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Multi-Objective Stochastic Programming in Microgrids Considering Environmental Emissions

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Abstract- *This paper deals with day-ahead programming under uncertainties in microgrids (MGs). A two-stage stochastic programming with the fixed recourse approach was adopted. The studied MG was considered in the grid-connected mode with the capability of power exchange with the upstream network. Uncertain electricity market prices, unpredictable load demand, and uncertain wind and solar power values, due to intrinsically stochastic weather changes, were also considered in the proposed method. To cope with uncertainties, the scenario-based stochastic approach was utilized, and the reduction of the environmental emissions generated by the power resources was regarded as the second objective, besides the cost of units' operation. The ε-constraint method was employed to deal with the presented multi-objective optimization problem, and the simulations were performed on a sample MG with one month of real data. The results demonstrated the applicability and effectiveness of the proposed techniques in real-world conditions.*

Keyword: Microgrid, Pollutant emission, Power market price, Stochastic scheduling, Uncertainty.

1. INTRODUCTION

This Microgrid (MG) is defined as a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries which acts as a single controllable entity with respect to the grid. An MG can connect and disconnect from the main grid to enable it to operate in both grid-connected and islanded modes [1]. As an efficient alternative to fossil fuels, renewable energy sources have received considerable attention due to their sustainable, cost-effective, and environmentally friendly characteristics [2]. The application of renewable energy sources is increasing in MGs worldwide.

Based on their control-ability, the power resources in MGs are divided into two main categories [3], [4]:

1) Controllable/dispatchable resources, as fuel cells (FCs), and diesel generators.
2) Uncontrollable/non-dispatchable resources, including photovoltaic (PV) cells, and wind turbines (WTs).

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In recent years, scheduling of MG with the high popularity of renewable resources has been a major topic in research, motivating extensive studies. In these studies, besides the economic issues, environmental aspects are considered as a new objective function in MG scheduling [5].

1.1. The literature review

The MGs scheduling problem is further complicated by the uncertainty involved in the demanded load and price of electricity in addition to the uncertainty of electrical power generated by the wind and solar power plants due to intrinsically inevitable weather changes. Three approaches are available to deal with these uncertainties: deterministic, probabilistic, and stochastic approaches. In the deterministic approach, the uncertain variables are considered equal to the expected/predicted values. In the other two approaches, the effect of uncertain variables is considered. In the stochastic approach, decision-making is performed under uncertainty and the corresponding output values are determined, while the probabilistic approach yields the probability density function (PDF) of outputs.

There are numerous studies regarding the optimal operation of MGs. In Ref. [6], a multi-objective optimization process based on modified particle swarm optimization was proposed to minimize total operation cost and environmental pollutant emissions (EPEs). Moreover, Ref. [7] presents an algorithm for energy management systems (EMSs) based on multi-layer ant colony optimization. Also, an economic scheduling approach was described in Ref. [8] for isolated MGs. In Ref. [9], an optimal planning method was proposed with the goal of minimizing the life cycle cost while taking into account EPEs. Furthermore, in Ref. [10], a multi-objective deterministic optimization approach based on the non-dominated sorting firefly algorithm was realized to optimize the economic and environmental objective functions. The intelligent EMSs introduced in references [11] and [12] to minimize the operation cost of MGs are based on resources' power generation forecasts considering weather condition changes, provided via the neural network-based forecast approach. Due to the stochastic nature of physical phenomena, even the most extreme models cannot accurately predict weather conditions. Therefore, the forecasted output power of WTs [13] and PV cells have large uncertainties. In the mentioned references, the impacts of uncertainty were not detailed and taken into account. In these studies, the problem was considered as a deterministic one, while deterministic approaches are not able to present reliable solutions, and uncertain factors are inevitable in the decision-making process.

The two-point estimate method is an approach for probabilistic uncertainty analysis in power systems [14]. In Ref. [15], a probabilistic approach based on the 2m point estimate method was utilized for the energy management of an MG, and the PDF of expected operating costs was extracted.

There are studies considering the stochastic nature of the MG energy management problem. For instance, Ref. [4] proposed a fuzzy multi-objective approach to minimize the total economic cost and network loss of MG. Also, this study entered the cost of converting EPEs, generated by resources, in the cost function. This approach was also adopted in Ref. [16] to consider emissions in the cost function. In Ref. [17], a stochastic framework was proposed with possible scenarios generated based on the forecast error of uncertain variables for the economic dispatch problem. In addition, Ref. [18] developed an improved multi-objective teaching-learning-based optimization method for cost and pollutant emission minimization. These goals were also realized in Ref. [19], where a fuzzy-based model was utilized. In Ref. [20], a new PV model was proposed, besides a scenario-based stochastic framework. Furthermore, Ref. [21] developed a stochastic framework based on scenarios for the coupled active and reactive market in smart distribution networks. Moreover, references [22] and [23] applied the scenario-based stochastic programming method for optimal scheduling realization in an MG. However, in these references, to cope with uncertainties, the problem was solved individually for each possible realization of the scenarios. Then, the weighted average of the respective results of scenarios was introduced as the stochastic problem's final solution. This approach, called the scenario result aggregation (SRA) method in this paper, failed to present realistic and reliable solutions. The non-reality of this approach is demonstrated in Case Study 2 in this paper and discussed in detail.

