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Optimal Energy Management of Microgrid in Day-Ahead and Intra-Day Markets Using a Copula-Based Uncertainty Modeling Method

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Abstract- *Recently, economic and environmental problems have created a strong attitude toward utilizing renewable energy sources (RESs). Nevertheless, uncertainty of wind and solar power leads to a more complicated energy management (EM) of RESs in microgrids. This paper models and solves the EM problem of microgrid from the generation point of view. To do this, mathematical formulation of a grid- connected microgrid including wind turbine (WT), photovoltaic (PV), micro turbine (MT), fuel cell (FC) and energy storage system (ESS) is presented. Furthermore an improved incentive-based demand response program (DRP) is applied in microgrid EM problem to flatten the load pattern. Comprehensive studying of EM in both intra-day and day-ahead markets is another contribution of this paper. However, the main novelty of this paper is proposing a new uncertainty modeling technique which is based on copula function and scenario generation. This paper tries to optimize operational cost and environmental pollution as the objective functions and solve them using group search optimization (GSO) algorithm. Numerical results approve the efficiency of the proposed method in solving microgrid EM problem.*

Keyword: Copula, Demand response, Intra-day market, Microgrid, Uncertainty.

NOMENCLATURE

Abbreviations

ADMM	Alternating direction method for multiplier
ARMA	Auto-regressive moving average
CDF	Cumulative distribution function
DG	Distributed generation
DRP	Demand response program
EM	Energy management
EMS	Energy management system
ESS	Energy storage system
FC	Fuel cell
IGDT	Information gap decision theory
MAS	Multi-agent system
MCP	Market clearing price
MT	Micro turbine
GSO	Group search optimization
PDF	Probabilistic distribution function
PV	Photovoltaic
RES	Renewable energy source
UG	Utility grid
WT	Wind turbine

Symbols, indexes and parameters

C	copula function
Cov	covariance
$C_{FC}, C_{MT}, C_{PV}, C_{WT}$	costs related to FC, MT, PV, WT ($)
$C_{Op\text{-}PV}, C_{Op\text{-}WT}$	operational costs of PV and WT ($)
$C_{Cons\text{-}PV}, C_{Cons\text{-}WT}$	constant costs of PV and WT ($)
C_{Fuel}	fuel cost ($)
C_{ESS}	costs of electrical energy storage ($)
$C_{Op\text{-}ESS}$	operation cost of ES ($)
$C_{Cons\text{-}ESS}$	constant cost of ES ($)
$C_{Op\text{-}MT}$ $C_{Op\text{-}FC}$	operation cost of MT and FC ($)
$C_{M\text{-}MT}$ $C_{M\text{-}FC}$	maintenance cost of MT and FC ($)
$D_{0,i}(t)$	initial load of i^{th} customer (kW)
$\partial D(t1)$	load change at $t=t_1$ (kW)
$D_i(t)$	load of i^{th} customer after DR (kW)
$E(t_1,t_2)$	elasticity coefficient

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E_{MT},E_{FC} E_{UG}	emission cost of MT, FC, UG ($)
F_X, F_Y	cumulative distribution functions of X and Y
F(cost)	total cost function
F(Emission)	total emission function
i	customer number
n	number of variables
$P_{buy}(t)$	amount of power that is bought from UG at time t (kW)
$P_{sell}(t)$	amount of power that is sold to UG at time t (kW)
P_{line}	line capacity (kW)
$P_{FC}(t)$ $P_{MT}(t)$ $P_{PV}(t)$ $P_{WT}(t)$ $P_{ES}(t)$	power of FC, MT, PV, WT and ESS at time t (kW)
rev(Di(t))	revenue of ith consumer t_1, t_2
U, V, X, Y	random variables
rev(Di(t))	revenue of ith consumer
u, v	realizations of U and V
$\alpha_{t,i}$	incentive payment ($) per kWh at tth hour for ith consumer
β_t	penalty value ($) per kWh
ρ	product moment correlation of two CDFs
ρ_r	rank correlation
$\partial\rho$	price modification at t=t_2 ($)
η_C, η_D	charge and discharge efficiency of ES
σ	Standard deviation
$\pi(t)$	electricity market price at time t

1. INTRODUCTION

In recent years, the economy is transitioned from a fossil fuel based manner to a renewable energy based one as a result of concerns on climate changes and cheaper wind and solar energy [1]. Therefore, various efforts have been made to integrate renewable energy sources (RESs), energy storage devices, distributed dispatchable generators along with demand response programs (DRP) into distribution networks [2]. These efforts have introduced the concept of microgrid; a smaller grid supplying the local load in an optimal and economical manner [3]. Microgrid is capable of supplying its demand by procuring power from the upper grid in grid-connected mode, as well as from local renewable and non-renewable energy sources in islanded mode [4]. The advantage of utilizing distributed generations (DGs) such as wind and photovoltaic in distribution networks is the improvement of power efficiency and stability [5]. However, the power generation of DGs is related to weather condition, and also the demanded load has a time-varying nature [6]. To cope with these uncertainties, the system operators are required to provide a specific amount of reserve to cover these uncertainties, and an energy management system (EMS) is required to fulfill the generation-consumption balance in microgrid [7]. A trivial solution to provide this reserve is to purchase more power from the upper grid, or to increase the number of local energy sources. However, these two solutions can cause an increment in the total cost or emission of the system [8]. Another solution to tackle generation-consumption balance is to utilize energy storage systems (ESSs). These sources are used to store power during cheap or off-peak hours and release it in peak or expensive periods [9]. The other method to manage the existing uncertainties is reducing the demanded load when the system faces with lack of energy resulted from wind and solar power uncertainty. This solution provides demand-side reserve with the ability to participate in energy markets too [10].

