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A stochastic optimal scheduling of multi-microgrid systems considering emissions: A chance constrained model

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ABSTRACT

With increasing demand in electrical energy and the development of distributed generation technologies, microgrids are formed to avoid the consequences of these changes. Furthermore, this leads to the arrival of multiple microgrids in the distribution network, better known as multi-microgrid systems. Renewable-based generators are indisputable parts of modern electrical energy systems, which might insert uncertainty to the mathematical modeling of the entities for the scheduling purposes. Thus, in this paper, chance-constrained programming is employed for the day-ahead scheduling of a multi-microgrid system in an uncertain environment. Alongside the renewable-based generation units, conventional units are being used, which may have environmental problems such as higher greenhouse gas emissions. Given the global policy for reducing pollutants, a framework for energy management of the multi-microgrid system aiming at decreasing emissions alongside other financial goals is proposed. Finally, a modified version of the IEEE 33-bus test system with multiple microgrids is selected for verification of the proposed methodology. The obtained results in various case studies indicated that considering the emission in the objective function, significantly affects the amount of greenhouse gas emission.

1. Introduction

The tendency to use renewable-based DGs has grown in the last decade, which is due to cost reduction, better economics, and environmental benefits which is because of decrements in greenhouse gas emissions (Huenteler et al., 2016; Lai and McCulloch, 2017). This growth brings many challenges to the operation of the power systems, which can be resolved by the formation of MGs. However, a variety of new technologies are integrating with the MGs and consequently, their structures are becoming more complex, which might cause them to confront so many challenges, e.g., high investment cost, market challenges and regulatory challenges (Bellido et al., 2018). Thus, a reliable and economical operation is required through a controlling unit. The controlling process could be categorized into short-term power management, which is intended for technical purposes, and long-term energy management, which usually determines the schedule of the system for the day-ahead horizon and is generally dedicated to financial goals (Aghdam and Kalantari, 2020a; Rahim et al., 2019).

In MGs, the energy management system is the main controlling unit, which is responsible for decision-making to handle the parameters associated with the system (Yazdaninejadi et al., 2019). In this process, some activities are done to determine the programs and duties of different entities of the system to minimize the operational costs. Many types of research have been done on the energy management problem of the MGs including, metaheuristic and mathematical approaches. In (Pourmousavi et al., 2010) PSO as a metaheuristic method has been employed for real-time optimal energy management of a stand-alone MG. The presence of uncertainties and power flow constraints have been avoided. Likewise, Hossain et al. (2019) have employed PSO for the real-time energy management of an MG to find optimal battery controls neglecting uncertainties and security constraints. The imperialist competition algorithm has been used in (Marzband et al., 2016a) for optimal energy management of MGs. The main drawback of this work is abandoning network constraints. Also, in (Marzband et al.,

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Nomenclature

Abbreviations

DG	Distributed generation
MG	Microgrid
MMG	Multi-microgrid
DN	Distribution network
WT	Wind turbine.
PV	Photovoltaic
CCP	Chance-constrained programming
LP	Linear programming
NLP	Non-linear programming
MILP	Mixed integer linear programming
MINLP	Mixed integer non-linear programming
PSO	Particle swarm optimization
IC	Internal combustion
PDF	Probability density function

Indices

i, j, k	Indices for bus
t	Index for time (hour)
omega	Index for microgrid number
min	Superscript for minimum amount of the variable
max	Superscript for maximum amount of the variable
stup	Superscript for start up of the diesel generator
operation	Superscript for operation of the diesel generator
IC	Superscript for internal combustion generator
wt	Subscript for the wind turbine.
in	Subscript for the cut-in speed for the wind turbine.
O	Subscript for the cut-out speed for the wind turbine.
rated	Superscript for the rated value of the unit
std	Subscript for the standard amount of irradiance
cer	Subscript for the certain amount of irradiance
bat	Superscript for battery
cap	Subscript for capacity
ch	Subscript for indicating charging status
disch	Subscript for indicating discharging status
load	Superscript for load
gen	Superscript for generation
net	Superscript for net value
fuel	Subscript for fuel
Avg	Subscript for average
cmpl	Superscript for complementary
con	Superscript for conventional
ren	Superscript for renewable
buy	Superscript for buying
sell	Superscript for selling
sh	Superscript for shortage
sur	Superscript for surplus
SubTr	Superscript for subtransmission

Parameters

ramp	Ramp rate of the diesel generator
$\alpha_1, \alpha_2, \alpha_3$	Cost function coefficients of diesel generator
C^{stup}	Start-up cost
κ	Shape factor of Weibull distribution
δ	Scale factor of Weibull distribution
μ	Expected value of normal distribution
σ	Standard deviation value of normal distribution
SOC_{int}	Initial state of charge of battery
SOC_{final}	Final state of charge of battery
r, x	Resistance and reactance of the line.
ξ	Cost of the fuel
Ψ	Emission coefficient
PTV	Pure thermal value
EC	Emission factor
OC	Oxidation factor
η	Reliability level in CCP
T_0, T_f	Initial and final scheduling period index
n_{IC}	Number of diesel generators in the network
n_{bat}	Number of batteries in the network
λ	Energy trading price.
n_b	Number of buses

Variables

P, P'	Active power
Q	Reactive power
S	Apparent power
Cost	Cost function
υ	Binary variable indicating the changes in the status of the generator
γ	Binary variable indicating the status of the unit
v	Wind velocity
Ir	Solar irradiance
SOC	State of charge for battery
V	Voltage magnitude
I	Current magnitude
$\Im$	Value of the inverse cumulative distribution function
O.F	Objective function
EM	Amount of emissions

2016b) multi-layer ant colony optimization as a metaheuristic approach has been used for day-ahead energy scheduling of MGs.

Notwithstanding the advantages of metaheuristic methods such as the capability of finding a solution for complex problems, the optimality of the found solution, is under question. Accordingly, it is mostly desired to use mathematical approaches such as LP, MILP, NLP, and MINLP. An MINLP-based method for energy management of islanded MGs has been presented in (Marzband et al., 2013) and (Olivares et al., 2014) neglecting penetration of renewable-based DGs and uncertainties. Also, Anvari-Moghaddam et al. (2015) have presented a solver-friendly MINLP model for optimal power flow, missing the uncertainties.

The most significant research gap in the reviewed literature is the ignorance of uncertainties. Although the electrical power systems were familiar with the concept of uncertainty as a result of load variations, these uncertainties could be handled due to the characteristics of power generators. However, arrival of renewable-based DGs revolutionized the concept of stochastic processes in the power systems. The output power of these DGs are dependant to the non-deterministic environmental circumstances such as weather temperature, wind velocity, etc. Thus, arrival of them has caused more penetration of uncertainties into the power systems. Accordingly, the energy management problem in the MG systems has been transformed into a stochastic programming optimization problem.

Stochastic programming problems are solved using various models such as recourse-based model, expected value model, and CCP. In (Shen et al., 2016), a stochastic energy management approach for an MG containing renewable energy sources, energy storage systems, diesel generators and loads have been proposed. The stochastic process has been handled through Monte-Carlo simulations. Also, network constraints and the uncertainty of wind and solar units have been ignored. Zheng et al. (2018) have presented a stochastic energy management algorithm for an MG system including biomass-based combined heat and power units aiming at minimizing the operating cost through an expected value model. A demand response program for both thermal and electrical loads has been applied in the problem. The power flow constraints in this work have been eliminated in the calculations. Silvente et al. (2017) have proposed an MILP-based optimal energy management strategy for MGs using expected-value formulation for modeling the uncertainties. A scenario-reduction technique is employed to decrease the burden of calculations. In this study, the network constraints are missing and the uncertainty modeling is not comprehensive. Giaouris et al. (2018) have presented a novel energy management approach with a new mathematical modeling in presence of various stochastic loads. It is known that the precision of the day-ahead forecasting for renewable-based DGs is low (Mayhorn et al., 2016) and uncertainty should be considered in day-ahead energy management. Thus, it is recommended using uncertainty modeling for the DGs as well as loads in (Giaouris et al., 2018). Alipour et al. (2015) have presented stochastic scheduling for MGs containing WTs, fuel cells as combined heat and power units, energy storage devices and different types of loads aiming at finding the optimal working points and considering various sources of uncertainty. In (Zhang et al., 2018), a two-stage stochastic robust model-based optimization approach for day-ahead scheduling of an MG neglecting security constraints has been proposed. The robust optimization might be too conservative for day-ahead energy management. Papari et al. (2017b) have presented a stochastic framework for the optimal operation of hybrid AC-DC MGs in the presence of renewable energy sources. Jirdehi et al. (2017) have suggested optimal energy management for the multi-energy type MGs, which is modeled as a multi-objective scenario-based stochastic problem. Li et al. (2017b) have proposed a new optimal energy trading strategy for multi-energy MGs using a recourse-based stochastic game model. Likewise, in (Li et al., 2017a), a data-driven charging strategy for electric vehicles has been proposed considering the behaviors of electric vehicles and demand levels as uncertainty sources and employing conditional value at risk. This method could be extended to be used in MGs.