As previously noted, in some early studies in the field of MG energy management, the cost of generation only was selected as the optimization objective. Today, with increasing environmental concerns and efforts to reduce the EPEs, caused by thermal power plants, and the expansion of renewable resources, environmental aspects should be into account in the energy management problem of MGs. In addition to the mentioned references, in Ref. [24] and Ref. [25], emission limitation was considered in EMS optimization problem constraints to consider environmental aspects. Also, penalty cost factors were utilized in Ref. [26] to consider the effect of EPEs in the optimization process. In Ref. [27], an augmented ε-constraint method was utilized to consider the environmental aspects besides the units' operation cost in a smart distribution system. However, the advantage of this method over the ε-constraint method is mainly observed for multi-objective problems [28]. It is also notable that multi-objective evolutionary algorithms (EAs) that use non-dominated sorting and sharing have been criticized mainly for their computational complexity, their non-elitism approach, and the need for specifying a sharing parameter [29]. Therefore, in the present paper, to optimize the two mentioned objective functions in MGs, the ε-constraint method was selected to avoid more unnecessary computations and directly obtain the accurate Pareto front. The taxonomy of the most relevant studies regarding the MG energy management is presented in Table 1.

1.2. The paper contribution

The intrinsically intermittent nature of uncontrollable resources, besides uncertain load demanded power and upstream network electricity price changes considered in the present paper further complicates the day-ahead programming problem of MGs. In this paper, the scenario-based form of the two-stage stochastic programming approach with fixed recourse [30] was utilized to appropriately formulate the problem. The scenario-based framework developed in this paper was based on historical real recorded data on uncertain variables. Day-ahead forecasted values of uncertain variables and the respective deviations from the forecast values were not required in this approach. Also, in this paper, a scenario reduction process was utilized to eliminate low-effective scenarios and decrease the computation burden.

In this paper, besides the optimal operation cost of power resources, the reduction of pollutant emission gasses by thermal resources in MGs was realized. To solve the multi-objective optimization problem, the ε-constraint approach was adopted, and the respective Pareto fronts were extracted.

1.3. The paper organization

The paper is organized in the following sections: Section 2 discusses the methods utilized in this paper, including two-stage stochastic problem formulations, coping with uncertainties and possible scenarios, conversion formulations of wind speed and solar irradiance, respectively, to the WT and PV output power, and dealing with multi-objective optimization problem via the ε-constraint method. Section 3 presents the simulation results in different case studies. The non-applicability of the deterministic approach and SRA versus the reliable results of the stochastic approach is illustrated in Case Studies 1, 2, and 3, respectively. The effectiveness of the strategy proposed in this paper is demonstrated in Case Study 4 on a test MG network with one month of real historical recorded data, considering all uncertainties and power resources' constraints, by implementing the day-ahead programming results in the next day, with really occurring values. Finally, conclusions are presented in Section 4.

2. METHODS

2.1. Two-stage stochastic programming with fixed recourse

The classical two-stage stochastic linear programming formulation with fixed recourse is as follows [30]:

$$\min Z = c^T x + E_\xi \left[\min\{q(\omega)^T y(\omega)\} \right] \tag{1}$$

S.T.:

$$\begin{aligned} &Ax = d \\ &T(\omega)x + Wy(\omega) = m(\omega) \\ &x \geq 0, y(\omega) \geq 0. \end{aligned} \tag{2}$$

Where, x and y are the first-stage and second-stage decision vectors, respectively. In this formulations, c and d are known vectors, and A and W are known matrixes. The recourse matrix, W, is fixed and does not

Table 1. The taxonomy of MG energy management studies

Reference no.		Deterministic	Probabilistic	Stochastic	The approach for modeling the environmental impacts
[6]	Day-ahead EMS	✓			Multi-objective: Non-dominated sorting based on particle swarm optimization (PSO) algorithm
[8]	Day-ahead EMS	✓			—
[10]	Day-ahead EMS	✓			Multi-objective: Non-dominated sorting based on firefly algorithm
[15]	Day-ahead EMS		✓		—
[4]	Day-ahead EMS			✓	Single-objective: Conversion/removal cost of pollutants
[16]	Day-ahead EMS			✓	Single-objective: Conversion/removal cost of pollutants
[17]	Day-ahead EMS			✓	—
[18]	Day-ahead EMS			✓	Multi-objective: Non-dominated sorting based on teaching-learning-based algorithm
[19]	Day-ahead EMS			✓	Multi-objective: Fuzzy-based combination of objective functions
[20]	Day-ahead EMS			✓	—
[21]	Day-ahead EMS			✓	Single-objective: Penalty cost of pollutant emissions
[22]	Day-ahead EMS			✓	—
[23]	Day-ahead EMS			✓	—
The present paper	Day-ahead EMS			✓	Multi-objective: ε-constraint method
[24]	Real-time EMS				Single-objective: Pollutant acceptable limits as the problem constraint
[25]	Real-time EMS				Single-objective: Pollutant acceptable limits as the problem constraint

change, while ω changes as a random event ($\omega \in \Omega$). Therefore, it is called fixed recourse formulation. However, $q(\omega)$, $T(\omega)$, and $m(\omega)$ are matrixes that change with changes in ω. In (1), the recourse term $E_\xi[]$ is the expectation of uncertain terms in the objective function.