Microgrid EMS has been well studied by researchers [12-20]. The literature review of microgrid EMS is summarized in Table 1. In Ref. [11], a comparative review of decision-making strategies, uncertainty modeling techniques and solution methods for microgrid EMS is presented. In Ref. [12], a grid-connected microgrid is studied to minimize the operation cost and pollutant emission as a multi-objective function without considering uncertainty. In addition, a price-offer package for DR model as well as a battery is considered as reserve energy source. Authors of Ref. [7] have solved the microgrid EMS as a multi-objective problem using multi-objective group search optimization (MOGSO) algorithm.

Table 1. Review of microgrid EMS methods

Ref.	Solving technique	Objective functions	Uncertainty modeling technique	DR	battery	Islanded	Grid-
[7]	MOGSO	• Operating cost • Emission cost	-	Incentive-based	✓	-	✓
[12]	MOPSO	• Operating cost • Emission cost	-	Price-offer package model	✓	-	✓
[13]	GAMS	• Profit function	ARMA	Shifting load to other periods	✓	✓	-
[14]	GAMS	• Operating cost	Scenario generation	Price-based Incentive-based	✓	✓	✓
[15]	GAMS	• Operating cost	IGDT	Shifting load to other periods	✓	-	✓
[16]	Dynamic programming	• Operation cost • Emission cost	PDF	-	✓	✓	-
[17]	MATLAB optimization toolbox	• Cost of energy	Monte Carlo	-	✓	-	✓
[18]	MAS	• Operation cost	-	-	✓	✓	-
[19]	Augmented ε-constraint method	• Operation cost • Emission cost	PDF	Incentive-based	✓	✓	-
[20]	ADMM	• Operation cost	-	Incentive-based	✓	✓	-

Ref. [13] has formulated the microgrid EMS as a stochastic problem utilizing auto-regressive moving average (ARMA) to model existing uncertainties. In addition, authors of this paper have utilized a DRP that modifies load pattern by transferring demand from peak-period to other time intervals. Application of both price-based and incentive-based DR program in microgrid EMS is studied in Ref. [14]. Moreover, the uncertainties related to price, load, wind speed and solar radiation is modeled using probabilistic distribution function (PDF) of each parameter.

An information gap decision theory (IGDT) is presented in Ref. [15] to obtain the bidding strategy of microgrid as an stochastic problem. In Ref. [16], an advanced dynamic programming method is presented to solve microgrid EMS problem where probabilistic models for uncertain parameters are also considered. Ref. [17] has developed a linear problem for EMS, and Monte Carlo simulation has been applied to cover uncertainties of biomass generation of microgrid. In Ref. [18], a novel multi-agent system (MAS) based model is presented to solve the optimization problem. The contribution of Ref. [19] is to solve the multi-objective problem of EMS using augmented ε-constraint method. In Ref. [20], an alternating direction method for multiplier (ADMM) has been proposed to schedule the operation of microgrid components.

In this paper, the studied microgrid is grid-connected, and is composed of WT, PV, fuel cell (FC), micro-turbine (MT) and ESS. This paper presents a new hybrid uncertainty modeling method to cover uncertainties associated with wind and solar power. The presented method is based on copula function and scenario generation. Firstly, the real and forecasted values of uncertain parameters are utilized to generate a two-dimensional conditional PDF using copulas. Then, a specified number of scenarios are generated by scenario generation technique. Introducing the improved incentive-based DRP is the second contribution of this paper. Computing more realistic values for penalty and incentive payments as a function of peak intensity, taking into account intra-day market which results in more accurate participation of consumers in DR, and considering the elasticity values as a function of costumer type and peak intensity are the properties of our proposed DR program. Considering the intra-day market in addition to day-ahead market, in the formulation and solving of the EM problem, is the third contribution of this paper. The latter allows microgrid components to make more accurate participation in EM of microgrid. Considering the operational cost and environmental pollution as the objective functions, the EM problem is solved using GSO algorithm.

In summary, this paper has the following prominent features:

- Proposing a copula-scenario based technique for uncertainty modeling
- Introducing an improved incentive-based DRP
- Considering both day-ahead and intra-day market in microgrid EM problem

The remainder of this paper is organized as follows: In Section 2 the proposed copula-based uncertainty modeling technique is presented. Section 3 describes the improved incentive-based DR program. The mathematical formulation of objective functions and constraints are presented in Section 4. The numerical results and conclusions are expressed in Section 5 and 6, respectively.

