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A New Hybrid Fuzzy-Stochastic Model for Day-ahead Scheduling of Isolated Microgrids

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***Abstract*—Scenario-based stochastic programming (SBSP) methods have been used broadly to cope with power system operation and planning uncertainties. For SBSP, probability density functions (PDFs) of uncertain parameters must be known and many scenarios are typically generated to precisely approximate the PDFs causing computational burden. On the other hand, uncertainties via fuzzy programming methods can be handled without knowing the related PDFs by considering fuzzy numbers. However, the respective solutions depend on the value of α-cut. As a result, to mitigate the aforementioned drawbacks and to exploit the benefits of both fuzzy optimization and SBSP, a novel hybrid fuzzy-stochastic programming model is proposed to model uncertainty in the day-ahead scheduling of isolated microgrids. A modified IEEE 33-bus test system is deployed as a case study to analyze the applicability of the proposed model, which was implemented in AMPL and solved using CPLEX solver. The comparison of results for the deterministic, the fuzzy programming, and the proposed method demonstrates that the proposed hybrid method enhanced the fuzzy programming model and guaranteed the robustness of the solutions by slightly increasing the total cost of the microgrid by 2.3%.**

Keywords—Fuzzy programming, energy management, microgrid, renewable energy, stochastic optimization, uncertainty.

I. INTRODUCTION

The main objective in conventional power systems was to keep the system's reliability as high as possible to guarantee the continuous delivery of electrical energy. However, such an approach led to excessive prices in electricity bills and substantial polluted gas emissions due to the high proportion of coal-based power stations in the centralized power generation [1]. Nowadays, engineers, researchers, and electricity utilities aim to minimize energy generation costs, while maintaining the system's resiliency and reliability in acceptable ranges [2]. Consequently, electricity generation is still a lucrative business, yet the system's efficiency improved thanks to deregulation and electricity markets [3]. Moreover, the emergence of new technologies linked to distributed generation (DG), electric vehicles (EVs), and distributed energy storage (DES) systems paves the way for the proliferation of renewable energy integration and utilization. Microgrids (MGs), in both isolated (islanded) and grid-connected modes, can also accommodate these new technologies and contribute to the transition from fuel-based centralized power systems toward decarbonized and decentralized ones [4]. The scheduling of MGs means determining the power generation of dispatchable DG units, the consumption of controllable loads such as EVs, and the charging and discharging of DES systems. To this end, and due to the importance of generation cost, day-ahead scheduling of MGs is modeled as an optimization problem in which the main objective is usually to minimize the total cost of MGs or to maximize the profit [5]. However, other objective functions such as voltage deviation, frequency deviation, emissions, and renewable curtailment also have been addressed [6]. Furthermore, a day-ahead scheduling of isolated MGs has been studied widely in the literature. In [7], a model for scheduling of isolated MGs is proposed, while unexpected failures and outages are included in order to guarantee high-level of reliability in isolated MGs. A novel model is presented in [8] to minimize the costs linked to the operation of isolated MGs, reactive power generation, spinning reserve, and load shedding. In [9], a multi-objective optimization model is proposed for isolated MGs so as to minimize voltage deviation, power loss, and total cost of MGs, while the voltage stability constraint is included in the model. In [10], different demand response programs and their impacts on optimal energy management of isolated MGs are analyzed and compared. A scheduling model for isolated MGs is suggested in [11] at which hydrogen-based energy storage and various demand response programs are accommodated in the model.

Uncertainty linked to renewable energy generation and electric loads such as electric vehicles can substantially affect the validity of the deterministic models [12]. Consequently, the modeling and handling of uncertainties play a decisive role in the scheduling of MGs. In [13], two-stage stochastic model is suggested to model energy management of MGs so as to minimize the cost in resilient unbalanced MGs. Moreover, a stochastic mixed-integer linear programming model is presented in [14], while uncertainties associated with wind speed, solar irradiance, demand, and electricity price are included. Reference [15] uses a fuzzy programming method to model uncertainties related to power demand, solar generation, and wind power generation in scheduling of MGs. This method is advantageous when the exact PDFs of uncertain parameters are unknown; consequently, stochastic optimization cannot be used directly. Nevertheless, due to the key role of uncertainty modeling in the optimal scheduling of MGs, in this study, a novel hybrid fuzzy-stochastic model is proposed to exploit the advantages of both stochastic and fuzzy programming models while avoiding the computational burden. The contributions of this paper can be highlighted as follow:

- A novel hybrid fuzzy-stochastic method for modeling uncertainties in the optimal scheduling of MGs to take

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advantage of both stochastic optimization and fuzzy programming, while trying to overcome drawbacks of stochastic programming, including computational burden and the need for probability density functions.