The purpose is the optimal operation scheduling of a grid-connected MG under uncertainties. The studied MG is connected to the upstream network and could exchange power. It contains a micro-turbine (MT), FC, battery energy storage system (BESS), and load demand. Load demand, which is called residual load (RL), and the upstream network electricity power price are subject to a high degree of uncertainty. The cost function (1) is as the following:

$$\begin{aligned} Z &= b_{MT} P_{MT} + b_{FC} P_{FC} + b_{BESS} P_{BESS} + \\ &E_\xi \left[\min\{b_N(\omega) P_N(\omega)\} \right] \end{aligned} \tag{3}$$

Where, b_X is considered as the bid of power received from X resource, and N denotes the upstream network.

The first-stage decision variables, x vector, contain MT, FC, and BESS output powers. The time of making the first-stage decisions is day-ahead. In the second-stage decision variable, $y(\omega)$, which contains $P_N(\omega)$, the MG's power exchange value with the upstream network will be determined. The time of making the second-stage decisions is the next day, when the value of b_N is determined by the upstream network.

Assume random vector ξ with finite support. The equivalent extensive form Ref. [30] of the two-stage stochastic programming with fixed recourse formulation is a linear problem as the following:

$$\min \left[c^T x + \sum_{k=1}^{n_s} \pi^{(k)} (q^{(k)})^T y^{(k)} \right] \tag{4}$$

S.T.:

$$\begin{aligned} &Ax = d \\ &T^{(k)} x + W y^{(k)} = m^{(k)}, \forall k \\ &x \geq 0, y^{(k)} \geq 0, \forall k, k = 1, ..., n_S . \end{aligned} \tag{5}$$

Where, k is the scenario counter index, and n_s is the total number of scenarios. The scheduling period in this paper is divided into hourly intervals. For each time period, the MG single objective optimization problem in the form of a linear programming problem considering constraints is as follows:

$$\min \left(b_{MT} P_{MT} + b_{FC} P_{FC} + b_{BESS} P_{BESS} + \sum_{k=1}^{n_s} \pi^{(k)} b_N{}^{(k)} P_N{}^{(k)}\right) \tag{6}$$

S.T.:

$$\begin{aligned} &P_{MT} + P_{FC} + P_{BESS} + P_N{}^{(k)} = P_{RL}{}^{(k)}, \forall k \\ &P_{MT}^{\min} \leq P_{MT} \leq P_{MT}^{\max} \\ &P_{FC}^{\min} \leq P_{FC} \leq P_{FC}^{\max} \\ &P_{BESS}^{\min} \leq P_{BESS} \leq P_{BESS}^{\max} \\ &P_N^{\min} \leq P_N^{(k)} \leq P_N^{\max}, \forall k, k = 1, ..., n_s . \end{aligned} \tag{7}$$

In these formulations, only the cost of units' operation and cost of power exchange with the upstream network are considered. The power balance constraint, the first line of Eq. (7), ensures that, for each scenario, the sum of total generated power by units, the power of BESS, and power exchanged with the upstream network are equal to the load demanded power. Other constraints preserve the sources' limitations. The problem can be solved by a linear programming problem-solver. It is assumed that the total output power of WT and PV units are received by the MG. Therefore, P_{WT} and P_{PV} are not the decision variables in the cost function. These are considered in problem constraints. In Eq. (7), P_{RL} that was introduced as the RL power is as follows:

$$P_{RL}{}^{(k)} = P_{LD}{}^{(k)} - P_{WT}{}^{(k)} - P_{PV}{}^{(k)} \tag{8}$$

P_{WT} and P_{PV} are dependent on weather condition, and respectively change as wind speed and solar irradiance change. As a result, P_{WT} and P_{PV} are uncertain variables, besides P_{LD} and b_N, in the problem.

2.2. Scenarios

Historical recorded data for uncertain variables, including the upstream network electricity price, load demand, wind speed and solar irradiance in the same hours of previous days can be considered as possible scenarios. Considering real values for one month, 31 probable values are obtained per variable every hour. Therefore, there will be 31^4 scenarios with four uncertain variables in each hour of the day. An effective scenario reduction process is necessary to decrease the number of scenarios and, consequently, reduce the calculation burden. The scenario reduction process is described below:

The distance between two scenarios $\xi^{(i)}$ and $\xi^{(j)}$ is defined as 2-norm:

$$d(\xi^{(i)}, \xi^{(j)}) = \left\| \xi^{(i)} - \xi^{(j)} \right\| \tag{9}$$

Where, i and j are the scenario numbers. Then, the scenarios reduction algorithm [31] is implemented iteratively until the desired numbers of scenarios remain.

1. Remove scenario $\xi^{(r)}$ satisfying:
   $$\pi^{(r)}.\min_{i \neq r} d(\xi^{(i)}, \xi^{(r)}) = \min_{k \in (1,2,...n_s)} \pi^{(k)}.\left(\min_{j \in (1,2,...n_s), j \neq k} d(\xi^{(k)}, \xi^{(j)}) \right)$$
2. $n_s \leftarrow (n_s - 1)$
3. $\pi^{(r^*)} \leftarrow \pi^{(r^*)} + \pi^{(r)}$, where $\xi^{(r^*)}$ is the nearest scenario to $\xi^{(r)}$
4. Repeat until the desired numbers of scenarios remain.