In scenario-based models, all the possible realizations of uncertainty are considered. However, the number of scenarios could be infinite and a scenario reduction method would be necessary. Removing scenarios might reduce the calculations; however, it might put the security and stability of the system in jeopardy due to power unbalance in case of some of the unseen scenarios. Furthermore, one of the drawbacks of recourse-based models is that the optimal solution is found through stages of realizations and corrective actions are done after every realization, which is not always possible. Accordingly, a feasible answer is not guaranteed. Also, the expected value model needs numerous scenarios to ensure the feasibility of the solution. Besides, in the robust optimization, the worst-case scenario is assumed, which might be a too conservative solution. Another method for modeling the uncertainties is CCP, which overcomes all the mentioned issues. In CCP, some uncertain constraints are defined with a reliability level and for this value, the optimization problem could be solved utilizing some approaches converting chance-constraints into deterministic ones (Ciftci et al., 2019). Thus, in CCP, the probability of violating some uncertain limitations remains at the desired level, which increases the stability and reliability of the system. Also, using deterministic equivalents of the CCP facilitates the solving of nonlinear problems in the presence of uncertainty. Accordingly, many researchers have employed CCP in stochastic power system problems.

In (Ciftci et al., 2019) a data-driven nonparametric CCP optimization for MG energy management has been proposed. Although a very good job has been done here, consideration of network and security constraints may enhance the quality of the work. A CCP-based model for energy management of grid-connected MGs has been presented in (Liu et al., 2018). Although the authors have done a good job in this reference, considering some of the vital tools in MGs such as energy storage devices and network constraints would enhance the quality of the study. Wang et al. (2018) have presented a multi-stage CCP framework for power system planning to facilitate coping with different sources of uncertainties in such systems. Liu et al. (2017) have studied the energy management problem under uncertainties for a grid-connected MG with the purpose of peak shaving as in demand response programs and frequency regulation. Huang et al. (2018) have proposed a CCP-based energy management for home appliances and considering demand response programs. The problem is solved using PSO, which might jeopardize the optimality of the problem.

Global warming is one of the main issues in modern society, which is mostly because of the existence of greenhouse gases in the atmosphere. One of the main sources of these emissions is the operation of conventional units, which should be minimized and substituted with cleaner production. Thus, in many studies, a penalty cost for emissions has been considered. Ju et al. (2016) have proposed a stochastic CCP planning approach as a multi-objective optimization model for virtual power plant scheduling contemplating the minimization of greenhouse gas emissions without considering the network constraints. Abdollahi et al. (2018) have introduced an enhanced energy management framework providing an optimal operation strategy in an MG considering constraints for the emissions without taking the network constraints into account. Damisa et al. (2019) have proposed a mathematical formulation for the joint economic and emission dispatch in an MG with the presence of renewable-based DGs. Uncertainty and power flow constraints have been ignored in the modeling. Papari et al. (2019) have investigated the optimal scheduling of hybrid AC-DC reconfigurable MGs. The problem is modeled as a multi-objective problem for minimizing cost and emission employing a heuristic method. Tabar et al. (2019) have proposed a new energy management strategy for a hybrid MG contemplating emission reduction and uncertainties. However, the security constraints are neglected and simple modeling for all the uncertainty sources using normal distribution has been used, which might banish the results from reality. A stochastic multi-objective optimal load dispatch of MGs through Monte-Carlo simulations has been proposed in (Lu et al., 2018). The power flow has been neglected in the optimization process and a heuristic method is used to solve the problem. Although using CCP instead of scenario-based optimization might reduce the burden of calculations, it might be helpful to consider the other sources of uncertainty beside the electric vehicles. A chance-constrained energy management system has been developed in (Shi et al., 2018) for islanded MGs containing distributed energy resources, energy storage devices and renewable energy-based generation units such as WTs. A multi-objective formulation consisting of generation, emission, and energy storage degradation costs has been proposed. Considering robustness in the optimization process might be conservative for day-ahead scheduling and only increase the burden of calculations. Also, considering power flow constraints and other sources of might enhance the study.

In all the reviewed studies, only the presence of one MG has been contemplated. However, more penetration of MGs in the DN leads to the genesis of a novel notion better known as MMG systems. In other words, the existence of several low-voltage MGs in the DN alongside various DGs and loads in the distribution system forms a high-level structure known as the MMG system (Vasiljevska et al., 2012). In such a system, many parts of the distribution system turn into active MGs. The interest in studying these systems is growing recently and so many studies are done for coping with the problems appearing by the arrival of MMG systems. A framework for the optimal scheduling of MMGs systems has been proposed in (Misaghian et al., 2018) using a hybrid stochastic-robust approach. In the energy management process, day-ahead and real-time energy prices are taken into consideration. Also, time-of-use demand response programs are contemplated as new tools for better operation of MGs. Besides, sources of uncertainties as WTs, PV systems, electric vehicles, and energy price are modeled using stochastic programming. Papari et al. (2017a) have proposed a new stochastic framework for optimal energy management of interconnected MGs aiming at minimizing the total cost of the system, including the cost of power generation by units and the cost of power exchange among the MGs themselves and with the main grid. In (Aghdam et al., 2018b), a contingency-based energy management approach for MMG systems has been proposed. In this approach, energy management is hired as a tool for managing contingency problems in the lines of an MMG system considering the probability of the contingency. Haddadian and Noroozian (2018) have presented a novel approach for the energy management of MMG-based DNs in the presence of demand response programs and uncertainties caused by renewable energy resources, loads, and prices. The energy management problem is modeled as a multi-objective problem and solved by employing a meta-heuristic approach named NSGA-II. Arefifar et al. (2017), have presented coordinated approaches for performing energy management in MMG systems. A new index for measuring the success of energy management procedure in the presence of uncertainties such as load, WTs and PV systems is defined. Furthermore, a distributed energy management approach has been proposed by Xu et al. (2018) for the coordinated operation of MMG systems containing both thermal and electrical systems.

As mentioned earlier, different aspects of operation of MGs and MMG systems with different approaches and structures have been investigated in the literature. Table 1 classifies the proposed methodologies in modeling and studying the operation of the MGs and MMG systems.

As obtained from the literature review, the energy management of MMG systems is a challenging issue, which is the main tool for the operation of the system reliably and economically. High penetration of renewable energy-based generation units as WTs and PV systems and load variations have caused an influx of uncertainties in the problems. Thus, the energy management of an MMG system under uncertainty could be considered to be a more complex problem. For instance, in some studies, such as (Liu et al., 2018) and (Shi et al., 2018), emission reduction in the presence of uncertainty using Monte-Carlo simulations and robust CCP approach have been given; however, both have considered a single MG in their structure. In addition, considering network constraints is missing. Thus, a comprehensive work for the day-ahead scheduling of MMG systems, regarding security constraints and aiming at reducing the operational costs alongside emissions of the systems is lacking. Also, due to the previously mentioned benefits for the CCP approach, it might be a perfect choice to model the uncertainties. In addition, using CCP facilitates consideration of the uncertainties and contemplating many uncertain variables does not put so much burden on the calculations. Furthermore, in hierarchical methods, the speed of calculations is important due to the existence of multiple stages of optimization, which again can be simplified with the characteristics of the CCP method. Thus, in this paper, the energy management of MMG systems under uncertainty with a hierarchical approach would be presented. CCP is selected for modeling the uncertainties. Furthermore, in the suggested framework, the cost of emissions aiming at reducing pollutants is contemplated to encourage the usage of renewable-based DGs. Also, convex power flow constraints have been taken into account ensure the security constraints of the network. The main contributions of the presented research are summarized as follows:

- CCP-based energy management framework for MMG systems.
- Evaluation of the energy management results in different CCP parameters.
- Hierarchical structure for energy management of an MMG system.
- Using convex power flow for considering the security constraints.
- Considering uncertainties of wind, PV and loads.
- Considering emissions in the day-ahead scheduling and its effect on the optimal scheduling of units.

The rest of the paper is organized as follows: Section 2 demonstrates system modeling and problem formulation for the energy management process. In Section 3, CCP would be illustrated. Section 4 is dedicated to the optimization process. The simulation results are brought in Section 5 and the final section includes the conclusion of the paper.

2. System modeling and problem formulation

MMG systems are distributions systems with multiple MGs and different independent entities such as dispatchable generation units (IC generators, etc.), renewable-based generation units (PV and wind systems), energy storage devices (batteries, etc.) and various loads. A typical MMG system is shown in Fig. 1. In this system, three MGs are forming the MMG system and beside them,

Table 1
Comparison of the proposed method with different studies.