- Modeling uncertainties related to wind power and photovoltaic units' generation through fuzzy numbers (i.e., fuzzy possibilistic distributions) and scenario generation for α-cut.

II. HYBRID FUZZY/STOCHASTIC PROGRAMMING

This section presents a novel method for modeling uncertainties based on fuzzy programming and stochastic optimization. In (1), a general form for i-th linear constraint in mathematical optimization is presented, where a_i and b_i are exact, crisp, and known parameters, and x is a continuous decision variable [16]. By taking advantage of fuzzy numbers, (1) can be rewritten as (2), in which the values of constraint coefficients (i.e., $\tilde{a}$ and $\tilde{b}$) are fuzzy and imprecise. The aforementioned fuzzy coefficients can be modeled via fuzzy numbers, which are a particular type of fuzzy set that are both convex and normalized [17]. The model is solvable by deploying off-the-shelf solvers like CPLEX by transforming these fuzzy constraints to the equivalent normal constraints using the fuzzy ranking concept, as presented in (3). By assuming that the fuzzy numbers have triangular membership functions ($\mu_{\tilde{a}_i}$and $\mu_{\tilde{b}_i}$), the new coefficients $L_{\tilde{a}_i}$, $M_{\tilde{a}_i}$, and $R_{\tilde{a}_i}$ are calculated based on the α-cut concept, according to (4)–(7), where a_i^p, $Cor_{\tilde{a}_i}$, and a_i^o are the pessimistic, core, and optimistic values of fuzzy number $\tilde{a}_i$, respectively [18], this concept is visualized in Fig. 1., illustrating that fuzzy programming is conceptually different from stochastic programming as there is no probability distributions. In a similar way, $L_{\tilde{b}_i}$, $M_{\tilde{b}_i}$, and $R_{\tilde{b}_i}$ can be calculated based on (8)–(11) in which b_i^p, $Cor_{\tilde{b}_i}$, and b_i^o are the pessimistic, core, and optimistic values of fuzzy number $\tilde{b}_i$. It is worth mentioning that α may take any value from 0 to 1 (i.e., $\alpha \in [0,1]$).

$$a_i x \le b_i\,;\ \forall i \tag{1}$$

$$\tilde{a}_i x \le \tilde{b}_i;\ \forall i \tag{2}$$

$$\tilde{a}_i x \le \tilde{b}_i \triangleq \begin{cases} L_{\tilde{a}_i}(\alpha)x \le L_{\tilde{b}_i}(\alpha);\ \ \forall i \\ M_{\tilde{a}_i}(\alpha)x \le M_{\tilde{b}_i}(\alpha);\ \forall i \\ R_{\tilde{a}_i}(\alpha)x \le R_{\tilde{b}_i}(\alpha);\ \ \forall i \end{cases} \tag{3}$$

$$L_{\tilde{a}_i}(\alpha) \triangleq min\{a|\mu_{\tilde{a}_i}(a) \ge \alpha\} = \left(Cor_{\tilde{a}_i} - a_i^p\right)\alpha + a_i^p;\ \forall i \tag{4}$$

$$R_{\tilde{a}_i}(\alpha) \triangleq max\{a|\mu_{\tilde{a}_i}(a) \ge \alpha\} = a_i^o - \left(a_i^o - Cor_{\tilde{a}_i}\right)\alpha;\ \forall i \tag{5}$$

$$M_{\tilde{a}_i}(\alpha) = \alpha Cor_{\tilde{a}_i} + 0.5(1-\alpha)\left(a_i^o + a_i^p\right);\ \forall i \tag{6}$$

$$Cor_{\tilde{a}_i} \triangleq \{a|\mu_{\tilde{a}_i}(a) = 1\} \tag{7}$$

$$L_{\tilde{b}_i}(\alpha) \triangleq min\{b|\mu_{\tilde{b}_i}(b) \ge \alpha\} = \left(Cor_{\tilde{b}_i} - b_i^p\right)\alpha + b_i^p \tag{8}$$