2.3. Wind speed to WT output power conversion

The output power of WT, while wind speed is v, can be calculated as follows [32]:

$$P_{WT} = \begin{cases} 0 & v < v_{cut-in} \text{ or } v > v_{cut-out} \\ \dfrac{v - v_{cut-in}}{v_{rated} - v_{cut-in}} P_{\max} & v_{cut-in} < v < v_{rated} \\ P_{\max} & v_{rated} < v < v_{cut-out} \end{cases} \tag{10}$$

Where, v_{cut-in} is the cut-in speed of the WT (m/s), $v_{cut-out}$ is the cut-out speed of the WT (m/s), v_{rated} is the rated speed of the WT (m/s) and P_{max} is the maximum output power of the WT (kW).

2.4. Irradiance to PV cell output power conversion

The PV equivalent circuit output current, I, can be expressed as a function of the module output voltage V, as follows [33]:

$$I(V) = I_{sc}\left\{1 - C_1\left[\exp\left(\frac{V + \Delta V}{C_2 \cdot V_{oc}}\right) - 1\right]\right\} + \Delta I \quad (11)$$

Where,

$$C_1 = \left(1 - I_{mp}/I_{sc}\right)\cdot \exp\left[-V_{mp}/(C_2 \cdot V_{oc})\right],$$

$$C_2 = \frac{V_{mp}/V_{oc} - 1}{Ln\left(1 - I_{mp}/I_{sc}\right)},$$

$$\Delta I = \alpha\left(S/S_{ref}\right)\Delta T + \left(S/S_{ref} - 1\right)\cdot I_{sc}, \quad (12)$$

$$\Delta V = -\beta \cdot \Delta T - R_s \cdot \Delta I,$$

$$\Delta T = T - T_{ref},$$

$$T = T_A + 0.02 \cdot S.$$

Where, α is the current change temperature coefficient at reference insolation (A/C°), β is the voltage change temperature coefficient at reference insolation (V/C°), I is the module current (A), I_{mp} is the module maximum power current (A), I_{sc} is the module short-circuit current (A), S is the total tilt insolation (kWh/m^2), S_{ref} is the reference insolation (kWh/m^2), R_s is the module series resistance(Ohms), T is the cell temperature (C°), T_A is the ambient temperature (C°), T_{ref} is the reference temperature (C°), ΔT is the change in cell temperature (C°), V is the module voltage (V), V_{mp} is the module maximum power voltage (V) and V_{oc} is the module open-circuit voltage (V).

The output power of PV could be calculated as $P_{PV} = V \cdot I$.

2.5. Multi-objective optimization with ε-constraint method

Scalarization method, the ε-constraint [34], was utilized to solve the multi-objective problem, and get the respective Pareto front. The multi-objective optimization problem Eq. (13) is substituted by ε-constraint problem, as Eq. (14):

$$\min \ \left(f_1(x), \ldots, f_p(x)\right) \quad (13)$$

$$\min \ f_j(x)$$

$$\text{S.T.:} \quad (14)$$

$$f_k(x) \le \varepsilon_k, k = 1, \ldots, p; k \ne j.$$

Where, $\varepsilon \in \mathbb{R}^p$.

Table 2. Power resources details

	Bid ($/kWh)	Min power (kW)	Max power (kW)
MT	0.5	0	30
FC	0.3	0	30
BESS	0.4	0	30
Network	0.45	-30	30

One objective of this paper is to minimize the cost of power generation units and exchange power with the upstream network. The other objective is the minimization of the value of EPEs generated by the power resources. The second objective is considered as a constraint based on Eq. (14). For each hour of the day, by changing the value of ε, the Pareto front is obtained.

3. SIMULATIONS

In this section, the simulation results regarding the proposed methods are presented. For this purpose, five case studies, including deterministic, SRA, stochastic recourse, and realistic cases are presented in detail.

3.1. Case study 1: Deterministic case

Suppose that an MG including MT, FC, and BESS is connected to the upstream network. The details on the MG are presented in Table 2. Power exchange with the upstream network is implementable. This set must supply part of the load demand known as P_{RL}, equal to 66 kW. To minimize the total cost of supplying RL for an hour, each resource's output power and P_N must be calculated.

The problem is formulated as:

$$\min \ (0.5P_{MT} + 0.3P_{FC} + 0.4P_{BESS} + 0.45P_N)$$

S.T.:

$$P_{MT} + P_{FC} + P_{BESS} + P_N = P_{RL},$$

$$0 \le P_{MT} \le 30,$$

$$0 \le P_{FC} \le 30,$$

$$0 \le P_{BESS} \le 30,$$

$$-30 \le P_N \le 30.$$

This is a linear programming problem. The relevant solutions for P_{MT}, P_{FC}, P_{BESS}, and P_N are 0, 30, 30, and 6 kW, respectively, and the total cost of supplying RL is \$23.7.

This solution was predictable, considering the bid of power resources. FC provides the most cost-effective power for meeting the needs, up to 30 kW; then, BESS and network power are more economic, respectively. Supposing that the bid of exchanging power with network changes from 0.45 to 0.55 \$/kW, then MT power generation will be more economic than the network power as well. If it changes to 0.35 \$/kW, receiving power from the network would be more economic than BESS. This makes some changes in the coefficient of P_N in the cost function. On the other hand, if the load demand changes, the cost function does not change, but the problem constraints will be altered and, as a result, the problem's solution will be different. Therefore, consideration of uncertainties in real-world conditions needs the application of an efficient approach.

