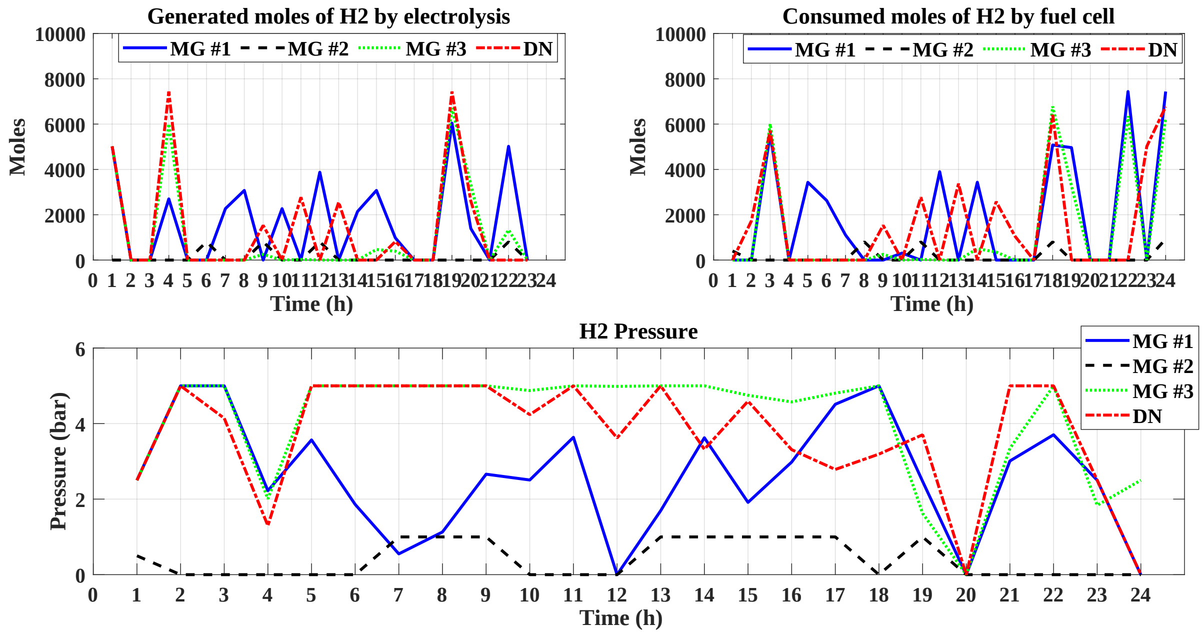

Figure 7. Consumed/generated moles of H_2 by fuel cell/electrolysis and H_2 pressure in tank in case 2.

Table 3 shows the operational costs of the MMG system in both cases. Obviously, decreasing the reliability level has lead to less cost of operation; however, it might put the usage of the system on jeopardy and may lead to load shedding. MG #2 has gained profit from its scheduling due to high generation of WT in comparison with its maximum demand. Also, comparing two test cases, the more benefit is gained in case 2 by decreasing the reliability. Figure 8 shows the changes in operational cost by increasing the reliability level.

Table 3. The operational costs of the entities.

Cost ($)	MG #1	MG #2	MG #3	DN	Total
Case 1	3224	–562	4151	6176	12989
Case 2	3056	–612	3794	5474	11712

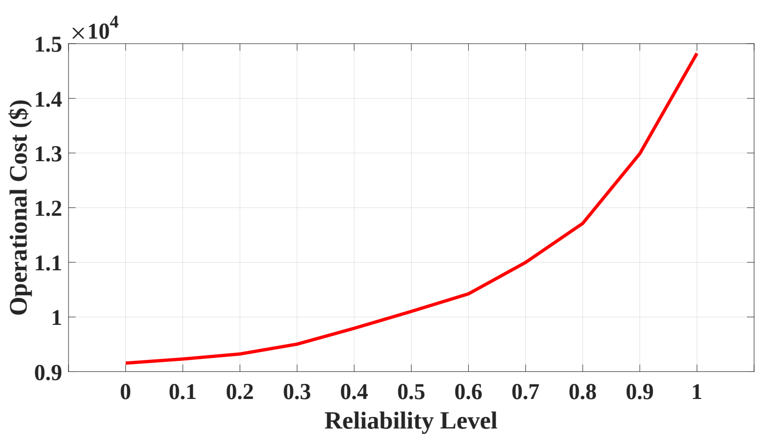

Figure 8. Changes in the cost by increasing the reliability level in CCP.

Table 4 presents the calculated objective function and running time for different approaches. As it can be seen, CCP approach outperforms the scenario-based method both in simulation time and objective function cost. Using decentralized method facilitates the calculations and reduces the computations burden.

Table 4. Calculated objective function and running time of different approaches.

Approach	Cost ($)	Time (s)
Decentralized CCP ($\alpha = 0.9$)	12989	77
Centralized CCP ($\alpha = 0.9$)	12993	101
decentralized deterministic	12238	78
Centralized deterministic	12251	108
decentralized scneraio-based stochastic	13781	194
Centralized scneraio-based stochastic	13810	256

5. Conclusion

Development of microgrids has accelerated in recent year as a result of high penetration of renewable based generation units. This development has lead to a novel structure known as multimicrogrid systems which may face more challenges in their operation. In this study, energy management process of multimicrogrid systems in presence of wind generation units has been studied. Chance-constrained programming method has been employed to model the uncertainties. Also, a decentralized approach has been selected as the solution methodology to benefit from its advantages such as privacy and less burden of calculations. The test system contained two types of storage systems as hydrogen storage systems and batteries. The energy management results showed that the storage systems were charged in lower price hours and discharged in higher price hours to maximize the benefits. Also the results showed that by choosing a decentralized approach, not only the privacy of the units is increased but also the burden of calculations and time of simulation is reduced. Two reliability levels as 90% and 80% have been selected in simulations. By decreasing the reliability level, the overall system cost has been reduced, however, it may put the technical operation of the system in jeopardy. It is recommended to use power flow constraints and linearization methods in future studies. Also, due to presence of the hydrogen storage and fuel cells in the structure of the MMG system, it is suggested to consider the heat demand in the optimizations to increase the efficiency.

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