$$R_{\tilde{b}_i}(\alpha) \triangleq max\{b|\mu_{\tilde{b}_i}(b) \ge \alpha\} = b_i^o - \left(b_i^o - Cor_{\tilde{b}_i}\right)\alpha \tag{9}$$

$$M_{\tilde{b}_i}(\alpha) = \alpha Cor_{\tilde{b}_i} + 0.5(1-\alpha)\left(b_i^o + b_i^p\right);\forall i \tag{10}$$

$$Cor_{\tilde{b}_i} \triangleq \{b|\mu_{\tilde{b}_i}(b) = 1\} \tag{11}$$

Although the fuzzy programming approach can be used to model uncertainty, the feasibility set and the optimal solution depends on the value of α. Hence, to address the dependency of the α values, the above fuzzy constraints and their equivalent crisp constraints can be transformed to hybrid stochastic-fuzzy constraints by considering a set of scenarios for the α value; for example, $\alpha \in \alpha_S$ where we can define $\alpha_S = \{0, 0.1, 0.2, \ldots, 0.9, 1.0\}$. Therefore, (3) can be rewritten as (12). As the number of scenarios is limited (e.g., 10 scenarios) and the constraints are linear, such new constraints can be used efficiently for modeling uncertainties in the day-ahead scheduling of isolated MGs, while keeping the problem tractable.

$$\tilde{a}_i x \le \tilde{b}_i \triangleq \begin{cases} L_{\tilde{a}_i}(\alpha_s)x \le L_{\tilde{b}_i}(\alpha_s);\ \ \forall i,s \\ M_{\tilde{a}_i}(\alpha_s)x \le M_{\tilde{b}_i}(\alpha_s);\forall i,s \\ R_{\tilde{a}_i}(\alpha_s)x \le R_{\tilde{b}_i}(\alpha_s);\ \ \forall i,s \end{cases} \tag{12}$$

III. MATHEMATICAL FORMULATION

A. *Fuzzy Programming Model for a Day-ahead Scheduling of Isolated MGs*

In (13)–(30), the fuzzy programming model for scheduling of isolated MGs is presented to minimize the operational cost of the MG, while including the uncertainties linked to photovoltaic (PV) and wind turbine (WT) generation, via fuzzy triangular numbers. In (13), the objective function is presented, where the cost of DG units is modeled via quadratic function in which $\omega_{dg,t}$ and $P_{dg,t}^{DG}$ are binary variables for commitment of DG units and their respective power generation at each period. Parameters a_{dg}, b_{dg}, and c_{dg} are associated with the DG unit's operational cost. In addition, cost associated with the energy not supplied is modeled in the second term, where $\Psi_{n,t}^{ENS}$ and $P_{n,t}^{ENS}$ are a constant parameter and a variable linked to energy not supplied cost and the amount of load which is shed, respectively. Parameter Δ_t corresponds to the duration of a period (i.e., 1 hour). In (14)–(19), the power flow in the MG is modeled. The active and reactive power balance is guaranteed through (14) and (15), respectively, where $P_{bn,t}$, $P_{pv,t}^{PV}$, $P_{wt,t}^{WT}$, $P_{n,t}^{L}$, and $P_{bs,t}^{BS}$ are real powers associated with in line bn, PV generation, WT generation, loads, and batteries. Similarly, $Q_{bn,t}$, $Q_{dg,t}^{DG}$ and $Q_{n,t}^{L}$ are related to reactive powers in line bn, DG unit reactive power generation, and reactive loads, respectively. Moreover, R_{bn}, X_{bn}, and $I_{bn,t}^{sqr}$ are associated with resistance, reactance, and current of line bn. The relation between power flowing through lines, voltages, and currents of the MG is modeled via (16) and (17), in which $V_{k,t}^{sqr}$ and Z_{kb}^{sqr} are the square of voltage at bus k and impedance of line kb, respectively. The physical limitations of the MG related to voltages and currents are included via (18) and (19), where $\underline{V}$ and $\overline{V}$ are the lower and upper bounds for voltage and $\overline{I}_{kb}$ is the current limit of line kb.

Constraints related to DG units operation are considered in (20) and (21), in which $\underline{P}_{dg}^{DG}$ and $\overline{P}_{dg}^{DG}$ are associated with lower and upper bounds of DG unit generation, while $Q_{dg,t}^{DG}$ and φ_{dg} are DG units reactive power generation and power factor, respectively.