3.2. Case study 2: SRA case

Suppose that, in the previous case study, there were two and three possible values for b_N and P_{RL}, respectively, as depicted in the scenario tree in Fig. 1. Values and corresponding probabilities are presented in Table 3. The probability for each scenario, $\pi^{(k)}$, is equal to $\pi^{(b_N)} \cdot \pi^{(P_{RL})}$.

The impacts of scenarios must be considered in the problem. In the first case, as a deterministic problem, selecting the uncertain variables equal to their average values makes b_N and P_{RL} equal to 0.45 \$/kW, and 66 kW, respectively. These are the values calculated in the deterministic case. It is clear that this approach does not present acceptable and realistic results. The other approach, that seems to be logical, is independently solving the problem for each scenario, and the aggregation of the results considering the probability of each scenario. This approach is referred as SRA in this paper. The results of this approach are presented in Table 4. In this table, the weighted average is the combination of scenario results, considering their relevant probabilities.

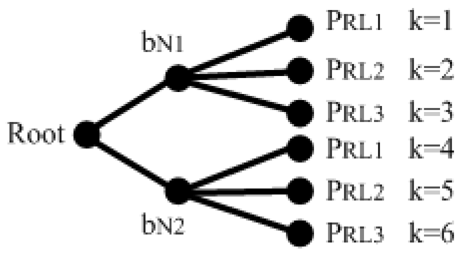

Fig.1. The scenario tree for case study 2

Table 3. The value of uncertain variables and scenario probabilities

b_N(\$/kWh), $\pi^{(b_N)}$	P_{RL}(kW), $\pi^{(P_{RL})}$	k, $\pi^{(k)}$
0.2, 0.75	40, 0.3	1, 0.225
	52.5, 0.4	2, 0.3
	110, 0.3	3, 0.225
1.2, 0.25	40, 0.3	4, 0.075
	52.5, 0.4	5, 0.1
	110, 0.3	6, 0.075

Table 4. Problem solution for each scenario

k	1	2	3	4	5	6	Weighted average
$\pi^{(k)}$	0.225	0.3	0.225	0.075	0.1	0.075	
P_{MT} (kW)	0	0	20	10	22.5	30	9.75
P_{FC} (kW)	10	22.5	30	30	30	30	23.25
P_{BESS} (kW)	0	0	30	30	30	30	14.25
P_N (kW)	30	30	30	-30	-30	20	18.75
Total cost (\$)	9	12.75	37	-10	-3.75	60	17.55

It seems that, for economically supplying RL, power resources should be set as the right-hand side column of Table 4. Applying the SRA, if Scenario 3 occurs with a probability of 0.225, MG encounters a \$21.3 cost in reality and lack of 44 kW power to supply RL. If Scenario 5 occurs with a probability of 0.1, MG encounters a \$40.05 cost and 13.5 kW extra power than RL power. Similar states will happen for other scenarios. Therefore, this approach is not suitable for this problem, and a method is needed to encounter with the problem scenarios, so that executing the obtained results in the real world must not lead to surplus power or power shortage.

3.3. Stochastic recourse case

This case study is similar to Case 2, but the stochastic recourse model described in Section 2.1 is utilized to obtain a correct and reliable solution. As described earlier, the first-stage decision variables are P_{MT}, P_{FC}, and P_{BESS}, and the second-stage decision variable is P_N. The results are given in Table 5.

The stochastic recourse model considers all scenarios simultaneously for making decisions. Based on Table 5, the decided values for P_{MT}, P_{FC}, and P_{BESS}, the first-stage variables are fixed while scenario realization changes. It must be noted that the decision on P_N is postponed until the time b_N is determined in the next day. By deciding to fix the first-stage variables as the above values, this model accepts a \$67 cost with a probability of 0.075 for decreasing the cost in other sce-

Table 5. Problem solution with two-stage stochastic programming by recourse model

k	1	2	3	4	5	6
$\pi^{(k)}$	0.225	0.3	0.225	0.075	0.1	0.075
P_{MT} (kW)	20	20	20	20	20	20
P_{FC} (kW)	30	30	30	30	30	30
P_{BESS} (kW)	30	30	30	30	30	30
P_N (kW)	-30	-27.5	30	-30	-27.5	30
Total cost (\$)	25	25.5	37	-5	-2	67
Expected total cost (\$)	26.05					

-narios. This approach is in contrast with the SRA case in which scenarios were considered individually. The stochastic approach has no extra power or lack of power for supplying RL, which is the correct solution. The expected total cost from the stochastic approach is equal to $\boldsymbol{\pi}^{(\mathbf{k})} \cdot \textbf{The total cost}^{(\mathbf{k})}$ is $\$\mathbf{26.05}$.

3.4. Case study 4: Real case

A typical grid-connected MG as Fig. 2, was employed to study a real case with real input data in this case study.

In Fig. 2, the MT is considered as the EPE source. CO and NOx emission values, 1.38 and 0.51 (lb/MWh), respectively, are negligible in comparison with the CO2 value, which is equal to 1765 (lb/MWh) for a typical MT [35]. The details of power resources in MG are provided in Table 6.

It is assumed that the battery bank is being fully charged during network electricity low-price periods by the MG's control center. The effect of keeping it ready to use is considered in the bid of BESS.