Reference	Uncertainities			Emissions	Power Flow	Single/Multi MG	Uncertainty modeling
	Load	PV	Wind				
Marzband et al. (2013)	–	–	–	–	–	Single MG	–
Shen et al. (2016)	–	✓	✓	–	–	Single MG	Scenario-based
Zhang et al. (2018)	–	✓	✓	–	–	Single MG	Recourse-based
Liu et al. (2018)	✓	✓	✓	–	–	Single MG	CCP
Papari et al. (2017a)	–	✓	✓	–	✓	MMG	Scenario-based
Aghdam et al. (2018b)	–	–	–	–	✓	MMG	–
Damisa et al. (2019)	–	–	–	✓	–	Single MG	–
Abdollahi et al. (2018)	–	✓	✓	✓	–	Single MG	Scenario-based
Lu et al. (2018)	✓	–	–	✓	–	Single MG	Scenario-based
Shi et al. (2018)	–	–	✓	✓	–	Single MG	CCP
Proposed	✓	✓	✓	✓	✓	MMG	CCP

there are individual independent units. MGs contain WTs, PV systems, energy storage devices, IC generators and loads. In this section, mathematical modeling of different units would be presented.

2.1. IC engine systems

IC engine generators are considered as dispatchable generation systems due to their controllable output power. Following equations demonstrate the relative equations and constraints of such systems:

$$0 \le P_{IC,t} \le \nu_{IC,t} P_{IC}^{max} \quad \nu_{IC,t} \in 0,1 \tag{1}$$

$$-ramp_{IC} \times P_{IC}^{max} \le P_{IC,t} - P_{IC,t-1} \le ramp_{IC} \times P_{IC}^{max} \tag{2}$$

$$P_{IC,t}^2 + Q_{IC,t}^2 \le S_{IC}^2 \tag{3}$$

The generation limit, ramp up rate and the complex power constraints are illustrated in (1), (2) and (3), respectively.

Usually, the cost function of these types of generators is considered as a quadratic function of their output power (Aghdam and Kalantari, 2020b). Besides, a start-up cost is contemplated in terms of the following equations.

$$Cost_{IC,t}^{operation} = \alpha_1 P_{IC,t}^2 + \alpha_2 P_{IC,t} + \alpha_3 \tag{4}$$

$$Cost_{IC,t}^{stup} = \gamma_{IC,t} \times C_{IC}^{SU} \tag{5}$$

$$\gamma_{IC,t} = max\left[(\nu_{IC,t} - \nu_{IC,t-1}), 0\right] \tag{6}$$

The cost of utilizing IC units is the sum of start-up and operation costs as following:

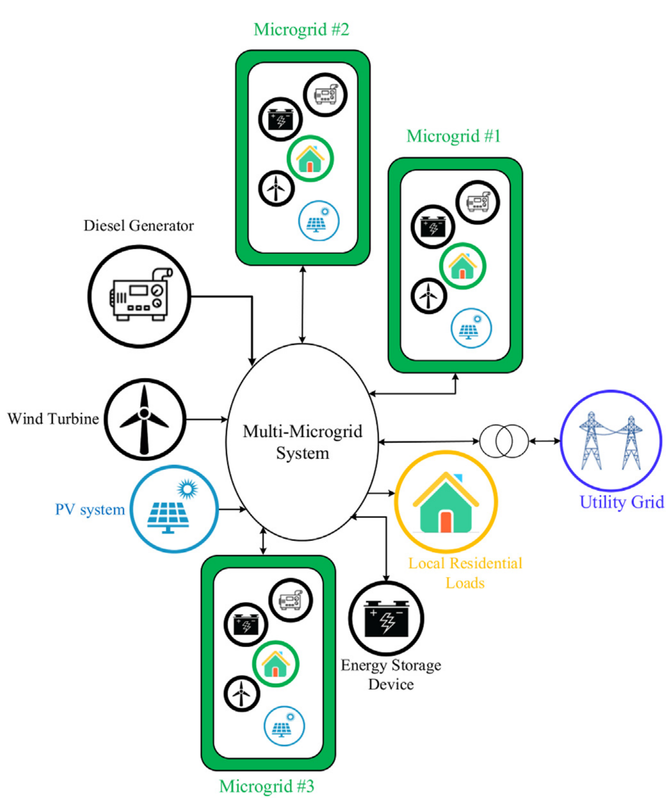

Fig. 1. Illustration of MMG system structure.

$$Cost_{IC,t} = Cost_{IC,t}^{operation}(P_{IC}) + Cost_{IC,t}^{stup} \tag{7}$$

2.2. Wind turbines

Wind generation units are one of the most promising and rapidly developing technologies for generating electrical energy from renewable-based energy resources. They contain WTs, which transforms the kinetic energy of the wind into electrical energy. Thus, their output power depends on the wind velocity, which in nature is a stochastic variable and accordingly, the generated electrical energy becomes uncertain.

The wind speed follows a Weibull PDF, which has two parameters based on the WT site known as the shape factor and scale factor and could be illustrated as below (Aghdam et al., 2018a):

$$f_V(v) = \left(\frac{K}{\delta}\right)\left(\frac{v}{\delta}\right)^{K-1} e^{-\left(\frac{v}{\delta}\right)^{K}} \quad 0 \le v \le \infty \tag{8}$$

The generated electrical power of the wind system is a function of the wind speed as presented in the following:

$$P_{wt} = \begin{cases} 0 & v \le v_{in}, \quad v \ge v_o \\ \dfrac{v - v_{in}}{v^{rated} - v_{in}} P_{wt}^{rated} & v_{in} \le v \le v^{rated} \\ P_{wt}^{rated} & v^{rated} \le v \le v_o \end{cases} \tag{9}$$

2.3. PV systems

The electrical energy generation by PV systems could be contemplated as one of the most common and easiest ways of producing renewable-based energy. This is due to their small size and lower cost in comparison with WTs, which results in the intense growth of installed capacity of PV panels (Aghdam and Abapour, 2016; Aghdam et al., 2016). The output power of PV units is a function of solar irradiance, which is a stochastic phenomena and is usually modeled by the lognormal PDF as following (Aghdam et al., 2018a):

$$f_{Ir}(Ir) = \frac{1}{Ir \cdot \sigma \cdot \sqrt{2\pi}} exp\left[\frac{-(\ln Ir - \mu)^2}{2\sigma^2}\right] \quad Ir \ge 0 \tag{10}$$

The output power of the PV system is associated with the solar irradiance as below:

$$P_{PV} = \begin{cases} P_{PV}^{rated} \times \left(\dfrac{Ir^2}{Ir_{std} \cdot Ir_{cer}}\right) & Ir \le Ir_{cer} \\ P_{PV}^{rated} \times \left(\dfrac{Ir^2}{Ir_{std}}\right) & Ir_{cer} \le Ir \end{cases} \tag{11}$$

2.4. Energy storage system

In this subsection, modeling of energy storage system would be discussed, which in this study is assumed to be battery storage. Equations 12–19 illustrate the technical constraints of a battery. Equations (12) and (13) show its charging and discharging power limitations. Equation (14) is the constraint for avoiding simultaneous charging and discharging. Equations (15) - (18) are the constraints for the state of charge or energy level of the battery system. Finally, equation (19) represents its stored/released power constraints.

$$0 \le P^{bat}_{ch,t} \le \nu^{bat}_{ch,t} P^{bat}_{cap} \tag{12}$$

$$0 \le P^{bat}_{disch,t} \le \nu^{bat}_{disch,t} P^{bat}_{cap} \tag{13}$$

$$\nu^{bat}_{ch,t} + \nu^{bat}_{disch,t} \le 1 \quad \nu^{bat}_{ch,t}, \nu^{bat}_{disch,t} \in 0,1 \tag{14}$$

$$SOC_t = SOC_{t-1} - \frac{1}{P^{bat}_{cap}} \left(P^{bat}_{disch,t} - P^{bat}_{ch,t} \right) \tag{15}$$

$$0 \le SOC_t \le 1 \tag{16}$$

$$SOC_{T_0} = SOC_{int} \tag{17}$$

$$SOC_{T_{final}} = SOC_{final} \tag{18}$$

$$P^{bat}_t = P^{bat}_{ch,t} - P^{bat}_{disch,t} \tag{19}$$

$P_{bat,t}$ shows the power of the battery, which has a positive value in the charging mode and a negative value in the discharging state.

2.5. Loads

Loads are one of the sources of uncertainty in the modeling of the electrical power systems due to the stochastic behavior of the consumers. Usually, the normal distribution function is applied for the modeling of the uncertainty of the load:

$$f_{load}(load) = \frac{1}{\sigma \cdot \sqrt{2\pi}} exp\left[\frac{-(load-\mu)^2}{2\sigma^2} \right] \quad load \ge 0 \tag{20}$$

2.6. Network modeling

MGs and DNs are usually modeled as radial networks. In these networks, it is assumed that the bus #1 is connected to the upstream grid and has a flexible power injection with a voltage level of 1. $p.u.$

The following equation shows the net complex power relation in bus k:

$$S_{k,t} = S^{bat}_{k,t} + S^{load}_{k,t} - S^{gen}_{k,t} \tag{21}$$

Also in order to model the power flow relations in a radial network, equations (22) - (26) are employed (Aghdam et al., 2018a).

$$P^{net}_{k,t} = P_{ik,t} - r_{ik} I^2_{ik,t} - \sum P_{kj,t} \tag{22}$$

$$Q^{net}_{k,t} = Q_{ik,t} - x_{ik} I^2_{ik,t} - \sum Q_{kj,t} \tag{23}$$

$$V^2_{k,t} = V^2_{i,t}(t) - 2(r_{ik} P_{ik,t} + x_{ik} Q_{ik,t}) + \left(r^2_{ik} + x^2_{ik} \right) I^2_{ik,t} \tag{24}$$

$$V^{min} \le V_{i,t} \le V^{max} \tag{25}$$

$$I^2_{ik,t} = \frac{S^2_{ik,t}}{V^2_{i,t}} \tag{26}$$

2.7. Emission modeling

With the increase in global warming due to greenhouse gas emissions, the tendency to use renewable energy sources and clean production has increased. However, due to uncertainties in the output power of these units, traditional sources of power generation using fossil fuels continue to be exploited, which emit greenhouse gases into the earth's atmosphere. Following the Paris convention and commitment of countries to reducing greenhouse gas emissions, and in line with clean energy production policies, there is a need to minimize emissions. Hence, in this section, the mathematical modeling of the gas emission of traditional generation units will be presented. Also, it will be illustrated that how it is going to be transformed into the cost for participation in the objective function.