2. Proposed copula-based uncertainty modeling technique

It is clear that there is a stochastic dependency between various random variables. For example, the forecasted and real-time wind power generations have a significant level of correlation. As a result, more accurate prediction of wind power results in more precise planning of real-time wind power utilization. This explanation can be applied for other stochastic variables such as solar radiation, electricity price and load. Various methods have been employed in order to manage the uncertainty of the aforementioned uncertain parameters in EM of microgrid. The scenario generation method in Ref. [21] generates various scenarios for uncertain parameter using the PDF of prediction error. However, in this method, the PDF is made by prediction error values regardless of pairing each error value to its real amount. The Monte Carlo method [22] is relied on repeated random samplings. The PDF function used in this method is the same as PDF of scenario generation technique. Another uncertainty modeling method which is based on PDF is point estimate method [23]. Along with aforementioned stochastic methods which are based on PDF, there exists other techniques such as fuzzy method [24], robust optimization [25], IGDT [26] and conditional value at risk (CVaR) [27]. However, the proposed copula-scenario based uncertainty modeling technique is a hybrid method which has utilized the copula function to improve the accuracy of the PDF. The generated PDF is more accurate since it is made by pairing real value and its associated prediction error. It is worth mentioning that the equivalent weighted hourly value for each of uncertain parameters at the last step of the proposed method has improved the computation speed in comparison to the existed stochastic methods.

2.1. Measurement of stochastic dependency

The rank correlation (ρr), is utilized to compute the severity of dependency between random variables [28]. The rank correlation of random variables X and Y with calmative distribution functions (CDFs) FX and FY is:

$$\rho_r(X, Y) = \rho(F_X(X), F_Y(Y)) \tag{1}$$

Here, ρ(FX(X),FY(Y)) is called the product moment correlation of two CDFs which is computed as:

$$\rho(F_X(X), F_Y(Y)) = \frac{Cov(F_X, F_Y)}{\sigma(F_X)\sigma(F_Y)} \tag{2}$$

Where, Cov and σ denote the covariance and standard deviation, respectively. It can be seen that the rank correlation is within interval [-1, 1] and is a factor that transforms random variables to uniform random variables. If ρr=1, the dependency between random variables is excellent. In contrast ρr=0 shows the independency of random variables.

2.2. Copula

Copulas are mathematical functions that formulate multivariate distribution functions by coupling multiple one-dimensional distribution functions [29]. This process is performed by transforming uniform distribution of all marginal variables into a multivariate distribution [30]. In mathematical terms, a copula is a function (C) with *n* variables in the range of $[0,1]^n$ with the following specifications:

1) The amount of C is in the unit interval [0,1];

2) Considering $u=(u_1,\ldots,u_n)$ in $[0,1]^n$, C(u) is zero if at least one coordinate is zero;

3) $C(u)=u_k$ if all of coordinates equal to 1 except u_k;

According to Sklar's theorem in Ref. [31] which is the basis of the copula application, a copula function joins multiple one-dimensional distribution functions together to generate multivariate distribution functions. Sklar also proved that if the marginal distributions are continuous, there exists only one copula representation. There exists two families of copulas; namely Ellipse family and Archimedean family. The commonly-used Gaussian and Student t are included in Ellipse category while Frank, Gumbel and Clayton are contained in Archimedean family [32].

Considering X and Y as random variables whose cumulative distribution functions are F_X and F_Y respectively, the copula C can join their distribution function as below:

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)) \tag{3}$$

Assume $F_X(x)$ =u and $F_Y(y)$ =v, where u and v are realizations of the uniform random variables U and V, respectively. As a result, Eq. (3) can be written as:

$$C_{V|U}(u, v) = F(x, y) = F(F_X^{-1}(u), F_Y^{-1}(v)) \tag{4}$$

Where, $C_{V|U}$ is the conditional distribution of V|U and F^{-1} is the inverse of univariate distribution function.

2.3. Our proposed method

In this section the steps describing our proposed uncertainty modeling technique is expressed. The proposed method utilizes predicted and real-time data as dependent random variables. The overall steps are as below:

1) Collect the hourly historical data for the uncertain parameter for 1 year

2) Predict hourly values of the parameter for one week using the collected historical data

3) Consider the predicted hourly values and the real-time amounts for the proportional time period as the random variables

4) Fit the data with copula function and generate conditional distribution function for real-time and predicted values of uncertain parameter

5) Generate joint conditional distribution estimation for prediction error

6) Generate specific number of scenarios using the method presented in Ref. [33]

7) Make weighted equivalent value for each hour of parameter as below:

$$Eq.param(t) = \Pr e.param(t) + \sum_{S=1}^{n_S} \Pr ob_S(t) * Value_S(t) \tag{5}$$

Here, Eq.param and Pre.param are the equivalent value and predicted value of uncertain parameter. Furthermore, $Prob_S$ and $Value_S$ are the probability and value of parameter at S^{th} scenario.

3. Improved incentive-based DR program

In this section, the mathematical formulation of the improved incentive-based DR (IBDR) program which is an expansion of the proposed model in Ref. [34] is presented. To begin with, it is crucial to define the concept of elasticity. This coefficient is defined as the ratio of demand modification at t_1 in response to relative price changes during t_2 as below:

$$E(t_1,t_2)=\frac{\rho_{0,DA}(t_2)}{D_0(t_1)}.\frac{\partial D(t_1)}{\partial \rho_{DA}(t_2)} \tag{6}$$

Where, $E(t_1,t_2)$, $\partial D(t_1)$ and $\partial \rho\ (t_2)$ are the elasticity coefficient, load change at $t=t_1$ and price modification at $t=t_2$, respectively. The time-dependent nature of elasticity relates the price changes at $t=t_2$ to the load variation at $t=t_1$. While $t_1 \neq t_2$, increment of price at $t=t_2$ will cause increment of load at $t=t_1$. When $t_1=t_2$, decrement of price at $t=t_2$ will result in increment of load at $t=t_1$ and vice versa. This is expressed in Eq. (7) as below:

$$\begin{cases} E(t_1,t_2)\le 0 & if\ t_1=t_2 \\ E(t_1,t_2)>0 & if\ t_1\neq t_2 \end{cases} \tag{7}$$

The aim of the IBDR program is to maximize the total benefit function which consists of incentive payment, penalty values and revenue.