Parameters of the WT and PV installed in MG are given in Tables 7 and 8, respectively. Also, the ambient temperature, T_A, was considered to be as Table 9.

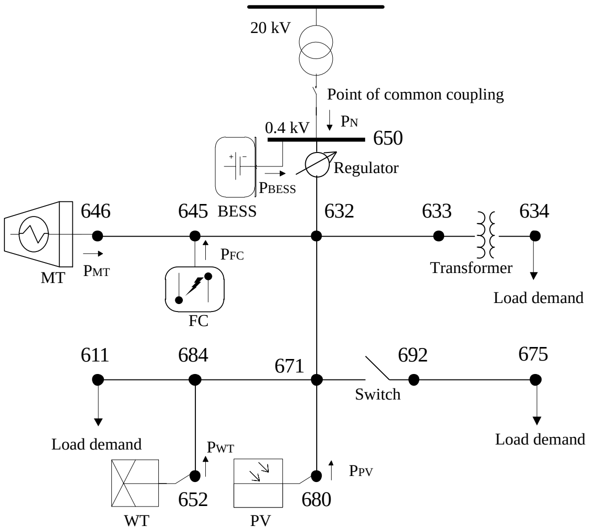

Fig. 2. The single-line diagram of the studied MG

Table 6. The details of MG in case study 4

Source	Bid ($/kWh)	Emission (lb/kWh)	Min power (kW)	Max power (kW)
MT	0.5	1.765	0	30
FC	0.3	—	0	30
BESS	0.4	—	0	30
Utility network	Uncertain	—	-30	30
P_{LD} (Uncertain)	—	—	0	115
P_{WT} (Uncertain)	—	—	0	20
P_{PV} (Uncertain)	—	—	0	10

Table 7. Parameters of the WT, aerodyn SCD 8.0/168 [36]

Rated power/P_{max} (kW)	Cut-in speed (m/s)	Cut-out speed (m/s)	Rated speed (m/s)	Hub height (m)
8000	3.5	25	11.5	100

Table 8. Parameters of the solar module, Siemens SM 50/H [37]

Electrical Parameter	Value
Rated power, $P_{max}(W)$	50
Rated current , $I_{mp}(A)$	3.15
Rated voltage, $V_{mp}(V)$	15.9
Short circuit current,$I_{sc}(A)$	3.35
Open circuit voltage, $V_{oc}(V)$	19.8
Temp. coefficient of the short-circuit current, (Change of I_{SC} with temperature), $\alpha(mA/°C)$	+1.2
Temp. coefficient of the open-circuit voltage, (Change of Voc with temperature), $\beta(V/C°)$	-0.077
Reference Irradiance, $E_{ref}(W/m^2)$	1000
Reference temperature, $T_{ref}(C°)$	25
Ambient temperature, $T_A(C°)$	20
Module Series Resistance$R_s(Ohms)$	0.39383

Table 9. T_A value in the next day

Hour	7	8	9	10	11	12	13	14	15	16	17	18
T_A(C°)	11	12	14	18	20	21	23	27	27	22	19	15

The real input data used in this case study include the network load demand extracted from Ref. [38], the wind speed in 99 m above the ground extracted from Ref. [39], and the solar irradiance extracted from Ref. [40]. The recorded data are extracted for all 24 hours of the day from August 1 2005 to August 31 2005. Furthermore, the network electricity price data are extracted from Ref. [41], from August 1 2018 to August 31 2018, for all 24 hours of the day. In this case study, the 24-hour period of the 1st day of September was considered as the programming period. The real data in this day are also extracted from the mentioned databases.

To coordinate the WT output power values with the intervals presented in Table 6, the calculated wind powers are divide by 400, and the number of parallel solar modules is considered to be 270#. Furthermore, the total load demand power is divided by 100000. For electricity price, all values are divide by 0.1, $(\frac{€}{\mathrm{MW}}/0.1) \rightarrow (\$/\mathrm{kW})$.

The number of possible scenarios for each uncertain variable is reduced to 10, as described in Section 2.2, and the results are illustrated in Figures 3 to 6.