The amount of emission in a conventional unit is a function of burnt fuel and can be acquired through the below relation (Aghdam et al., 2018a; Aghdam and Hagh, 2019):

$$Em_{IC,t} = \psi_{IC} \cdot \frac{Cost^{operation}_{IC,t}}{\xi_{fuel,IC}} \tag{27}$$

In (27), $Cost^{operation}_{IC,t}$ is the cost of power generation by the conventional unit, which has been presented in terms of (4). The emission coefficient is obtained by the following equation:

$$\psi_{IC} = PTV_{IC} \cdot EC_{IC} \cdot OC_{IC} \tag{28}$$

Based on the fuel type, ψ_{IC} varies and for gas and oil the values for this coefficient are shown in Table 2 (Aghdam et al., 2018a).

To minimize the release of pollutants, it is required to define an objective function for the emissions in the unit of currency so that it can be added with the other cost functions. A penalty factor ($\hbar$) is multiplied to the amount of emission and transforms it into the currency as following.

$$Cost^{emission}_{IC,t} = \hbar_{IC} \times Em_{IC,t} \tag{29}$$

For calculating penalty factor ($\hbar$), the algorithm 2 is used (Kulkarni et al., 2000):

Algorithm 1. Calculating penalty factor ($\hbar$)

procedure START
Get system data i.e. information of generators
loop 1:
Set i=1
Calculate ith generator average cost using:
$Cost_{Avg,i} = \frac{Cost^{operation}(P^{Max}_{IC})}{P^{Max}_{IC}}$
Calculate ith generator average emission using:
$Em_{Avg,i} = \frac{Em_{IC}(P^{Max}_{IC})}{P^{Max}_{IC}}$
Calculate ith generator penalty factor using:
$\hbar_{gen,i} = \frac{Cost_{Avg,i}}{Em_{Avg,i}}$
$i \leftarrow i+1.$

3. Chance constrained programming (CCP) approach

One of the main tools for uncertainty modeling is CCP. In this method, the optimization problem is formulated under

Table 2
Emission coefficients for different fuel types.

Fuel type	PTV(KJ/Kg)	EC(tCO_2/TJ)	OC(%)	ψ ($tCO_2/tFuel$)
Oil	48,000	74	99	3.51
Gas	43,000	53.1	99	2.25

probabilistic constraints. In CCP modeling, the occurrence of some constraints, which involve uncertainty, should remain at a predetermined certainty level. A general formulation for a CCP problem better known as $P - Model$ can be defined as follows (Charnes and Cooper, 1963):

$$min\, f(x) \tag{30}$$

$$s.t. \quad g_i(x) \geq 0 \quad i = 1, \ldots, n \tag{31}$$

$$Pr\left[h_j(x, \psi) \geq 0\right] \geq \eta \quad j = 1, \ldots, m \tag{32}$$

In the above formulation, equation (31) demonstrates deterministic constraints and equation (32) stands for chance constraints. η is the confidence or reliability level, which is defined by the operator. Equation (32) ensures that the probability of occurrence of respective constraints despite stochastic variables is more than η.

The chance constraint formula as in (32) is known as the separate chance constraint. The joint chance constraint is introduced by Li et al. (2008), where the intersection of probabilities should satisfy a determined level and can be written as below equations.

$$Pr[h_1(x, \psi) \geq 0, \ldots, h_m(x, \psi) \geq 0] \geq \eta \tag{33}$$

$$Pr[\bigcap_{i=1}^{m} h_i(x, \psi) \geq 0] \geq \eta \tag{34}$$

In the energy management problem of the MMG systems, wind and solar generation units beside loads can be encountered as the uncertainty source. These random variables took part in equation (21). Thus, this equation can be modified to transform the main problem into a CCP problem as follows:

$$Pr\left[\bigcap_{k=1}^{n_b} \left(S_{k,t} - S_{k,t}^{bat} \geq S_{k,t}^{load} - S_{k,t}^{gen}\right)\right] \geq \eta \tag{35}$$

Equation (35), is a joint CCP problem, which involves n_b constraints that should satisfy η confidence level.

The joint CCP problem is a difficult and hard to solve problem. In low dimension problems, when the PDF of the random variable is determined, it might be solved using numerical approaches (Prékopa, 2013). However, energy system problems are usually large and complex problems and contain many variables, which cannot be solved directly. Thus, a method proposed by Ozturk et al. (2004) and Manickavasagam et al. (2015) is employed to solve the joint CCP problem. In this method, the joint CCP problem is converted into a deterministic model. The complementary equation of relation (35) can be expressed as below:

$$Pr\left[\bigcup_{k=1}^{n_b} \left(S_{k,t} - S_{k,t}^{bat} \geq S_{k,t}^{load} - S_{k,t}^{gen}\right)^{cmpl}\right] \leq 1 - \eta \tag{36}$$

To satisfy (36) the following relation is considered as a sufficient condition:

$$Pr\left[\left(S_{k,t} - S_{k,t}^{bat} \geq S_{k,t}^{load} - S_{k,t}^{gen}\right)^{cmpl}\right] \leq \frac{1-\eta}{n_b} \tag{37}$$

Using the complementary of (37) the below equation is obtained:

$$Pr\left[S_{k,t} - S_{k,t}^{bat} \geq S_{k,t}^{load} - S_{k,t}^{gen}\right] \geq 1 - \frac{1-\eta}{n_b} \quad for\ k = 1, \ldots, n_b \tag{38}$$

Equation (38) separates the joint CCP and by knowing the PDFs of the random variable at each bus, the deterministic equivalent can be written.

The right-hand-side of the inequality inside the probability is the pure injected power to the bus, which is the subtraction of demand level and generation. Due to the stochastic nature of load and generation of renewable-based DGs, the generation part should be divided into two parts as dispatchable and renewable; accordingly, Eq. (38) can be rewritten as follows:

$$Pr\left[S_{k,t} - S_{k,t}^{bat} + S_{k,t}^{gen,con} \geq S_{k,t}^{load} - S_{k,t}^{gen,ren}\right] \geq 1 - \frac{1-\eta}{n_b} \tag{39}$$

In the above equation, $S_{k,t}^{load}$ and $S_{k,t}^{gen,ren}$ are stochastic variables with known PDFs as mentioned in previous section. Thus, in the right hand-side of the equation a random variable with cumulative distribution function, Λ, exists. Using this fact, Eq. (39) can be rewritten as below:

$$\Lambda\left[S_{k,t} - S_{k,t}^{bat} + S_{k,t}^{gen,con}\right] \geq 1 - \frac{1-\eta}{n_b} \tag{40}$$

Considering $\Im = \Lambda^{-1}\left(1 - \frac{1-\eta}{n_b}\right)$, the upcoming equation can be inferred from Eq. (40):

$$S_{k,t} - S_{k,t}^{bat} + S_{k,t}^{gen,con} = \Im \tag{41}$$

In above equation, Λ^{-1} is inverse cumulative distribution function and numerical and iterative methods are employed to find the $\Im$. One method has been proposed by Manickavasagam et al. (2015) and the process is shown in Fig. 2.

4. Hierarchical day-ahead scheduling of MMG system

In this section, the energy management procedure of the MMG system would be discussed. In the proposed method, first, each MG executes optimum programming for its day-ahead horizon, determining its provide-able power for the upstream network. According to the collected data, the upstream network begins its optimization process and informs different entities about their programs that should be performed the next day.