Incentive payments are paid to the i^{th} consumer, when it changes its demand from $D_{0,i}(t)$ to $D_i(t)$ as a result of price variation. The amount of incentive payment is computed as:

$$inc_i(t)=\alpha_t(peak\ density)[D_{0,i}(t)-D_i(t)] \tag{8}$$

Here, $\alpha_{t,i}$ represents the incentive payment ($) per kWh at t^{th} hour for i^{th} consumer. This coefficient is a function of peak intensity of t^{th} hour, and results in more incentive payment for load reduction during peak hours.

The penalty value of consumers for breach of contract is:

$$pen_i(t)=\beta_t(peak\ density)[RL_i(t)-[D_{0,i}(t)-D_i(t)]] \tag{9}$$

Where, $RL_i(t)$ and $[D_{0,i}(t)-D_i(t)]$ demonstrate the real and promised load reduction, respectively. β_t represents the penalty value ($) per kWh of contract violation.

Considering $rev(D_i(t))$ as the revenue of i^{th} consumer, the total benefit function for i^{th} consumer is:

$$ben_i(t)=rev(D_i(t))-D_i(t).\rho(t)+inc_i(t)-pen_i(t) \tag{10}$$

According to classical optimization rules, the benefit function is maximized when its deviation equals to zero. After mathematical simplifications [35], the optimal consumption of customer during 24 h is as below:

$$D_i(t_1)=D_{0,i}(t_1).\exp(\sum_{t_1=1}^{24}\sum_{t_2}^{24}E_i(t_1,t_2). \\ \frac{\left(\rho(t_1)+\alpha_{t_1}(peak\ density)+\beta_{t_1}(peak\ density)-\rho_0(t_1)\right)}{\rho_0(t_1)}) \tag{11}$$

4. Microgrid energy management problem formulation

The mathematical formulation of microgrid energy management problem considering objective functions and constraints are discussed in this section.

4.1. Objective functions

In this paper, the aim of the EMS problem formulation is to find the optimal hourly planning for the microgrid components including generators (WT, PV, MT, FC) and ESS while satisfying various technical constraints. The cost and revenue of microgrid as a result of power exchange by utility grid is included in mathematical modelling. In addition, in the paper the EMS of microgrid in both day-ahead and intra-day markets are considered. Two objective functions including total operational cost of microgrid and environmental pollution are to be minimized simultaneously.

4.1.1. Total operational cost of microgrid

The first objective function is total operational cost of microgrid expressed by:

$$F(Cost)=\sum_{t=1}^{24}(C_{Wind}(t)+C_{PV}(t)+C_{MT}(t)+C_{FC}(t) \\ +C_{Buy}(t)-C_{Sell}(t)+C_{ESS}(t)) \tag{12}$$

Where,

$$C_{Wind}(t)=\sum_{t=1}^{T}C_{Op-WT}.P_{WT}(t)+C_{Cons-WT} \tag{13}$$

$$C_{PV}(t)=\sum_{t=1}^{T}C_{Op-PV}.P_{PV}(t)+C_{Cons-PV} \tag{14}$$

$$C_{MT}(t)=\sum_{t=1}^{24}\left(\frac{C_{Fuel}.P_{MT}(t)}{\eta_{MT}}+C_{Op-MT}.P_{MT}(t)\right)+C_{M-MT} \tag{15}$$

$$C_{FC}(t)=\sum_{t=1}^{24}\left(\frac{C_{Fuel}.P_{FC}(t)}{\eta_{FC}}+C_{Op-FC}.P_{FC}(t)\right)+C_{M-FC} \tag{16}$$

The costs related to WT, PV, MT, FC are explained in Eqs. (13)-(16). According to Eqs. (13) and (14), operational costs of WT and PV are composed of variable and fixed terms. The first term of Eq. (15) represents the power generation cost of MT while the second and third terms are the operational and maintenance costs, respectively. Similarly, the first term of Eq. (16) indicates the fuel cost of FC while the second and third terms are the operational and maintenance costs, respectively.

$$C_{Buy}(t)=\sum_{t=1}^{T}\pi(t).P_{Buy}(t) \tag{17}$$

$$C_{Sell}(t)=\sum_{t=1}^{T}\pi(t).P_{Sell}(t) \tag{18}$$

$$C_{ES}(t)=\sum_{t=1}^{T}C_{Op-ES}.P_{Es}(t)+C_{Cons-ESS} \tag{19}$$

The costs related to power exchange by the upstream grid are described in Eqs. (17) and (18). Eq. (17) represents the costs of buying power while Eq. (18) is the cost of selling power. In addition, operational and maintenance costs of ESS are given in Eq. (19).

4.1.2. Pollution cost of microgrid

The total emission cost of microgrid and utility grid (UG) is calculated as below:

$$F(Emission)=\sum_{t=1}^{24}(E_{MT}(t)+E_{FC}(t)+E_{UG}(t)) \tag{20}$$

Where,

$$E_{MT}(t)=\sum_{t=1}^{24}P_{MT}(t).EF_{MT} \tag{21}$$

$$E_{FC}(t)=\sum_{t=1}^{24}P_{FC}(t).EF_{FC} \tag{22}$$

$$E_{UG}(t)=\sum_{t=1}^{24}P_{Buy}(t).EF_{UG} \tag{23}$$

Here, Eqs. (21)-(23) are the emitted pollution by MT, FC and UG.

