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A Stochastic Approach for Environmental Operation in Microgrids Considering Parameters Uncertainty

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ABSTRACT

The uncertainty of variables such as the intermittency of renewable energy sources (RES), electrical demand alteration, and market price volatility is considered an important issue in the optimization model of microgrids (MG). At present, MG has received growing interest, which needs to administrate the variation related to future changes. The main contribution of this study is to present a stochastic optimization approach for planning the electrical energy of MG considering the intermittency of RES, market price instability, and electrical demand variation. The optimal daily energy scheduling of the MG is required to minimize the pollutant emissions over a 24-h horizon. The general algebraic modeling system (GAMS) is used to solve the optimization problem formulated in this paper. In the suggested stochastic approach, uncertainty modeling of the uncertainty of RESS, electrical demand, and the market price is modeled by the well-known scenario approach, in which the fuzzy C-means (FCM) is employed to cluster the scenarios generated. For the overlapped data set, the FCM gives the best result for it. Thus, FCM operates well than the standard hard clustering algorithm. The results obtained validate the effectiveness of the solution.

Keywords: Energy management; environmental operation; microgrid; renewable energy sources; stochastic approach.

1 INTRODUCTION

One of the most vital challenges fronting the world is climate variation caused by the emissions of fossil fuel power stations. Consequently, transforming traditional power plants into intelligent power plants (smart grids) has received substantial attention [1-2]. Smart grids have many environmental profits: reduced burning of fossil fuels, reduced greenhouse gases, improved interaction between customers and smart grid operators, and increased installation of renewable energy resources (RESs) [3-4]. Microgrid (MG) has an important role to convert traditional grids into smart grids. A microgrid is a localized grid that comprises different types of distributed generator, storage system, and electrical load [5-7].

At present, the energy management of MG with minimizing the total operation cost of MG and the greatest employment of the RES to lessen the environmental pollution has become the most important issue in the microgrid operation system [8]. Whereas power generation from fossil fuel releases numerous pollutants, such as carbon dioxide(CO_2), sulfur dioxide (SO_2), and nitrogen dioxide (NO_x), into the atmosphere [9].

Consequently, the energy management (EM) of MGs is employed for getting an optimal generation schedule of the different DGs and ES to achieve the objective function while complying with the operating constraints. However, random demand, the intermittent nature of RES, and the volatile market price have an important influence on the EM of MGs [10]. Accordingly, the most important challenge facing MG operators is the considered the uncertainty of future variables, such as RESs, market price, and electrical load.

In the literature, some researchers [11-15] considered the objective function to minimize pollutant emission of the MG while ignoring the uncertain parameter. To redress this gap, in this paper a stochastic optimization method is proposed for scheduling the energy of MG considering random demand, the intermittent nature of RES, and the volatile market price to minimize the pollutant emissions over a 24-h horizon. The typical MG considered includes different distributed generators such as a photovoltaic (PV), wind turbine (WT), micro-turbine (MT), fuel cell (FC), and battery storage system as shown in Figure 1 [16].

2 Uncertainty Modeling

In the stochastic approach, indicating the suitable scenarios is serious to uphold decisions depending on authentic measurements of variations [16].Consequently, the guesses of uncertainty parameters must be express the measurement procedure in a true way. Uncertainty modelling is a usual approach to epitomize the variation of the output power of RESs, volatile market price, and variation of demand rather than supposing sure data of known parameters in the deterministic method, therefore random distributions are utilized as input of random optimization to simulator the probability of parameters [17].

A set of scenarios are created to represent the variables variation's possibilities of the systems. Each scenario has a definite probability. Clustering methods may be categorized into two kinds soft clustering and hard clustering. When dividing the data in to clusters where each data goes to only single cluster. But in the soft clustering such as the presented algorithm (FCM) each data may belong to more than one cluster depended on their participation levels which show the level to which the data items go to the different clusters [17].

FCM clustering is utilized to group a certain number of data (M) into a pre-set number of clusters (O) where O=5 in this work. It is worth noting that a higher number of scenarios make the problem more extensive and complicated and require a higher computational burden. The data required to be clustered are gathered in a matrix Z including a set of column vectors zj where $j \in \{1,2,....M\}$. FCM clustering requires two parameters to group Z: O and the component of fuzziness (d), where $d \in k$, and $d>1$. A pre-set tolerance (eps) is presupposed to end the process. Figure 2 shows the steps of the FCM algorithm in details [18]. FCM is used to create the scenarios of the electrical demand, market price, and the output power of RESs and also is utilized to cluster the scenarios into a certain number of scenarios.