The MG operator should decide on its reliability level (η) according to the penetration of renewable-based DGs in its network. Due to this value and utilizing the procedure presented in Fig. 2, $\Im$ is calculated for each bus. It is noteworthy to mention that in each node, different sources of uncertainty may exist. For instance, in one node, there might be a wind generation unit, while the other might be a load bus. Finally, for MG energy management, the following optimization problem should be solved.

$$\min O.F._{MG,\omega} = \sum_{t=T_0}^{T_f}\left(\sum_{IC=1}^{n_{IC,\omega}}\left[Cost_{IC,t} + Cost_{IC,t}^{Emission}\right] + \lambda_t^{buy}.P_{\omega,t}^{sh} - \lambda_t^{sell}.P_{\omega,t}^{sur}\right)4$$
$$s.t.\ \ Eqs.\ (1)-(3),\ (12)-(19),\ (22)-(26)\ and\ (40) \tag{42}$$

The DN operator gathers the information obtained from the energy management of MGs and starts global day-ahead scheduling contemplating a predetermined reliability level, η. The optimization problem in this stage is:

$$\min O.F._{DN} = \sum_{t=T_0}^{T_f}\left(\sum_{IC=1}^{n_{IC}}\left[Cost_{IC,t} + Cost_{IC,t}^{Emission}\right] + \sum_{\omega=1}^{n_{MG}}\left[\lambda_t^{sell}.P\prime_{\omega,t}^{sur} - \lambda_{\omega,t}^{buy}.P\prime_{\omega,t}^{sh}\right]\right.$$
$$\left. + \lambda_t^{buy,SubTr}.P_{Dn,t}^{sh} - \lambda_t^{sell,SubTr}.P_{DN,t}^{sur}\right) \tag{43}$$

$$s.t.\ \ Eqs.\ (1)-(3),\ (12)-(19),\ (22)-(26)\ and\ (40)$$

$$0 \le P\prime_{\omega,t}^{sur} \le P_{\omega,t}^{sur} \tag{44}$$

$$0 \le P\prime_{\omega,t}^{sh} \le P_{\omega,t}^{sh} \tag{45}$$

$P\prime_{\omega,t}^{sur}$ and $P\prime_{\omega,t}^{sh}$ are announced by the DN operator to each respective MG, ω, which indicate the amount of purchasable or sellable power from/to that MG. According to this data, each MG reschedules its entities. The flowchart for the optimization process is depicted in Fig. 3.

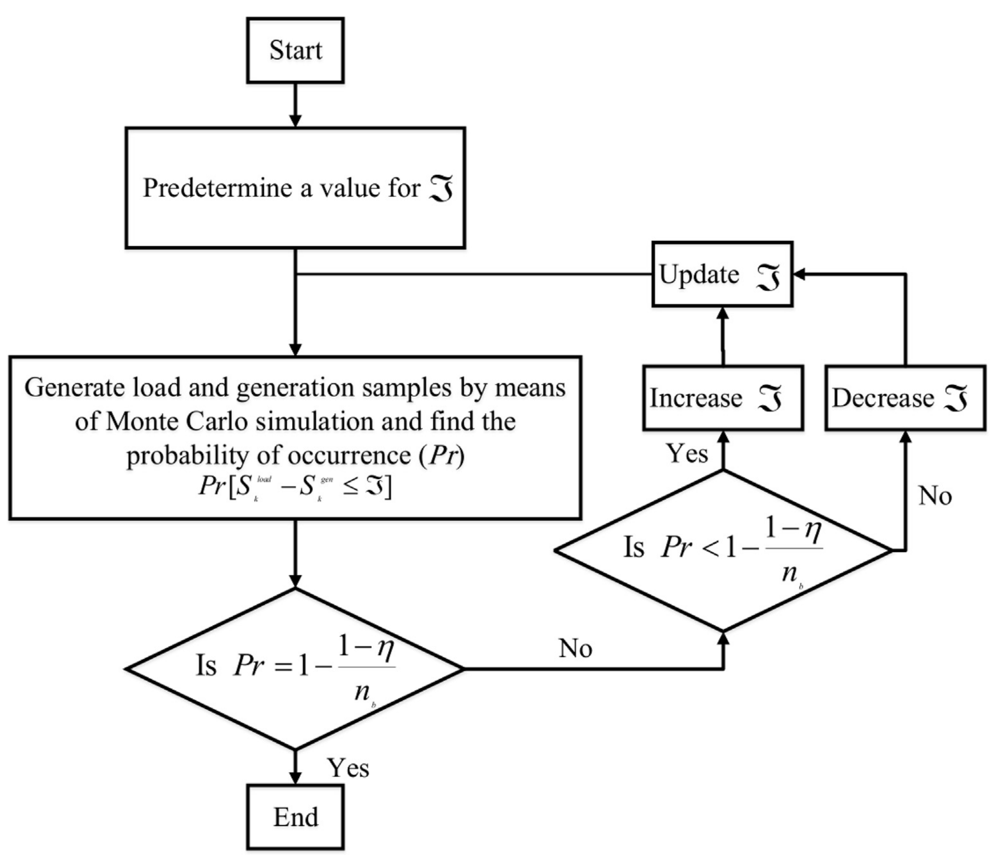

Fig. 2. Flowchart of finding $\Im$

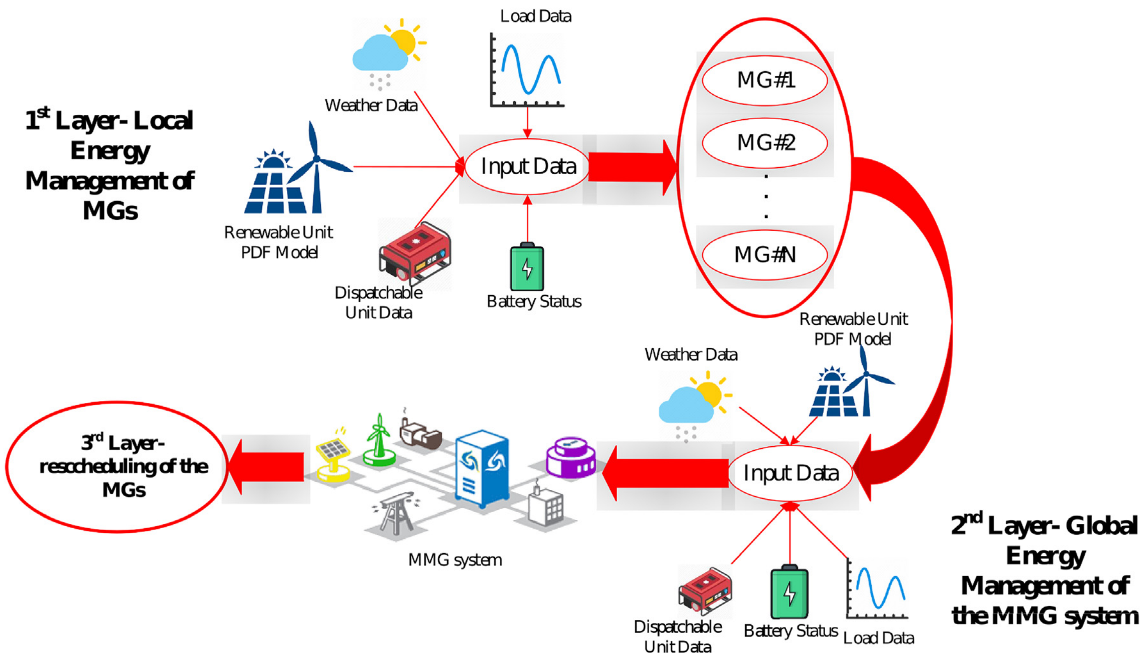

Fig. 3. Hierarchical energy management layers for MMG system.