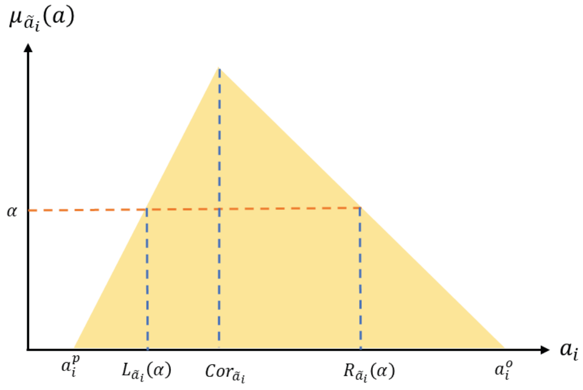

Fig. 1. Fuzzy number $\tilde{a}_i$ and its respective α-cut

(22) and (23) are related to uncertainty modeling considering PV and WT units generation, in which $\tilde{P}_{pv,t}^{PVmin}$, $\tilde{P}_{pv,t}^{PVmax}$, $\tilde{P}_{wt,t}^{WTmin}$, and $\tilde{P}_{wt,t}^{WTmax}$ are fuzzy numbers determining the fuzzy interval for the availability of renewable energy generation. Batteries operation is modeled via (24)–(30), where $P_{bs,t}^{BS+}$ and $P_{bs,t}^{BS-}$ are two continuous variables to model charging and discharging power of batteries. In addition, $\sigma_{bs,t}^{+}$ and $\sigma_{bs,t}^{-}$ are binary variables that correspond with charging and discharging modes to avoid concurrent charging and discharging in the batteries according to (26). The relation between energy stored in batteries and charging and discharging power is modeled in (28) and (29), where $E_{bs,t}^{BS}$, $\ddot{E}_{bs}^{BS}$, η_{bs}^{Ch}, η_{bs}^{Dis}, and β_{bs} denote energy of batteries, initial state of charge of batteries, charging efficiency, discharging efficiency, and self-discharge rate of batteries. (30) guarantees that the batteries are charged and discharged in a proper way to avoid overcharging and deep discharging to maintain the lifespan of batteries.

$$\begin{aligned} min(F) = min\Bigg(& \sum_{dg\in DG}\sum_{t\in T}\Big(a_{dg}\omega_{dg,t} + b_{dg}P_{dg,t}^{DG}\Delta_t \\ & + c_{dg}\big(P_{dg,t}^{DG}\Delta_t\big)^2\Big) \\ & + \sum_{n\in N}\sum_{t\in T}\Psi_{n,t}^{ENS}P_{n,t}^{ENS}\Delta_t\Bigg) \end{aligned} \tag{13}$$

$$\begin{aligned} \sum_{kb}P_{kb,t} - \sum_{bn}\big(P_{bn,t} + R_{bn}I_{bn,t}^{sqr}\big) + \sum_{pv|b_{pv}=b}P_{pv,t}^{PV} & \\ + \sum_{wt|b_{wt}=b}P_{wt,t}^{WT} + \sum_{dg|b_{dg}=b}P_{dg,t}^{DG} & \\ = P_{n,t}^{L} - P_{n,t}^{ENS} + \sum_{bs|b_{bs}=b}P_{bs,t}^{BS};\ \ \forall b,t & \end{aligned} \tag{14}$$

$$\begin{aligned} \sum_{kb}Q_{kb,t} - \sum_{bn}\big(Q_{bn,t} + X_{bn}I_{bn,t}^{sqr}\big) + \sum_{dg|b_{dg}=b}Q_{dg,t}^{DG} & \\ = Q_{n,t}^{L};\quad \forall b,t & \end{aligned} \tag{15}$$

$$\begin{aligned} V_{k,t}^{sqr} - V_{b,t}^{sqr} = 2\big(P_{kb,t}R_{kb} + Q_{kb,t}X_{kb}\big) & \\ + I_{kb,t}^{sqr}Z_{kb}^{sqr}; \qquad \forall kb,t & \end{aligned} \tag{16}$$

$$V_{b,t}^{sqr}I_{kb,t}^{sqr} \geq \big({P_{kb,t}}^2 + {Q_{kb,t}}^2\big); \qquad \forall kb,t \tag{17}$$

$$\underline{V}^2 \leq V_{b,t}^{sqr} \leq \overline{V}^2; \qquad \forall b,t \tag{18}$$