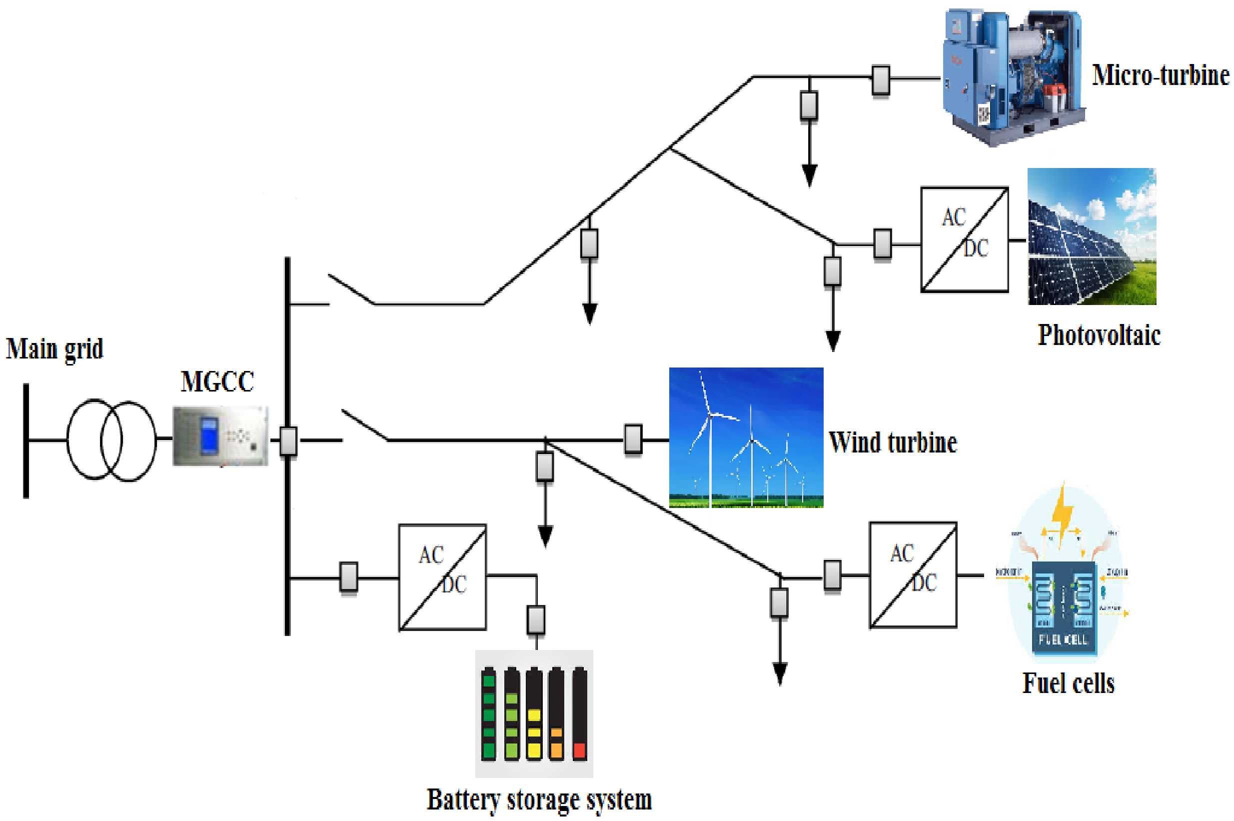

Figure 1: The microgrid model

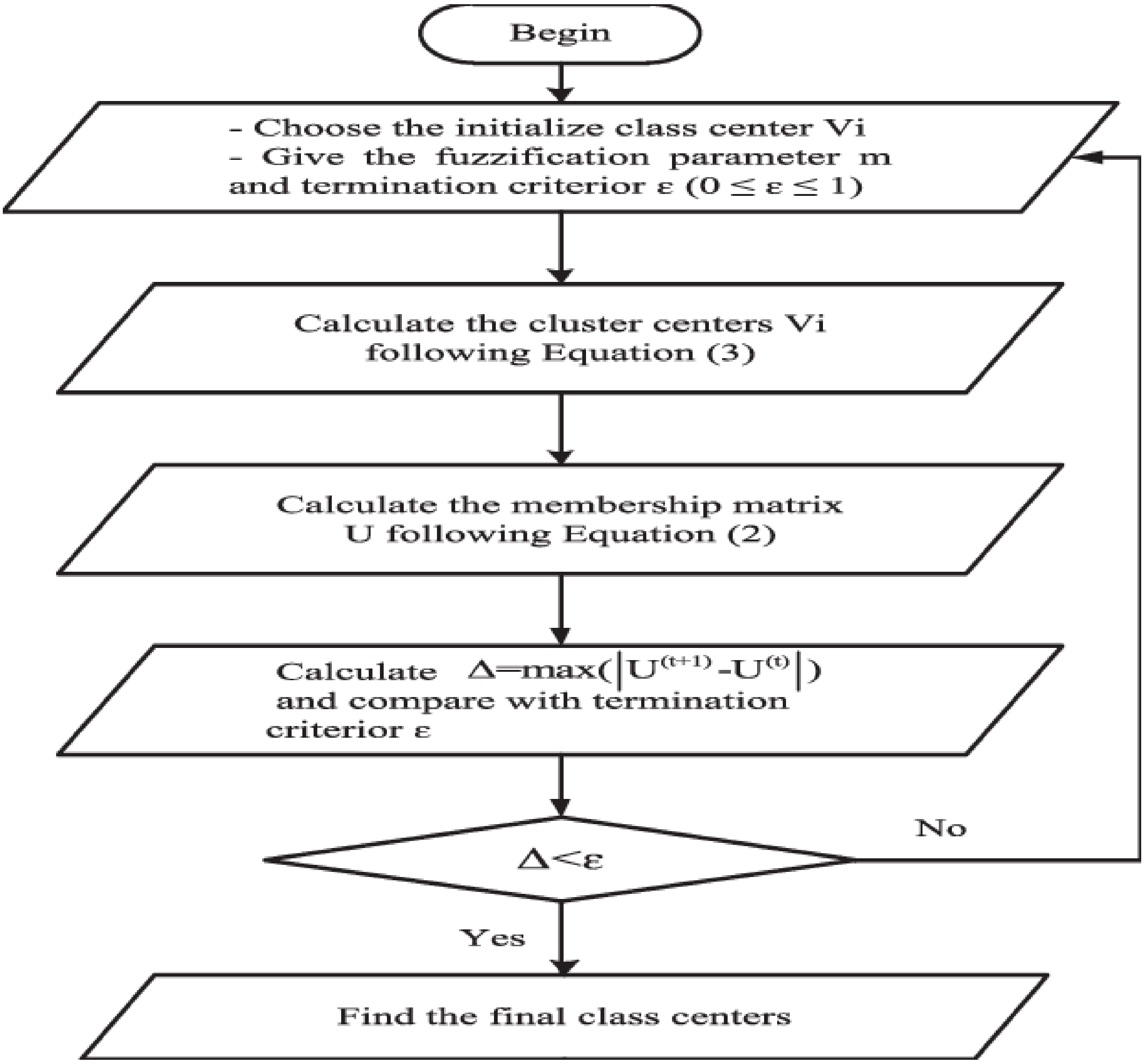

Figure 2: Fuzzy c-means clustering algorithm [18]

3 Problem Formulation

This section presents the objective function and constraints of the problem.

3.1 Emission function formulation

The main objective function (f(x)) is to minimize the total MG emissions during taking into account market price, electrical load, and RES uncertainties. The main cause of emissions out of the MG is generating sources. The emissions contain CO_2, SO_2, and NO_x. The mathematical formula of the total emissions of grid-connected MG (f(x)) at time h can be expressed in (1).

$$min\, f(x) = \sum_{h=1}^{H}[\, \sum_{s=1}^{NS}(\chi^{s,h} \times k_{grid,s,h}^{co_2} \times k_{grid,s,h}^{So_2} \times k_{grid,s,h}^{No_x} \times P_{grid,h}) + \sum_{s=1}^{MS}\left(\omega^{s,h} \times k_{PV}^{co_2} \times k_{PV}^{So_2} \times k_{PV}^{No_x} \times PV_{P,s}^{h}\right) + \sum_{s=1}^{WS}\left(Љ^{s,h} \times k_{WT}^{co_2} \times k_{WT}^{So_2} \times k_{WT}^{No_x} \times WT_{P,s}^{h}\right) + \left(m_{FC}^{h} \times k_{FC}^{co_2} \times k_{FC}^{So_2} \times k_{FC}^{No_x} \times FC_{P}^{h}\right) + \left(m_{MT}^{h} \times k_{MT}^{co_2} \times k_{MT}^{So_2} \times k_{MT}^{No_x} \times MT_{P}^{h}\right) + (k_{batt}^{co_2} \times k_{batt}^{So_2} \times k_{batt}^{No_x} \times P_{batt}^{h})] \qquad (1)$$