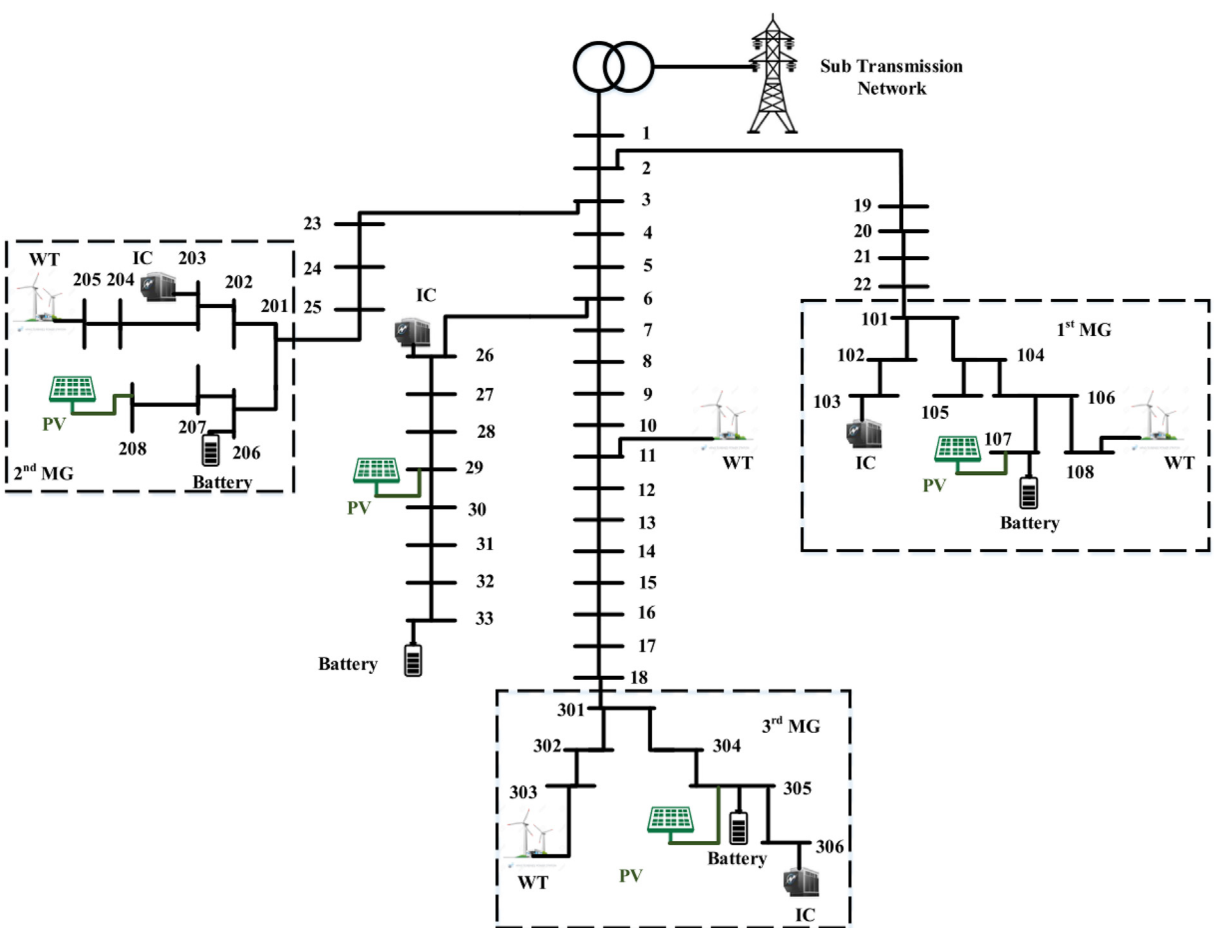

Fig. 4. Modified IEEE 33-bus test system.

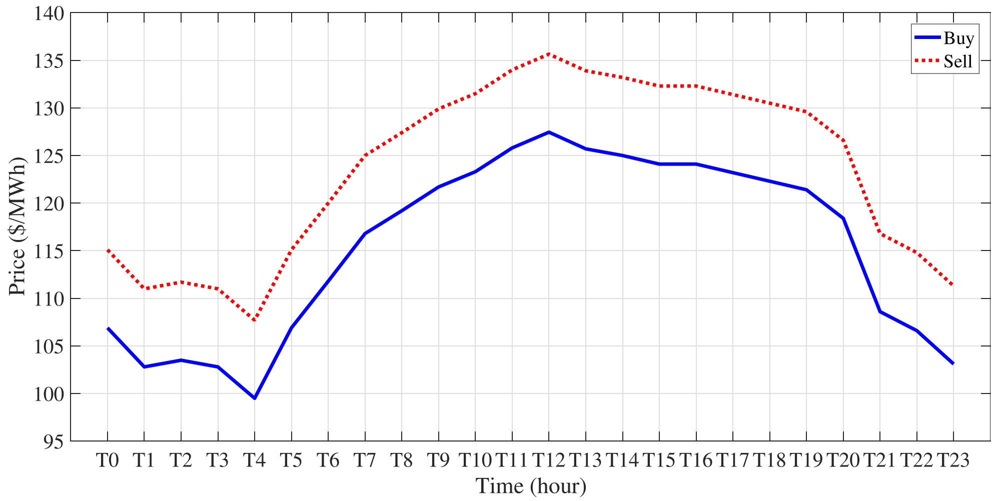

Fig. 5. Electrical energy prices.

Table 3
Characteristics of units of different entities.

	WT (MW)	PV (MW)	Battery (MWh)	SOC_{T_0} $(\%)$	$SOC_{T_{final}}$ $(\%)$	IC (MW)	α_1 $(\$/MW^2h)$	α_2 $(\$/MWh)$	α_3 $(\$/h)$	C_{IC}^{SU} $(\$)$
DN	2	1.5	5	30	20	2	10	75	20	20
MG1	1	0.5	3	30	15	1	12	80	25	10
MG2	0.5	0.15	1	50	20	1	11	85	20	20
MG3	1.5	1	2	20	10	1	12	85	25	20

Table 4
MG1 line impedances.

Line No.	From	To	r (p.u.)	x (p.u.)
1	101	102	0.001	0.0002
2	102	103	0.0039	0.001
3	101	104	0.0027	0.0009
4	104	105	0.0028	0.0009
5	104	106	0.0052	0.0011
6	106	107	0.0012	0.0002
7	106	108	0.0071	0.0024

Table 5
MG2 line impedances.

Line No.	From	To	r (p.u.)	x (p.u.)
1	201	202	0.0012	0.0003
2	202	203	0.0018	0.004
3	203	204	0.0037	0.0015
4	204	205	0.0016	0.0006
5	201	206	0.0031	0.0016
6	206	207	0.0019	0.00012
7	207	208	0.0067	0.0028

Table 6
MG3 line impedances.

Line No.	From	To	r (p.u.)	x (..)
1	301	302	0.0013	0.0006
2	302	303	0.0019	0.0007
3	301	304	0.0017	0.0005
4	304	305	0.0012	0.0004
5	305	306	0.0018	0.0006

5. Simulation results

In this section, simulations on a test system are illustrated to demonstrate the effectiveness of the proposed methodology. The simulations are done in the GAMS environment on a system with Core i7 CPU and 8 gigabytes of RAM. Furthermore, for calculating $\Im$, MATLAB software has been employed.

The test system has three MGs, some independent generators, an energy storage system, and loads. Also, each MG contains the mentioned units. The structure of the test system is shown in Fig. 4. The characteristics of units are tabulated in Table 3. Furthermore, electrical energy prices in the DN are shown in Fig. 5 (Bui et al., 2016). The information for the structure of the MGs is presented in Tables 4–6.

Four case studies are considered in this part as follows:

I Considering emission cost in the cost function and $\eta = 0.95$.
II Considering emission cost in the cost function and $\eta = 0.9$.
III Neglecting emission cost in the cost function and $\eta = 0.95$.
IV Neglecting emission cost in the cost function and $\eta = 0.9$.

In the first case, the cost of the emission has been considered in the objective function. Also, the reliability level has been set to 0.95. To see the effect of decreasing the reliability level, in the second case, the value of reliability level has been reduced to 0.9. In the other two cases, the cost of the emission has been ignored to see the effect of its presence in the objective function. Some other cases could be contemplated with different levels of reliability for each MG and the DN, which have not been considered in this research.

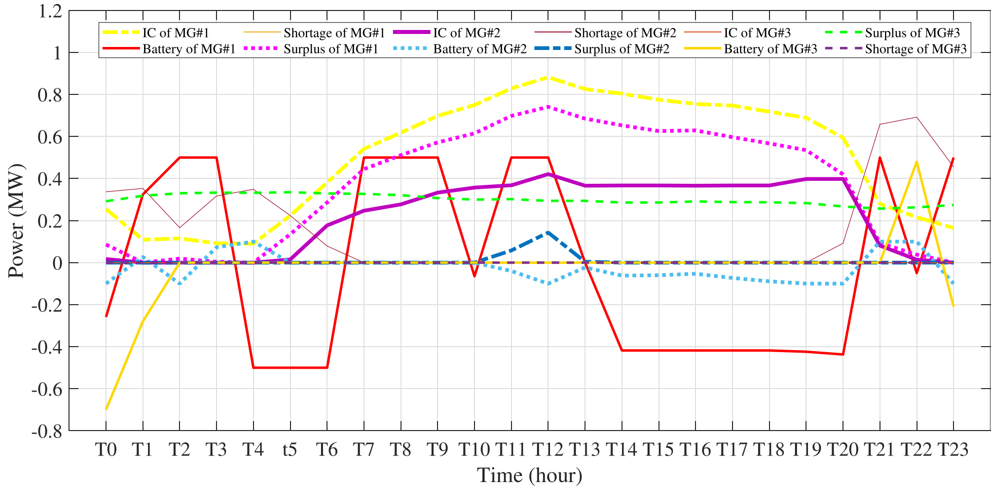

Fig. 6. Day-ahead scheduling of MGs for $\eta = 0.95$ and considering emission.

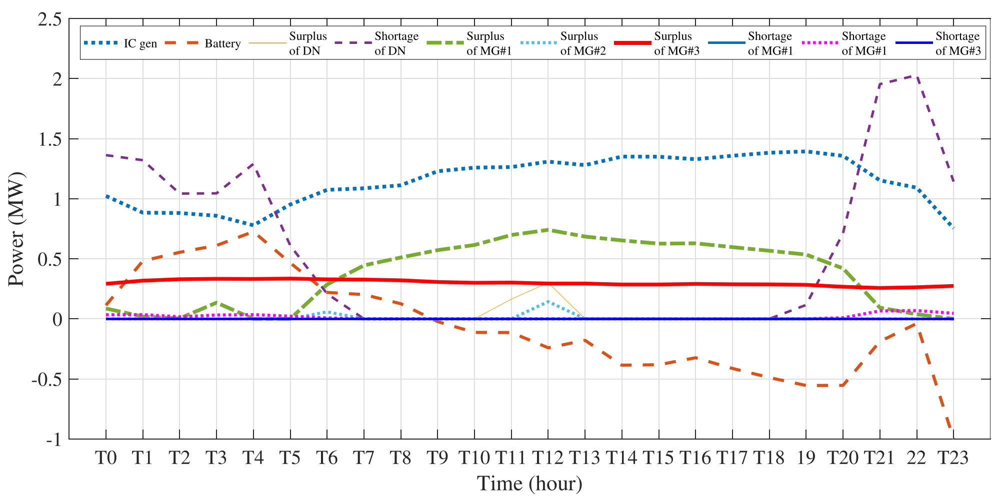

Fig. 7. Day-ahead scheduling of the DN for $\eta = 0.95$ and considering emission.