4.2. Constraints

Microgrid EMS contains multiple constraints such as power balance, and constraints associated with ES, power generation by DGs etc. Meeting these constraints can result in reaching a feasible solution for EMS problem. In this paper, the following constraints are considered for the operation of microgrids:

$$\begin{aligned} load(t)=\sum_{t=1}^{24}(&P_{WT}(t)+P_{PV}(t)+P_{MT}(t)+\\ &P_{FC}(t)+P_{ESS}(t)+P_{Buy}(t)-P_{Sell}(t)) \end{aligned} \tag{24}$$

$$P_{FC}(t)\le P_{FC}^{\max} \tag{25}$$

$$P_{MT}(t)\le P_{MT}^{\max} \tag{26}$$

$$\begin{cases} \dfrac{P_{ESS}(t)}{\eta_D}\le P_{E-discharge}^{\max} & for\ disch(P_{ESS}(t)>0) \\ -\eta_C.P_{ESS}(t)\le P_{E-charge}^{\max} & for\ ch(P_{ESS}(t)<0) \end{cases} \tag{27}$$

$$P_{Buy}(t)or\ P_{Sell}(t)\le P_{Line} \tag{28}$$

The summation of the produced power by all members of microgrid (DGs+ESS) in each time interval must be equal to the total load of that period as given by the power balance Eq. (24). The limitations related to power generation of FC and MT are given in Eq. (25) and (26), respectively. The constraints on the charging-discharging powers of ESS is specified by Eq. (27). In this equation, state of charging and discharging are separated using positive and negative values, respectively. The thermal capacity of line which connects microgrid to main-grid is limited by Eq. (28).

5. Numerical Results

In this section, numerical studies are presented. First, the studied microgrid have been introduced. Then, the simulation results of copula-based uncertainty modeling technique are presented. At this step, two-dimensional probability distribution function (PDF) of uncertain parameters including wind and solar power have been extracted. Subsequently, the updated load patterns as a result of utilizing incentive-based DRP in intra-day and day-ahead market are depicted. The last part of simulation results is assigned to the hourly power management values of the microgrid components and the main grid. This section has presented hourly EMS values using GSO in day-ahead and intra-day markets. A detailed introduction about GSO algorithm has been presented in our previous work [7]. It is worth mentioning that the simulations are performed using MATLAB R2013a, running on a PC with a 1.5 GHz AMD Quad core A4 CPU and 4GB RAM.

5.1. Studied microgrid

The studied microgrid has been adopted from Ref. [36] and shown in Fig. 1. It consists of a WT, two PVs, FC, MT and an ESS system. It is clear that the microgrid is connected to the utility grid. The values of emission factors of MT, FC and UG are given in Table 2. The values of power limitations, efficiency values along with operation and maintenance costs for microgrid components are given in Table 3.

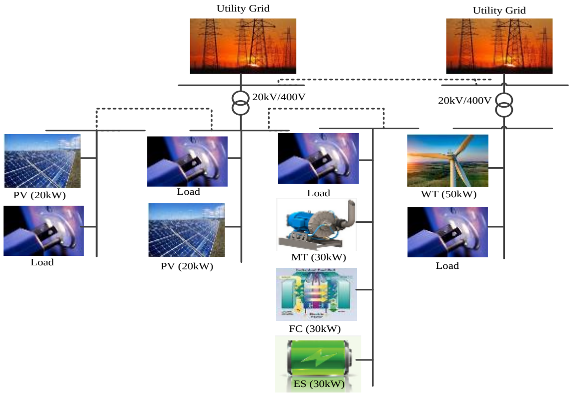


Fig. 1. The studied microgrid [36]

Table 2. Emission factors (kg/MWh) [37]

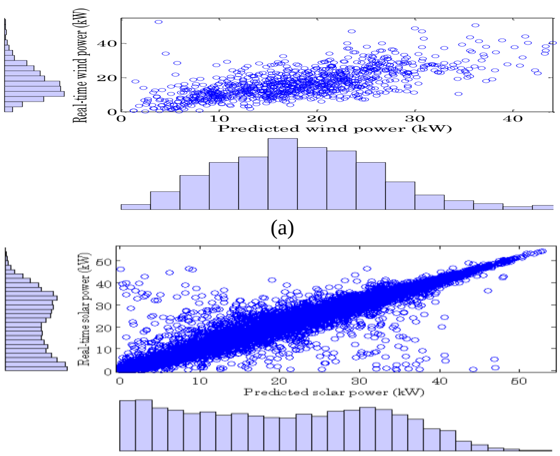
Emission type	MT	FC	UG
CO_2	724	460	922
SO_2	0.0036	0.003	3.583
NO_X	0.2	0.0075	2.295

Table 3. Power limitation, efficiency factors and costs of microgrid components [37]

DG type	Power limit (kW)		efficiency	Costs	
	Min	Max		Maintenance ($)	Operation ($/kW)
MT	6	30	0.3	0.001	0.004
FC	3	30	0.3	0.001	0.003
WT	0	50	0.59	0.002	0.005
PV	0	40	-	0.001	0.003
ESS	-30	30	0.95	0.001	0.004