where $k_{grid,s,h}^{co_2}$, $k_{PV}^{co_2}$, $k_{WT}^{co_2}$, $k_{FC}^{co_2}$, $k_{MT}^{co_2}$, and $k_{batt}^{co_2}$ are the CO_2injected from the main grid, PV, WT, FC, MT, and BSS, respectively. $k_{grid,s,h}^{So_2}$, $k_{PV}^{So_2}$, $k_{WT}^{So_2}$, $k_{FC}^{So_2}$, $k_{MT}^{So_2}$, and $k_{batt}^{So_2}$ are the SO_2injected from the main grid, PV, WT, FC, MT, and BSS, respectively. $k_{grid,s,h}^{No_x}$, $k_{PV}^{No_x}$, $k_{WT}^{No_x}$, $k_{FC}^{No_x}$, $k_{MT}^{No_x}$, and $k_{batt}^{No_x}$ are the NO_xinjected from the main grid, PV, WT, FC, MT, and BSS, respectively.

3.2 Constraints

3.2.1 Active power limits of generating units

The output power of each distributed generator in the MG should be within its limits as expressed in (2)-(6).

$$P_{grid,h}^{min} \le P_{grid,h} \le P_{grid,h}^{max}, \qquad \forall h \tag{2}$$

$$PV_{P,s}^{h-min} \le PV_{P,s}^{h} \le PV_{P,s}^{h-max}, \qquad \forall h \tag{3}$$

$$WT_{P,s}^{h-min} \le WT_{P,s}^{h} \le WT_{P,s}^{h-max}, \qquad \forall h \tag{4}$$

$$FC_{P}^{h-min} \le FC_{P}^{h} \le FC_{P}^{h-max}, \qquad \forall h \tag{5}$$

$$MT_{P}^{h-min} \le MT_{P}^{h} \le MT_{P}^{h-max}, \qquad \forall h \tag{6}$$

3.2.2 Balance of electrical loads

The energy generated from the all distributed generators in the MG and the main grid must be equal to the total electrical load scenarios ($P_{load,s,h}$) and their probabilities (LS with probabilities $\psi^{s,h}$) as expressed in (7).

$$MT_P^h m_{MT}^h + FC_P^h m_{FC}^h + WT_{P,s}^h + PV_{P,s}^h + P_{grid,h} + P_{batt}^{h-dis} = \sum_{s=1}^{LS} \psi^{s,h} \times P_{load,s,h}) + P_{batt}^{h-ch} \tag{7}$$

4 Simulation Results and Discussion

Table 1 shows the emission information and the power limits of the main grid and each distributed generator in the studied MG [2]. Based on historical data, the FCM was used to generate 1000 scenarios to represent the uncertainty of electrical load, volatile market price, and PV and WT output power alteration.

To facilitate the operation process, the FCM clustering algorithm is applied to decrease the generated scenarios to the most announced five scenarios. The clustered scenarios of electrical load and market price at each hour are shown in Figure 3.

The clustered scenarios of the output power of PV and WT are shown in Figure 4. Figures 5,6,7,and 8 show the probability of the existence of the scenarios of RESs, electrical demand, and market price. Figure 4 shows that the output power of PV at hour 1 to hour 7 and at hour 18 to hour

24 is the same equal to zero, thus the probability of occurrence of PV scenarios in these intervals is the same as shown in Figure 5.

Table 1: Emissions information of the main grid and distributed generators

Units	WT	PV	MT	FC	Grid
Min power (kW)	0	0	6	3	-30
Max power (kW)	15	25	30	30	30
CO_2(Kg/MWh)	0	0	720	460	0
SO_2(Kg/MWh)	0	0	0.0036	0.003	0
NO_x(Kg/MWh)	0	0	0.0075	0.0075	0