Table 7
The emission and objective function values for the MGs in case *I*.

Entity	MG1	MG2	MG3	DN	Total
Emission (tCO_2)	10.1	1.4	0	15.3	26.8
Objective function ($)	241.5	1033.1	−828.9	6486.8	6932.5

5.1. Case I

In this case, the cost of the emission has been considered in the simulation process. Also, the reliability level in the CCP model is assumed to be 95%. In the first stage of optimization, each MG performs local day-ahead scheduling. To contemplate CCP in the process, $\Im$ is calculated using the Monte-Carlo simulation and the algorithm shown in 2.

The results of this stage are shown in Fig. 6. This figure illustrates IC power generation, battery charging and discharging power, and shortage or surplus power of each MG. The IC generator in the third MG produces zero energy. The MGs try to propose the maximum amount of power to the DN in the hours with higher energy prices, whilst they try to buy in the periods with lower prices. This can be seen in the shortage and surplus power curves and also in the battery charging/discharging decisions. For instance at noon, when the electricity price is in its maximum, the IC generators of all the MGs are working in the ninety percent of their maximum capacity and they offer surplus power to the DN in order to increase their benefits. The reason for not reaching the maximum limit is due to minimizing the emissions, which prevents them from their rated capacity.

The emission amount and objective function value of each MG are shown in Table 7. The MG #2 has the highest objective function, due to its high emissions in comparison with MG1. Also, the third one has gotten a negative value due to the dominance of clean production in its units.

After termination of the local optimization, the process for energy management in the DN begins. The DN collects the data for surplus and shortage power of each MG and performs global scheduling. The results of energy management are depicted in Fig. 7. The DN operator sends signals of buying/selling energy to the MG owners and they perform a rescheduling. The objective function value and emissions are shown in Table 7. The overall system pollutant release into the atmosphere during the 24-h horizon has become 26.8 tCO_2.

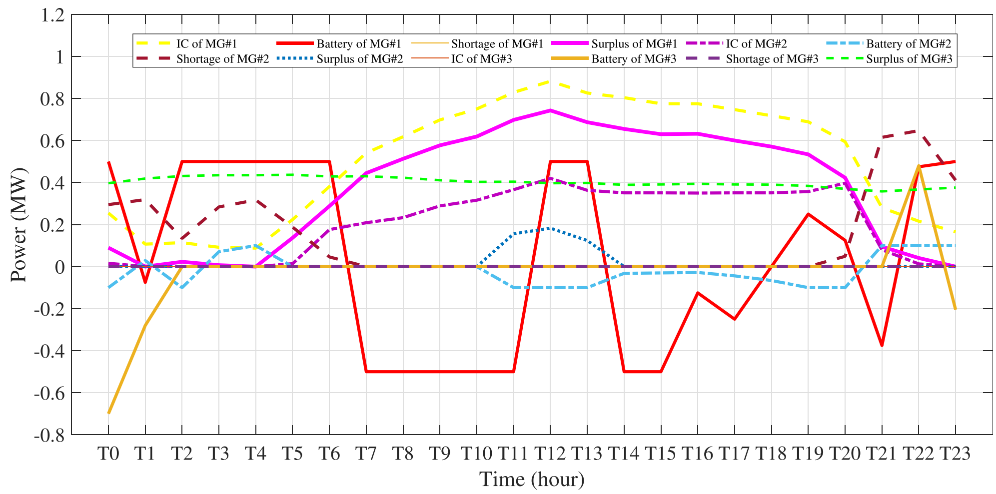

Fig. 8. Day-ahead scheduling of MGs for $\eta = 0.9$ and considering emission.

Table 8
The emission and objective function values for the MGs in case *II*.

Entity	MG1	MG2	MG3	DN	Total
Emission (tCO_2)	9.9	1.2	0	14.1	25.2
Objective Function ($)	234.8	915.4	−1114.9	5989.3	6024.6

5.2. Case II

In this case, likewise the previous one, the emission cost has been considered in the objective function. However, the reliability level, in this case, has decreased to 90%. The results of the first level are presented in Fig. 8.

The amount of emission and value of the objective function each entity are also tabulated in Table 8. The values have been reduced in comparison with the case *I*. This means that taking more risks by the system operator, might be more beneficial; however, this jeopardizes the security of the system, which is obtained through the power balance equation. The justification for emission reduction is that the system relies more on the generation of the clean production units and consequently, the generation of the IC systems is reduced.

The results of the second stage are illustrated in Fig. 9. Also, the objective function and emission values of the DN are presented in Table 8. The overall system pollutant release into the atmosphere during the 24-h horizon has been reduced to 25.2 tCO_2.

5.3. Case III

In this case, the emission cost has been neglected in the objective function to see its effect on the scheduling of the system. The reliability level, in this case, has been chosen as 95%. The results of the day-ahead scheduling for the MGs and the DN are depicted in Figs. 10 and 11, respectively. It can be inferred from these figures, that the utilization of IC generators has been raised, which might be harmful to the environment due to increment in the emission. For instance, in comparison with case *I*, IC generators of MGs #1 and #2, are working in their maximum limit from 6 o'clock till the end of the day, while in case *I*, just in 1 h it produces in its ninety percent of capacity. This obviously leads to more emissions in the system.

Table 9 illustrates the emission amount and objective function value of each MG and the DN. In comparison with case *I*, the objective function values have been reduced significantly. This is due to removing the cost of emission from the objective function. However, the emission amount has risen, which seems not to be

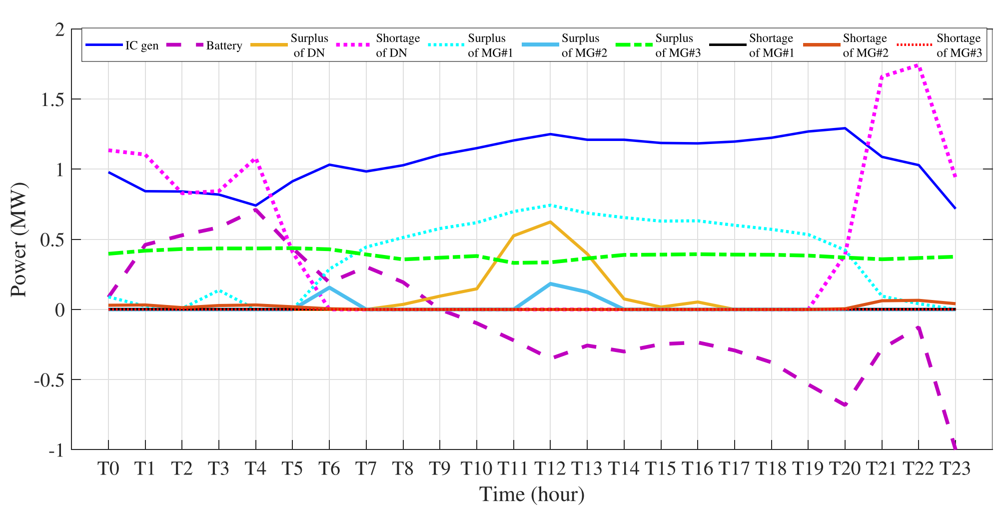

Fig. 9. Day-ahead scheduling of the DN for $\eta = 0.9$ and considering emission.

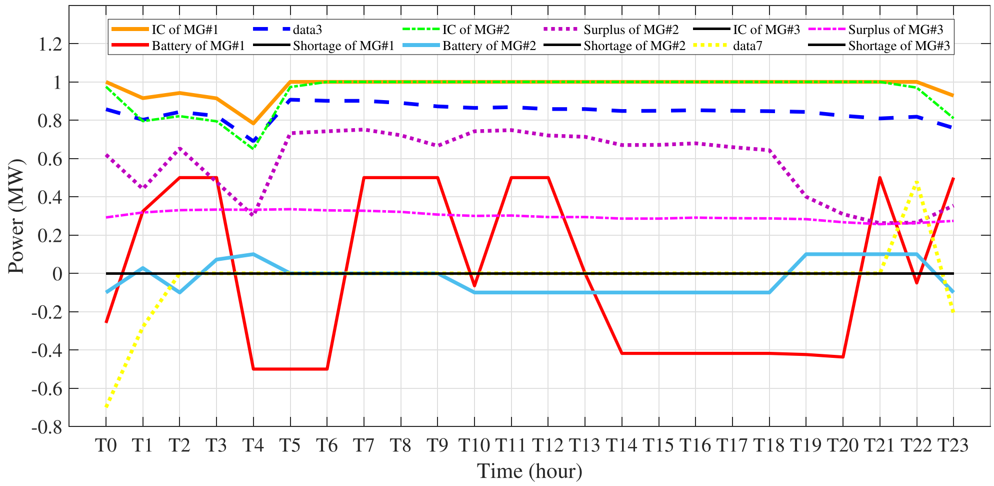

Fig. 10. Day-ahead scheduling of MGs for $\eta = 0.95$ and neglecting emission.