$$0 \leq I_{kb,t}^{sqr} \leq \overline{I_{kb}}^2; \qquad \forall kb,t \tag{19}$$

$$\underline{P}_{dg}^{DG}\omega_{dg,t} \leq P_{dg,t}^{DG} \leq \overline{P}_{dg}^{DG}\omega_{dg,t}; \qquad \forall dg,t \tag{20}$$

$$\begin{aligned} -P_{dg,t}^{DG}\tan\big(\cos^{-1}(\varphi_{dg})\big) \leq Q_{dg,t}^{DG} & \\ \leq P_{dg,t}^{DG}\tan\big(\cos^{-1}(\varphi_{dg})\big); \qquad \forall dg,t & \end{aligned} \tag{21}$$

$$\tilde{P}_{pv,t}^{PVmin} \leq P_{pv,t}^{PV} \leq \tilde{P}_{pv,t}^{PVmax}; \qquad \forall pv,t \tag{22}$$

$$\tilde{P}_{wt,t}^{WTmin} \leq P_{wt,t}^{WT} \leq \tilde{P}_{wt,t}^{WTmax}; \qquad \forall wt,t \tag{23}$$

$$0 \leq P_{bs,t}^{BS+} \leq \overline{S}_{bs}^{BS}\sigma_{bs,t}^{+}; \qquad \forall bs,t \tag{24}$$

$$0 \leq P_{bs,t}^{BS-} \leq \overline{S}_{bs}^{BS}\sigma_{bs,t}^{-}; \qquad \forall bs,t \tag{25}$$

$$\sigma_{bs,t}^{+} + \sigma_{bs,t}^{-} \leq 1; \qquad \forall bs,t \tag{26}$$

$$P_{bs,t}^{BS} = P_{bs,t}^{BS+} - P_{bs,t}^{BS-} \qquad \forall bs,t \tag{27}$$

$$\begin{aligned} E_{bs,t}^{BS} = \ddot{E}_{bs}^{BS} + \Delta_t\big(P_{bs,t}^{BS+}\eta_{bs}^{Ch} - P_{bs,t}^{BS-}/\eta_{bs}^{Dis} & \\ - E_{bs,t}^{BS}\beta_{bs}\big); \quad \forall bs,t|t = 1 & \end{aligned} \tag{28}$$

$$\begin{aligned} E_{bs,t}^{BS} = E_{bs,t-1}^{BS} + \Delta_t\big(P_{bs,t}^{BS+}\eta_{bs}^{Ch} - P_{bs,t}^{BS-}/\eta_{bs}^{Dis} & \\ - E_{bs,t}^{BS}\beta_{bs}\big); \quad \forall bs,t|t \geq 1 & \end{aligned} \tag{29}$$

$$\underline{E}_{bs}^{BS} \leq E_{bs,t}^{BS} \leq \overline{E}_{bs}^{BS}; \qquad \forall bs,t \tag{30}$$

Constraint (22) and (23) can be rewritten as (31) and (32), while the value of $\tilde{a}_{pv,t}$, $\tilde{b}_{pv,t}$, $\tilde{a}_{wt,t}$, and $\tilde{b}_{wt,t}$ can be calculated based on (33)–(36). Therefore, fuzzy constraints (31) and (32) have the same structure as (2), so can be replaced by equivalent normal constraints, as presented in (3). Hence, the equivalent normal constraints associated with (31) and (32) are presented in (37) and (38).

$$1 \leq \tilde{a}_{pv,t}P_{pv,t}^{PV} \leq \tilde{b}_{pv,t}; \qquad \forall pv,t \tag{31}$$

$$1 \leq \tilde{a}_{wt,t}P_{wt,t}^{WT} \leq \tilde{b}_{wt,t}; \qquad \forall wt,t \tag{32}$$

$$\tilde{a}_{pv,t} = 1/\tilde{P}_{pv,t}^{PVmin}; \qquad \forall pv,t \tag{33}$$

$$\tilde{b}_{pv,t} = \tilde{P}_{pv,t}^{PVmax}/\tilde{P}_{pv,t}^{PVmin}; \qquad \forall pv,t \tag{34}$$

$$\tilde{a}_{wt,t} = 1/\tilde{P}_{wt,t}^{WTmin}; \qquad \forall wt,t \tag{35}$$

$$\tilde{b}_{wt,t} = \tilde{P}_{wt,t}^{WTmax}/\tilde{P}_{wt,t}^{WTmin}; \qquad \forall wt,t \tag{36}$$