5.2. Uncertainty modeling based on copula function

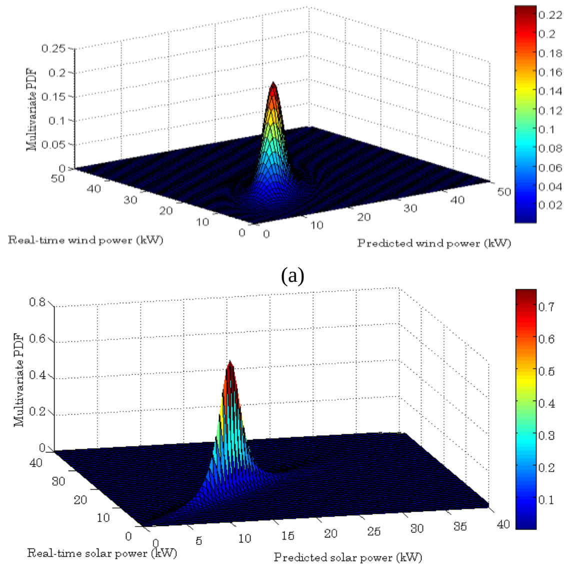
This section focuses on the simulation results of the proposed uncertainty modeling technique. As mentioned before, the presented method requires the real-time and predicted values of uncertain parameter for one year time duration. The data related to actual and forecasted values of wind and solar power are extracted from [38]. Utilizing these data, the probabilistic relationship between each pair of real-time and predicted hourly values of wind power and solar power are shown by scatter plot in Fig. 2. The marginal distribution function for each of the actual and estimated values are also plotted by its proportional axis. According to Ref. [39], the Gaussian copula is more appropriate in modeling multivariate PDFs. Considering this fact, this paper uses Gaussian copula in the study case. Figure 3 demonstrates the joint conditional distribution function for actual and forecasted values of uncertain parameters. The proposed results approve logical conditional distributions which are close to real PDFs.



(a)

(b)

Fig. 2. Scatter plot of the joint distribution of the actual and forecast values of (a) wind power, (b) solar power



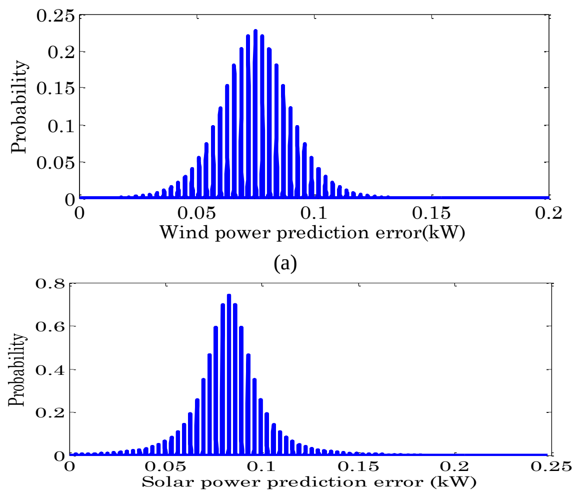
(a)

(b)

Fig. 3. 3-D view of the joint conditional distribution estimation of the actual and forecast values of (a) wind power, (b) solar power

Based on the conditional distribution functions of Fig. 3, the joint conditional distribution function for prediction error of each parameter is extracted and shown in Fig 4. To do this, the prediction error for each pair of real-time and predicted values are computed, and the probability amount are taken from conditional distribution values of Fig. 3.

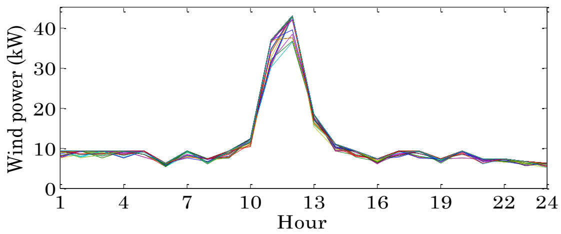
After generating the joint distribution function of prediction errors, it is time to generate appropriate scenarios to cover uncertainties. Firstly, random values are generated and then by comparing the generated random amounts by prediction error values of Fig. 4, the occurrence probability for each scenario is extracted. All of the generated scenarios for four uncertain parameters of this study are shown in Fig. 5.



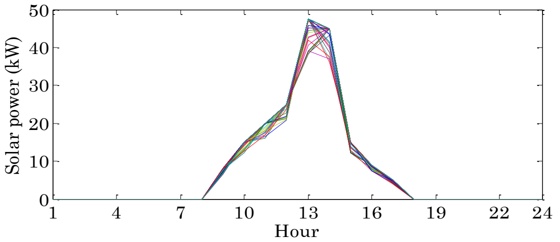
(a)

(b)

Fig. 4. Joint conditional distribution estimation of the prediction error for (a) wind power, (b) solar power

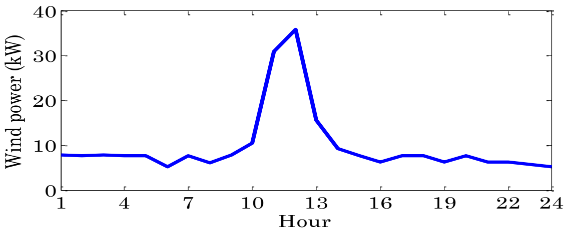


(a)