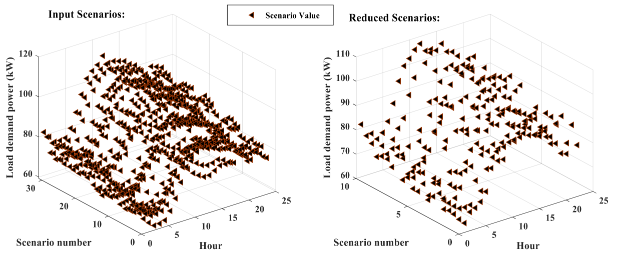

Fig. 3. Load demand scenario values

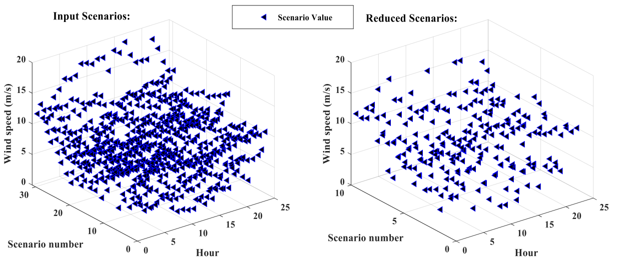

Fig. 4. Wind speed scenario values

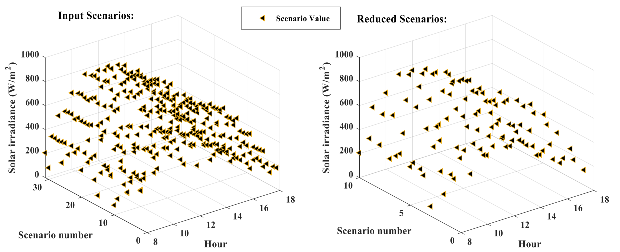

Fig. 5. Solar irradiance scenario values

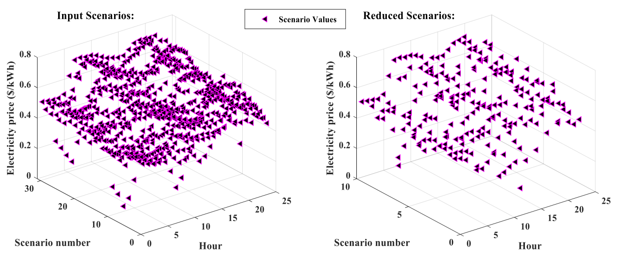

Fig. 6. The upstream network electricity price scenario values

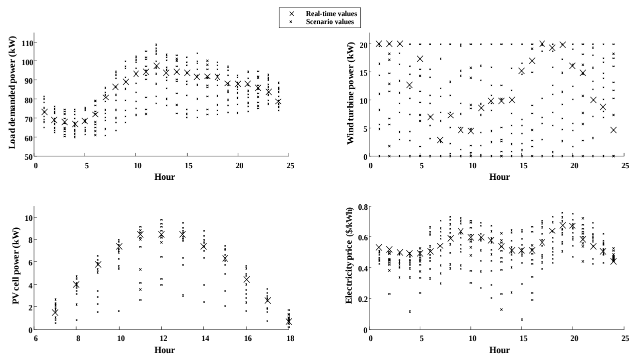

Fig. 7. The comparison between day-ahead scenarios and real values happened in the next day

Wind speed values after the scenario reduction process are converted into WT output power, as described in Section 2.3. In addition, solar irradiance scenario values are converted into PV output power, as described in Section 2.4. These values, besides the upstream network electricity price, and load demand scenarios are compared with real values occurring in the next day, with the results depicted in Fig. 7.

The resultant solution of the presented scheduling approach, without EPE consideration, is summarized in Table 10. In this table, the positive P_N denotes receiving power from the upstream network, and the negative sign denotes sending power from the MG to it.

Table 10. The solution results of case study 4, without pollutant emission consideration

h	Day-Ahead Decisions Results				The Next Day Decision and Results	
	P_{MT} (kW)	P_{FC} (kW)	P_{BESS} (kW)	Anticipated Total Cost ($)	P_N (kW)	Total Cost ($)
1	0	30	30	21.9836	-18.82	11.0078
2	0	30	30	20.6323	-23.34	8.9678
3	0	30	30	20.0934	-24.22	8.9983
4	0	30	30	19.5744	-3.17	19.4450
5	0	30	30	20.1152	-12.94	14.6489
6	16.79	30	30	21.5046	-3.43	27.6639
7	16.56	30	30	22.5230	10.91	35.1765
8	16.18	30	30	25.7528	13.06	36.8127
9	18.20	30	30	27.4073	17.04	40.9085
10	21.85	30	30	28.6192	18.18	42.7664
11	26.85	30	30	29.4409	9.41	40.0028
12	30	30	30	30.7759	7.28	40.1781
13	4.78	30	30	29.3538	28.38	38.6435
14	3.49	30	30	28.3202	29.94	38.0305
15	3.28	30	30	28.5796	16.99	31.2848
16	3.15	30	30	29.0005	10.59	27.9946
17	21.92	30	30	28.8319	-15.83	23.0254
18	25.3	30	30	28.4808	-16.31	23.2408
19	25.79	30	30	28.0526	-21.32	19.5257
20	30	30	30	26.0581	-18.76	23.4189
21	27.86	30	30	25.3859	-13.33	27.1494
22	25.98	30	30	26.4399	-2.11	32.8581
23	30	30	30	27.9944	-5.84	33.0698
24	0	30	30	25.2465	23.78	31.4227
Sum				620.1668		676.2409

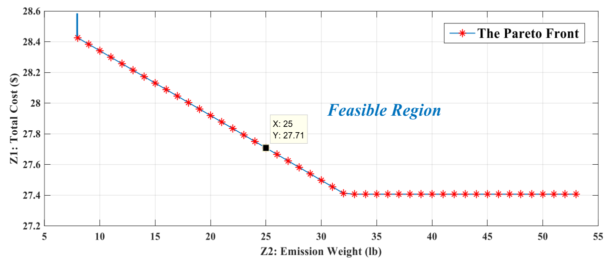

Fig. 8. The resultant Pareto front with multi-objective optimization for 9 a.m.

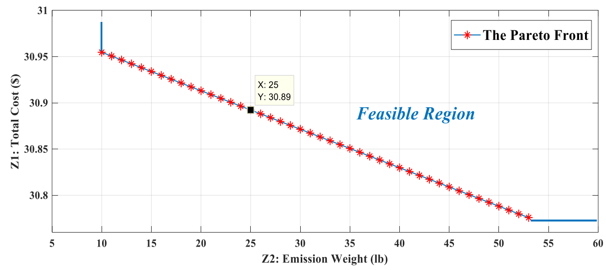

Fig. 9. The resultant Pareto front with multi-objective optimization for 12 a.m.