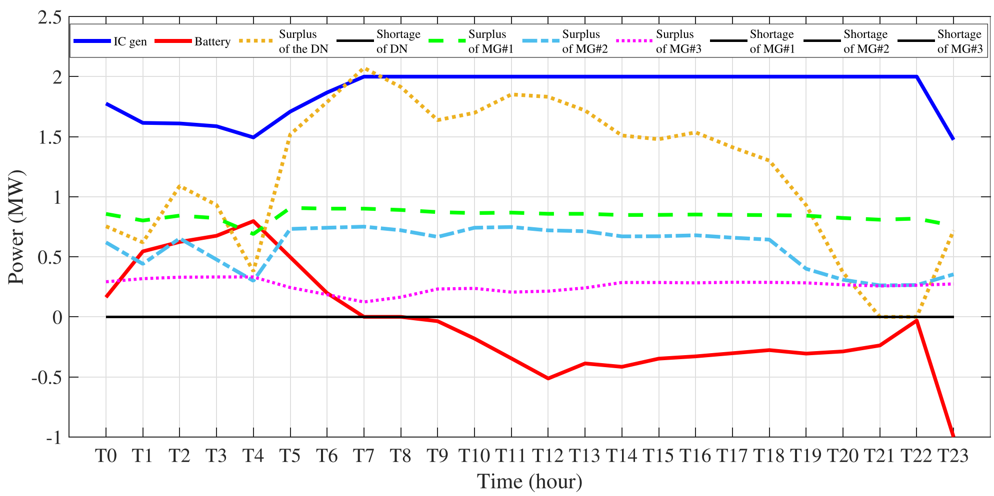

Fig. 11. Day-ahead scheduling of the DN for $\eta = 0.95$ and neglecting emission.

Table 9
The emission and objective function values for the MGs in case *III*.

Entity	MG1	MG2	MG3	DN	Total
Emission (tCO_2)	19.5	5.7	0	24.9	50.1
Objective Function ($)	−185.7	547.2	−828.9	5313.3	4845.9

environment-friendly. The total emission during the scheduling period has reached a remarkable value of 50.1 tCO_2. Although the values of the objective function for the MGs #1 and #2 have been reduced, the objective of the MG #3 does not face a change. This is due to the higher penetration of renewable-based DGs in its structure, which makes its output independent from the emission costs. This can be considered in line with the policy of reducing greenhouse gas emissions and controlling the global warming.

5.4. Case IV

In this case, the reliability level has been decreased to 90% and the cost of emission has been neglected in the objective function. Figs. 12 and 13 demonstrate the results of day-ahead scheduling for the first and second stages. Likewise case *III*, the utilization of IC generators has been raised in comparison with cases *I* and *II*, however in comparison with case *III* it has been reduced slightly, which is a result of more reliance on the renewable-based DGs and taking more risks.

Table 10 illustrates the emission amount and objective function value of each MG and the DN. In comparison with case *III*, the values of the objective function have seen a small reduction, but considering cases *I* and *II*, it shows a significant decrease which is a result of ignoring emissions. The total emission has reached 49.7 tCO_2.

6. Conclusion

More penetration of the MGs in distribution systems has caused the arrival of a new definition better known as MMG systems. The energy management of such systems is challenging. Considering the uncertainties makes this issue even more difficult. In this paper, the CCP-based approach has been employed for the day-ahead scheduling of MMG systems as a hierarchical approach. Utilizing the CCP has many benefits, e.g., increasing the reliability of system, reducing the burden of calculations, etc. In the mentioned method, in the first layer, each MG performs a local optimization and collecting the data obtained from this stage, DN operator performs global scheduling and informs the MGs and other entities about their scheduling.

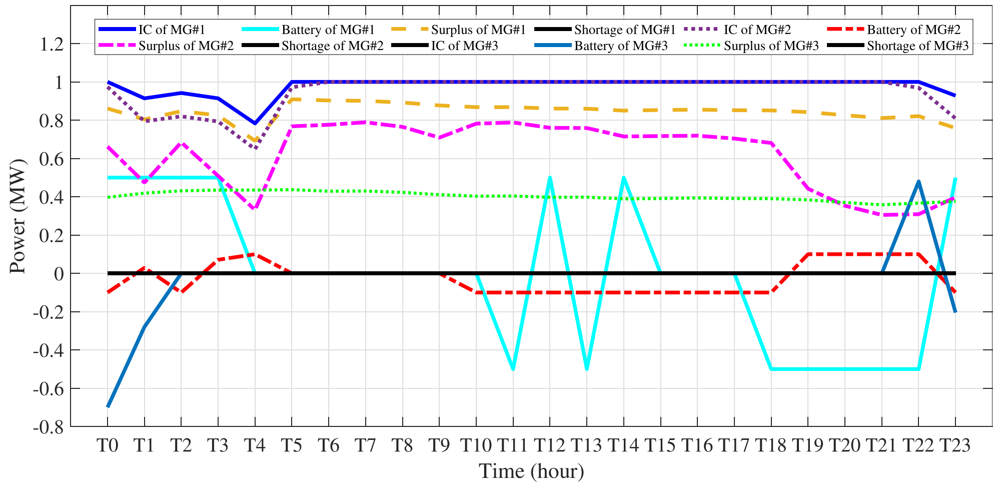

Fig. 12. Day-ahead scheduling of MGs for $\eta = 0.9$ and neglecting emission.

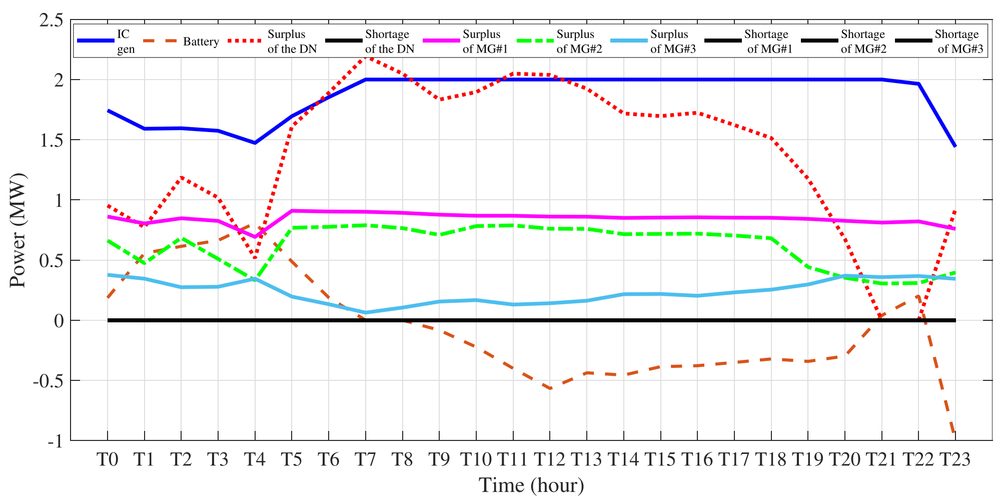

Fig. 13. Day-ahead scheduling of the DN for $\eta = 0.9$ and neglecting emission.

Table 10
The emission and objective function values for the MGs in case *III*.

Entity	MG1	MG2	MG3	DN	Total
Emission (tCO_2)	19.4	5.6	0	24.7	49.7
Objective Function ($)	−192.4	434.4	−1114.9	4860.8	3987.9

Finally, each MG executes a rescheduling based on the data received from the DN. To reduce the greenhouse gases emission, the cost function for the emissions has been proposed aiming at minimizing the pollutants. Four different case studies with different reliability levels in the CCP model and considering or neglecting the emissions have been selected. The simulation results have indicated that by considering the emission cost in the objective function, a significant reduction in the value of released gases has occurred. Also, the simulations have suggested using more clean generation units. Furthermore, decreasing the reliability level and taking more risks, have shown a decrease in the objective function. For future works, it is suggested performing a linearization to model the problem as a linear problem and obtain a global optimum. Also, proposing a bidding strategy for the MMG system in the presence of emissions and CCP modeling of the system might be very interesting for future studies. In addition, considering a decentralized method for solving the problem in CCP environment, might enhance the optimization process ensuring the privacy of the MGs.

CRediT authorship contribution statement

Farid Hamzeh Aghdam: Conceptualization, Methodology, Software, Writing - original draft, Writing - review & editing, Visualization. **Navid Taghizadegan Kalantari:** Supervision, Writing - review & editing. **Behnam Mohammadi-Ivatloo:** Conceptualization, Writing - review & editing.

Declaration of competing interest

There is none.

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