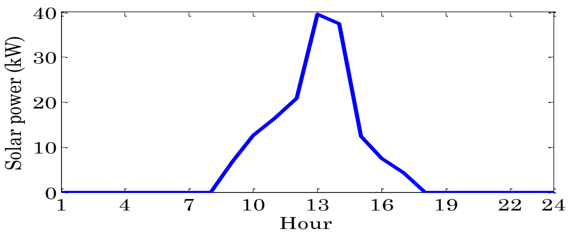


(b)

Fig. 5. Generated scenarios for (a) wind power, (b) solar power



(a)



(b)

Fig. 6. Hourly equivalent amounts after uncertainty modeling technique for (a) wind power, (b) solar power

To simplify the computation and speed up the optimization process, a weighted equivalent scenario is generated using Eq. 5. The resulted equivalent scenario for each uncertain parameter is shown in Fig. 6. The generated scenario will cover effects of all prediction error values and their proportional occurrence probability.

Combining copula as a mathematical function with scenario generation method proposed a new hybrid uncertainty modeling technique which was not presented up to now. Application of the copula function in modeling uncertainties is another prominent feature of this method. The copula generates 3-D PDF based on the scatter plot of the predicted and real-time values. It can be seen that in the scatter plot each point is a pair of real-time value and its proportional prediction value. However, in PDF generation of the existed methods, the utilized data are not pair and it is not important that which prediction is proportional to which real-time value. Because, the PDF of copula-scenario based method is generated by pairs of prediction-actual amounts, its PDF has more accuracy than existed methods. Totally, this method has tried to improve the accuracy of the PDF functions using copulas. Making a weighted equivalent value for each hour of uncertain parameters can be considered as another prominent feature of this technique since this point can improve the computing speed in comparison to the existed stochastic methods. Along with abovementioned advantages, the proposed uncertainty modeling technique is not a certain method and is based on the probabilities. This is the first disadvantage of the proposed technique. Furthermore, requirement of a large amount of historical hourly data can be considered as another drawback of this method.

5.3. Load patterns as a result of incentive-based DRP

The numerical studies related to efficiency of our proposed incentive-based DRP is presented in this section. The amounts of self and cross elasticity values are extracted using fitting process of hourly historical data which is explained more in detail in [35]. Table 4 provides the elasticity coefficient values in day-ahead and intra-day market. The positive values of this table mean an inverse relation between price and demand, i.e. price increment results in demand reduction and vice versa. The opposite statement is true for the negative values.

The equivalent weighted load scenario for the microgrid is shown in Fig. 7. This figure also demonstrates the load curve after applying the proposed incentive-based DRP in day-ahead and intra-day markets. It is evident that our proposed DRP program is successful in diminishing the peak load and restoring it during off-peak and cheap periods. In addition, considering intra-day market results in more accurate load pattern modifications since it is closer to real-time operation.

Table 4. Self and cross elasticity values in day-ahead and intra-day market [35]

		valley	Off-peak	peak
Day-ahead market	valley	-0.0107	0.015	0.012
	Off peak	0.0147	-0.011	0.01
	peak	0.008	0.01	-0.01
Intra-day market	valley	-0.017	0.016	0.014
	Off peak	0.0157	-0.012	0.012
	peak	0.012	0.011	-0.009

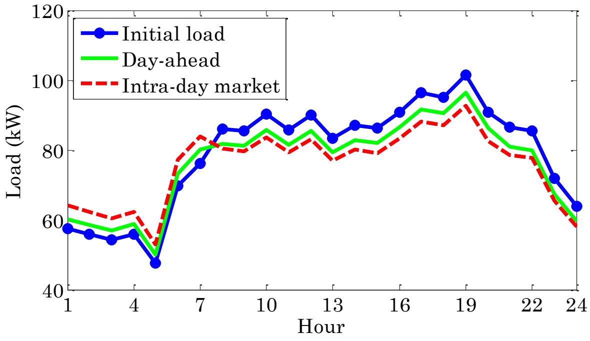


Fig.7. Impact of the proposed DRP on the load profile

5.4. Hourly microgrid EMS results

The numerical results of the microgrid EMS are obtained as an optimization problem including two main subcategory in which the effects of day-ahead and intra-day markets on EMS of microgrid are studied. The convergence process of GSO algorithm in simultaneous minimization of cost and emission corresponding to day-ahead and intra-day market are shown in Figs. 8 and 9, respectively.

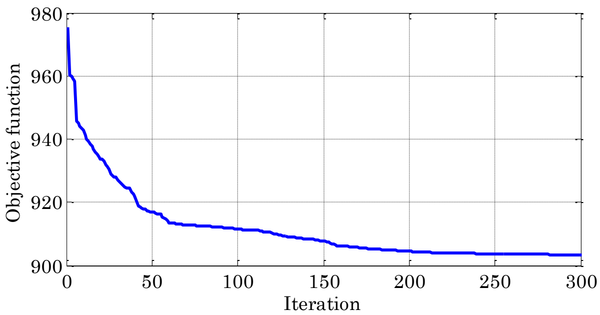


Fig. 8. Convergence process of GSO in day-ahead market

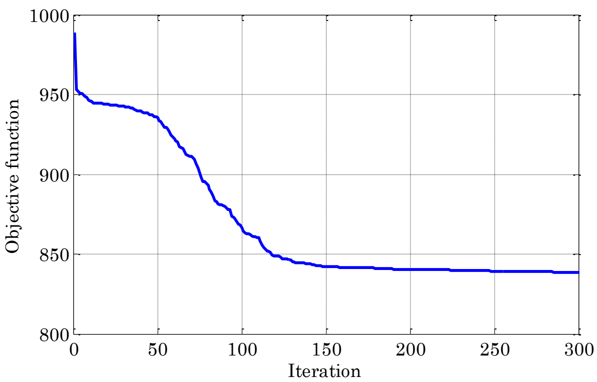


Fig. 9. Convergence process of GSO in intra-day market

The hourly simulation results for microgrid components in day-ahead and intra-day markets are given in Tables 5 and 6, respectively. In day-ahead market, the total cost is 538.62 $ with the emission equaling to 364.66 kg. However, the associated value of total cost and emission related to the same study case of Ref. [7] is 728.19 and 598.58, respectively.