*NA: Not applicable

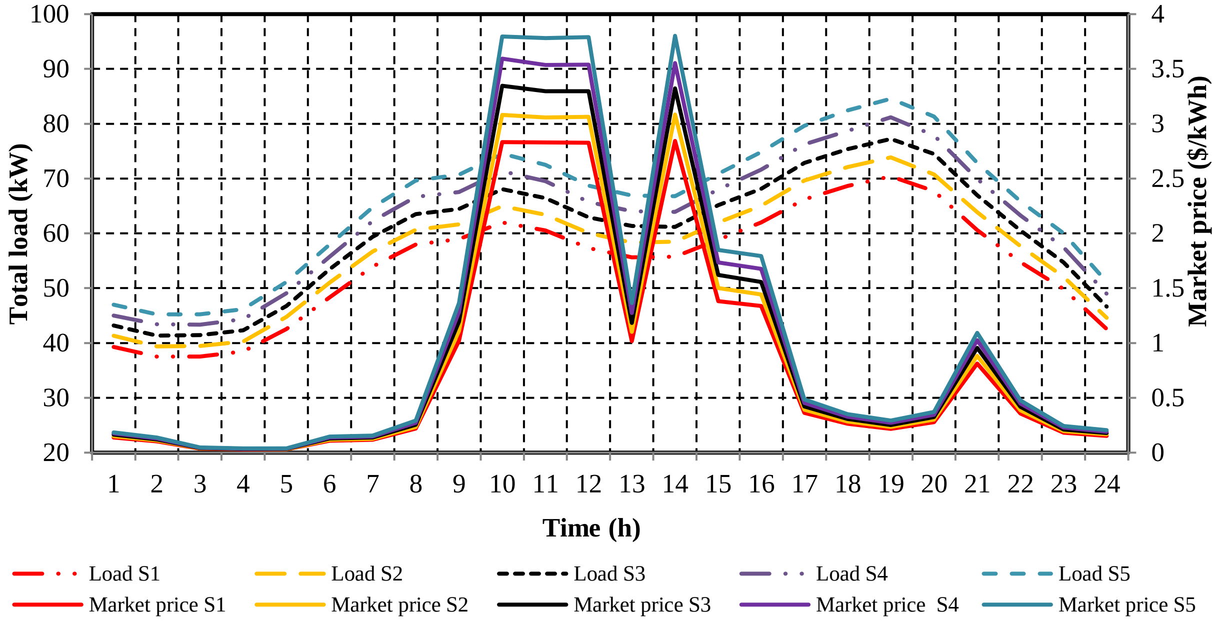

Figure 3: Market price and electrical load scenarios

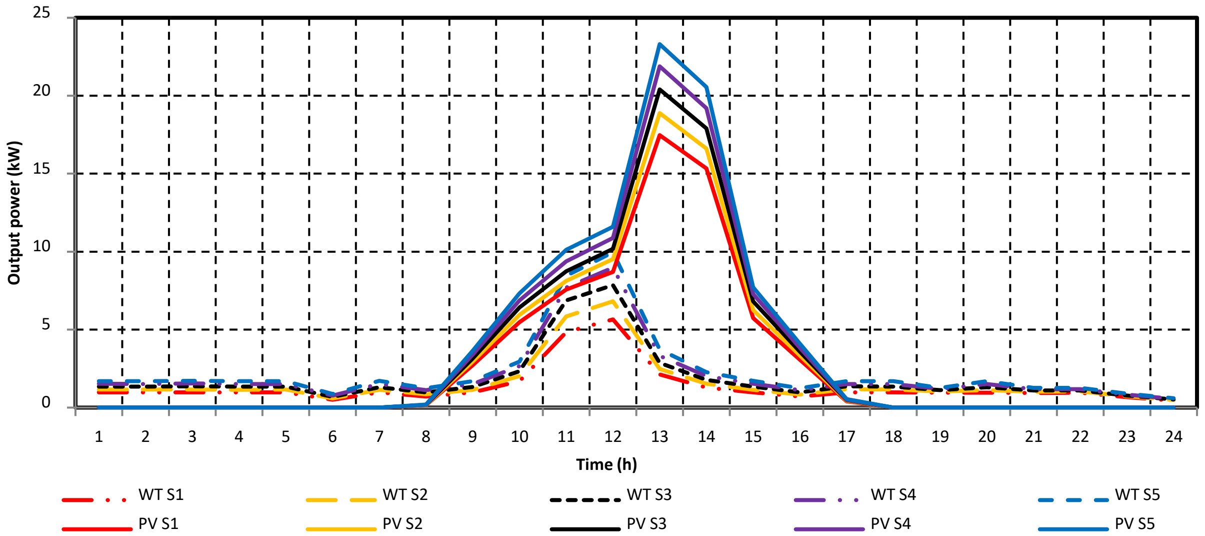

Figure 4: The output power of PV and WT scenarios

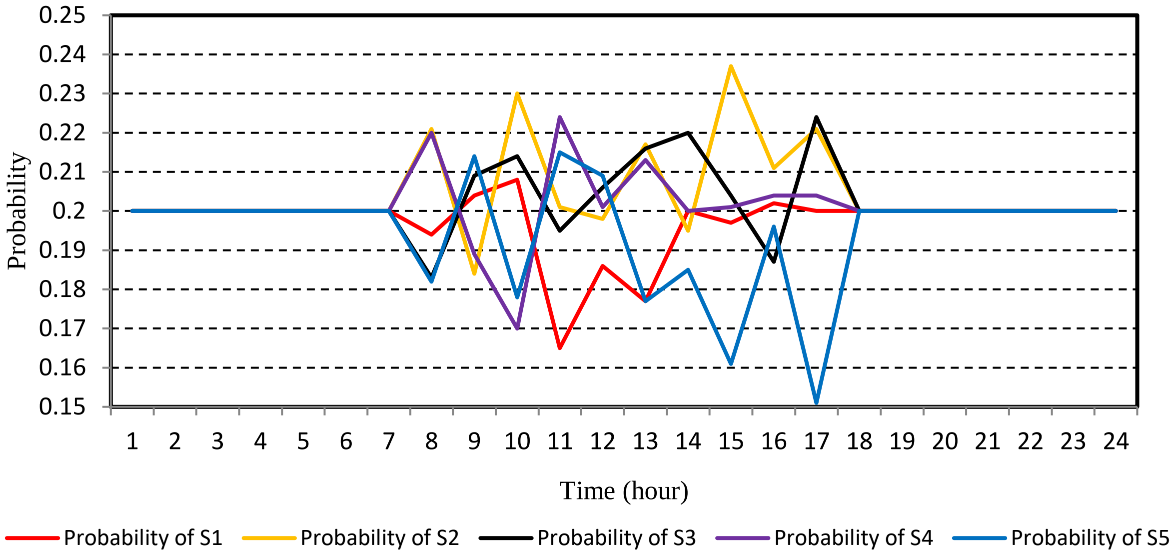

Figure 5: The probability of PV scenarios

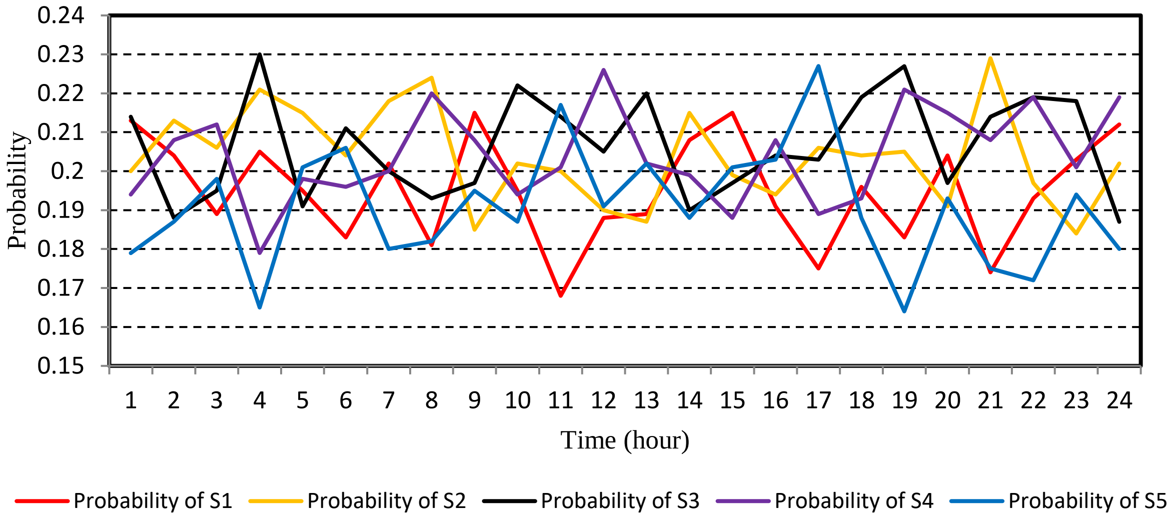

Figure 6: The probability of WT scenarios

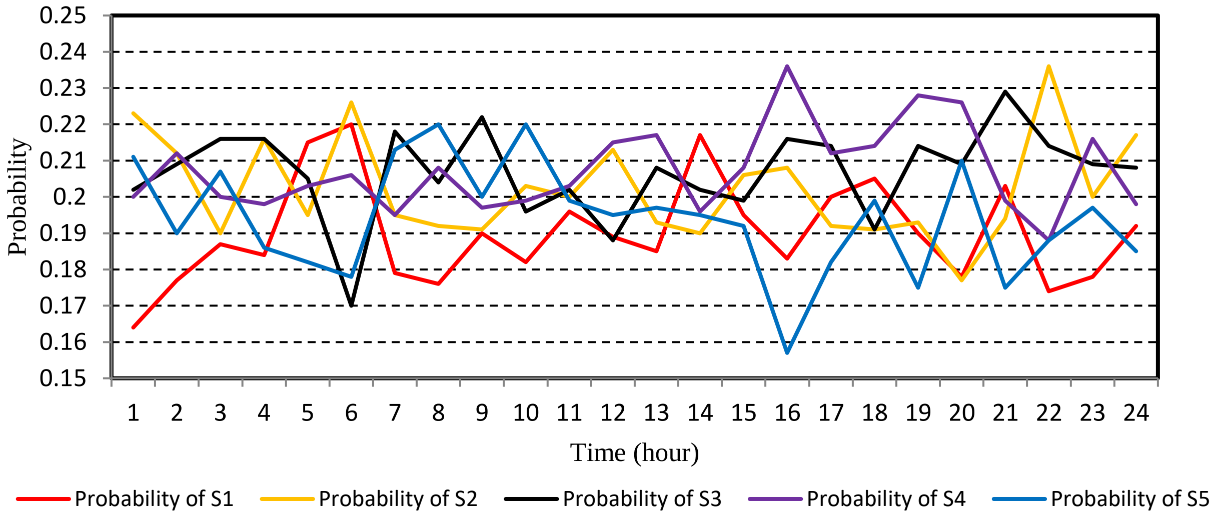

Figure 7: The probability of demand scenarios

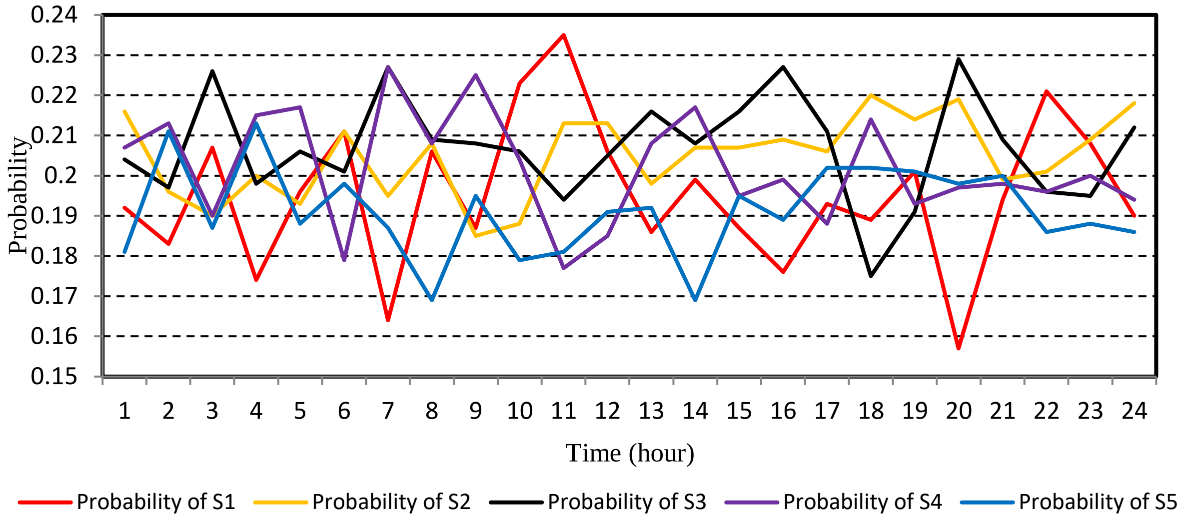

Figure 8: The probability of market price scenarios

The optimal stochastic model for scheduling the energy of MG is executed to minimize the total emissions of the MG. We can see from Table 2 that the total operating cost of the MG is 1132.9 €ct/day and the total emission of the MG is 324.4 Kg/day.

Table 2: The total operating cost and emission of the MG

	Result
The total operating cost (€ct/day)	1132.901
Total emission (Kg/day)	314.439

The output powers of the main grid and distributed generators in the MG under random demand, the intermittent nature of RES, and the volatile market price are shown in Figure 9. Optimal power planning is requested to achieve the minimum emission of the MG during the day. Figure 9 shows that the output power of PV, WT, MT, FC, and the power exported from the MG to the main grid depend on the emissions emitted from each source in addition to the considered constraints. It is clear from Table 1 that the renewable sources (PV and WT) are zero-emissions sources. Thus, the power available from WT and PV is fully consumed over a 24-h horizon as shown in Figure 9.