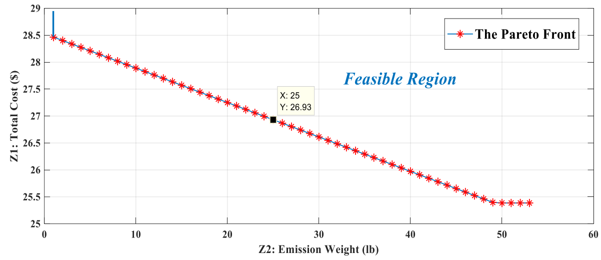

Fig. 10. The resultant Pareto front with multi-objective optimization for 9 p.m.

Table 11. The solution results of case study 4, with maximum pollutant emission weight of 25 lb

h	Day-Ahead Decisions Results				The Next Day Decision and Results	
	P_{MT}(kW)	P_{FC}(kW)	P_{BESS}(kW)	Anticipated Total Cost ($)	P_N (kW)	Total Cost ($)
1	0	30	30	21.9836	-18.82	11.3978
2	0	30	30	20.6323	-23.34	9.3579
3	0	30	30	20.0934	-24.22	9.3883
4	0	30	30	19.5744	-3.17	19.8350
5	0	30	30	20.1152	-12.94	15.0389
6	14.16	30	30	21.5084	-0.80	28.4202
7	14.16	30	30	22.6604	13.31	36.0169
8	14.16	30	30	25.9215	15.08	37.7415
9	14.16	30	30	27.7083	21.08	42.1955
10	14.16	30	30	28.9545	25.87	44.2509
11	14.16	30	30	29.8470	22.098	41.9257
12	14.16	30	30	30.8923	23.12	42.0974
13	4.78	30	30	29.3538	28.38	39.1529
14	3.49	30	30	28.3202	29.94	38.5078
15	3.28	30	30	28.5796	16.99	31.7567
16	3.15	30	30	29.0005	10.59	28.4634
17	14.16	30	30	29.1727	-8.07	24.2699
18	14.16	30	30	29.5597	-5.17	25.5221
19	14.16	30	30	29.5851	-9.69	22.2922
20	14.16	30	30	28.0665	-2.92	26.8637
21	14.16	30	30	26.9313	0.36	29.0373
22	14.16	30	30	27.5586	9.71	34.0323
23	14.16	30	30	28.5363	9.99	33.8407
24	0	30	30	25.2465	23.78	31.8127
Sum				629.8021		703.2177

If the air pollutant emission of MT is considered as Table 6, the resultant Pareto fronts for sample hours are illustrated in figures 8-10. By taking the maximum pollutant emission weight equal to 25 lb, the scheduling results are presented in Table 11. As expected, it is observed that considering a limitation for EPEs increased the total cost of operation.

4. CONCLUSIONS

In this paper, a day-ahead two-stage stochastic multi-objective framework was proposed to reduce EPEs, besides the cost of units' operation in grid-connected MGs. This was realized considering four uncertainty sources: uncertain load demand, wind speed, solar irradiance, and electricity price. The optimization process was implemented on a typical MG with real input data. The ε-constraint method was adopted to deal with the presented multi-objective optimization problem. The proposed approaches were validated as they were tested with real-world uncertain variables. The findings confirmed the applicability of the proposed approaches and the robustness of the results under vast uncertainties.

In the deterministic case study, the optimal scheduling problem was studied in a simple MG. However, the other cases considered uncertainties. Then, six possible realizations were considered in the SRA case. The inefficiency of the SRA approach was demonstrated numerically, followed by a simple stochastic recourse case, simultaneously considering all possible realizations, in order to obtain realistic solutions. In the next case (the Real one), all uncertainties and limitations of resources were taken into account, and different problems with and without pollutant emission consideration were solved. The outline of the findings in different case studies is presented in Table 12.

In Case Study 4, the proposed approach was validated using numerical simulations on real-world data collected for different variables. Based on the results depicted in Table 12, the error ((real total cost − the anticipated total cost)/real total cost) is equal to 8.3% and 10.4% with and without considering emission, respectively. It was observed that the proposed stochastic approach ensured the supply of the load demand by increasing the cost by only about 10% more than the anticipated values, satisfying all constraints. This additional cost is acceptable and reasonable while considering various uncertainties.

Table 12. The review of results for different case studies

Case study	Deterministic	SRA	Stochastic recourse	Real	
Test base	A simple MG problem	A simple MG problem	A simple MG problem	MG with one month real data	
Considered Uncertainty	—	✓	✓	✓	
Anticipated Total cost ($)	23.7	Unacceptable results	26.05	Emission not considered	Emission considered < 25 lb
				620.1668	629.8021
Real Total cost ($)				676.2409	703.2177

It is hoped that this research will contribute to the understanding of the way to meet the uncertainties in power system scheduling. The decision-making process under uncertainty proposed in this paper can be generalized to any number of uncertain variables and different types of power resources as well. The limitation of this approach, however, is in the need for the recorded historical data, which are nowadays accessible for most areas of the world.

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