Table 5. The hourly optimal solution in day-ahead market (Cost=538.62, Emission=364.66)

Hour	MT (kW)	FC (kW)	PV (kW)	WT (kW)	ESS (kW)	UG (kW)
1	6	4.28	0	2.05	17.86	30
2	6	29.98	0	2.18	-9.51	30
3	6	9.46	0	6.32	5.18	30
4	6	29.97	0	1.93	-9.13	30
5	13.44	3	0	5.76	-1.53	29.39
6	16.46	3	0	4.8	23.85	25.13
7	6	7.47	0	6.75	29.76	30
8	6.09	29.9	0	3.77	11.98	30
9	19.45	29.86	6.76	1.11	-5.89	30
10	7.41	29.79	12.63	0.07	5.83	30
11	13.8	18.4	3.62	25.56	-9.9	30
12	13.76	3	16.63	34.8	-5.95	23.15
13	6	4.27	21.24	1.39	16.32	30
14	16.19	29.26	28.31	5.93	-26.85	30
15	9.41	12.31	1.8	5.16	23.21	30
16	8.7	28.54	7.52	0.35	11.26	30
17	6	27.98	4.32	5.01	18.22	30
18	9.2	18.76	0	2.46	30	30
19	18.6	26.24	0	4.12	17.51	30
20	6	24.6	0	3.3	22.44	30
21	11.45	15.49	0	2.2	21.68	30
22	17.56	3	0	6.13	30	23.14
23	6	15.89	0	4.87	10.55	30
24	6	3	0	5.01	30	15.65

Table 6. The hourly optimal solution in intra-day market (Cost=507.2, Emission=330.93)

Hour	MT (kW)	FC (kW)	PV (kW)	WT (kW)	ESS (kW)	UG (kW)
1	15.36	3.2	0	1.59	13.86	30
2	16.97	3	0	1.91	26.21	14.15
3	12.57	3	0	7.55	26.87	10.38
4	7.22	27.76	0	6.29	-9.12	30
5	8.92	22.61	0	6.33	-14.96	30
6	6	26.2	0	1.1	13.75	30
7	26.22	25.32	0	1.89	0.43	30
8	6	13.83	0	5.93	24.53	30
9	28.83	5.16	2.59	3.16	9.97	30
10	14.3	8.41	10.49	0.39	19.93	30
11	20.34	3	12.52	29.81	30	-16.38
12	6	8.76	19.61	24.57	-6.01	30
13	6.09	3.55	21.75	14.5	0.94	30
14	16.59	3	25.62	0.1949	30	4.81
15	6	3.4	7.42	2.35	30	30
16	12.75	3	3.84	5.91	30	27.85
17	13.06	9.95	4.32	0.8	30	30
18	18.24	3	0	5.85	30	29.9
19	14.39	12.7	0	5.45	30	30
20	6	8.7	0	7.73	30	30
21	6	9.76	0	2.9	30	30
22	20.39	3	0	6.16	30	18.05
23	16.76	3	0	1	30	14.64
24	11.97	3	0	1.51	30	11.45

This great reduction in the values of cost and emission is as a result of utilizing the improved incentive based DRP and applying the proposed copula-scenario based uncertainty modeling method. While the DRP utilized in Ref. [7] was the preliminary version of this paper's DRP. In addition, the studies related to uncertain parameters were not performed in Ref. [7]. On the other hand, optimizing the cost and emission in intra-day market results in more accurate values since it is closer to real time. The total of cost and emission in this subcategory is 507.2 $ and 330.93 kg.

6. CONCLUSIONS

This paper tries to simultaneously optimize the operational cost and environmental pollution of a microgrid in EM problem using GSO algorithm. To reach this goal, the uncertainties related to wind and solar power are taken into account by a new method which is based on combination of copula function and scenario generation method. This paper has also applied an improved DRP in solving EM problem. Considering the incentive payments as a function of peak intensity, assuming the elasticity coefficients as a function of costumer type and consumption time, considering intra-day market in load pattern modifications are the three main properties of the proposed DRP. The proposed DRP results in two load patterns which correspond to day-ahead and intra-day markets. The numerical hourly results associated with microgrid EM have been extracted in both day-ahead and intra-day markets. The new hybrid uncertainty modeling technique generates two-dimensional PDF for uncertain parameters using copula function. Then a specific number of scenarios have been extracted by scenario generation method. In the last step, a weighted equivalent scenario is generated. Simulation results approve the efficiency of the proposed uncertainty modeling technique, improved DRP and microgrid EM method. Furthermore, the objective functions are more realistic in intra-day market since the load profile is closer to the real time. “”

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