It can be seen from Table 1 that the MT emission is high. Hence, the power consumed from the MT is low to create pollution-free environments. In the intervals that have high load and low power output of renewable energy need to consume power from the MT although it pollutes the environment to satisfy the MG constraint. Also, it can be seen from Figure 9 that the battery energy storage did not affect the operation of the MG to achieve the minimization of the MG emission because the sum of available energy from renewable energy sources at each hour is less than the total electrical load, so it is fully used to supply the load electricity and also the use of MT and FC in cases of achieving electrical balance only because they are polluting sources of the environment.

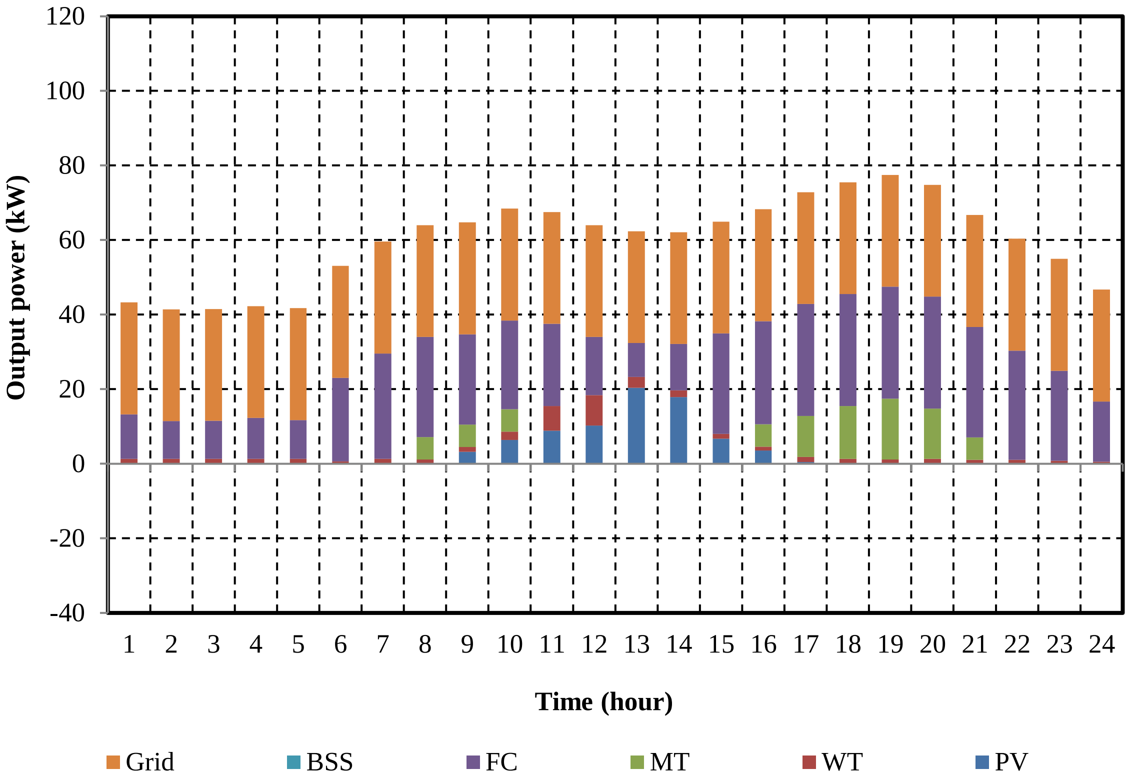

Figure 9: Optimal hourly output powers of the grid, BSS, FC, MT, WT, and PV under uncertainty parameters

5 Conclusions

A stochastic optimization approach is introduced to plan the power of the MG, taking into account random demand, the intermittent nature of RES, and the volatile market price. Based on historical data, the FCM was applied to generate scenarios to represent the uncertainty of electrical load, volatile market price, and PV and WT output power alteration. This paper introduces a schedule for the energy of the MG to minimize the pollutant emissions over a 24-h horizon taking into account numerous constraints linked to the operation of the MG and the uncertainty of parameters. The output power of PV, WT, MT, FC, and the power exported from the MG to the main grid depend on the emissions emitted from each source in addition to the considered constraints. The renewable sources are zero-emissions sources. Thus, the power available from WT and PV is fully consumed over a 24-h horizon. Also, the power consumed from the MT is low to create pollution-free environments Lastly, the issue that was outside the work of the study, and will be comprised in future works, is the techno-environmental concern to minimize the total operation cost and the pollutant emission MG over a 24-h horizon at the same time with taking into account numerous constraints linked to the system operation and the uncertainty of parameters.

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