$$\begin{aligned} & 1 \leq \tilde{a}_{pv,t}x \leq \tilde{b}_{pv,t} \\ & \triangleq \begin{cases} 1 \leq L_{\tilde{a}_{pv,t}}(\alpha)x \leq L_{\tilde{b}_{pv,t}}(\alpha); & \forall pv,t \\ 1 \leq M_{\tilde{a}_{pv,t}}(\alpha)x \leq M_{\tilde{b}_{pv,t}}(\alpha); & \forall pv,t \\ 1 \leq R_{\tilde{a}_{pv,t}}(\alpha)x \leq R_{\tilde{b}_{pv,t}}(\alpha); & \forall pv,t \end{cases} \end{aligned} \tag{37}$$

$$\begin{aligned} & 1 \leq \tilde{a}_{wt,t}x \leq \tilde{b}_{wt,t} \\ & \triangleq \begin{cases} 1 \leq L_{\tilde{a}_{wt,t}}(\alpha)x \leq L_{\tilde{b}_{wt,t}}(\alpha); & \forall wt,t \\ 1 \leq M_{\tilde{a}_{wt,t}}(\alpha)x \leq M_{\tilde{b}_{wt,t}}(\alpha); & \forall wt,t \\ 1 \leq R_{\tilde{a}_{wt,t}}(\alpha)x \leq R_{\tilde{b}_{wt,t}}(\alpha); & \forall wt,t \end{cases} \end{aligned} \tag{38}$$

B. *Fuzzy-stochastic Programming Model for Day-ahead Scheduling of Isolated MGs*

The fuzzy model for the optimal scheduling of isolated MGs was presented in the previous subsection. As explained before, (3) can be transformed to (12) to include scenarios related to α value. In a similar way, (37) and (38) can be rewritten as (39) and (40). It is worth mentioning that scenarios are exclusively considered for α (not for uncertain parameters) since possibility distributions are deployed to model uncertainties.

$$\begin{aligned} & 1 \leq \tilde{a}_{pv,t}x \leq \tilde{b}_{pv,t} \\ & \triangleq \begin{cases} 1 \leq L_{\tilde{a}_{pv,t}}(\alpha_s)x \leq L_{\tilde{b}_{pv,t}}(\alpha_s); & \forall pv,t,s \\ 1 \leq M_{\tilde{a}_{pv,t}}(\alpha_s)x \leq M_{\tilde{b}_{pv,t}}(\alpha_s); & \forall pv,t,s \\ 1 \leq R_{\tilde{a}_{pv,t}}(\alpha_s)x \leq R_{\tilde{b}_{pv,t}}(\alpha_s); & \forall pv,t,s \end{cases} \end{aligned} \tag{39}$$

$$\begin{aligned} & 1 \leq \tilde{a}_{wt,t}x \leq \tilde{b}_{wt,t} \\ & \triangleq \begin{cases} 1 \leq L_{\tilde{a}_{wt,t}}(\alpha_s)x \leq L_{\tilde{b}_{wt,t}}(\alpha_s); & \forall wt,t,s \\ 1 \leq M_{\tilde{a}_{wt,t}}(\alpha_s)x \leq M_{\tilde{b}_{wt,t}}(\alpha_s); & \forall wt,t,s \\ 1 \leq R_{\tilde{a}_{wt,t}}(\alpha_s)x \leq R_{\tilde{b}_{wt,t}}(\alpha_s); & \forall wt,t,s \end{cases} \end{aligned} \tag{40}$$

IV. TESTS AND RESULTS

The presented model is validated using a modified IEEE 33-node network. As depicted in Fig. 2, the MG consists of 33 buses, 32 lines, 2 WT (each 900 kW), 4 PV (each 500 kW), 3 dispatchable DG units, and 3 batteries (BS). More details linked to the components are given in Table I and Table II. The forecasts associated with WT and PV generation, as well as demand for the next day, are depicted in Fig. 3. Three case studies are considered. In Case I, the deterministic model for the optimal scheduling of MGs is solved by neglecting any uncertainties linked to renewable generation. In Case II, the fuzzy programming model is used for handling uncertainties and the model is solved for $\alpha = 0.5$. The hybrid fuzzy-stochastic model is simulated in the last case study (Case III). It is noteworthy that all the models were implemented in AMPL [19] and solved by deploying CPLEX solver [19] in a system with in Intel i5-1135G7 processor and 16 GB of RAM.

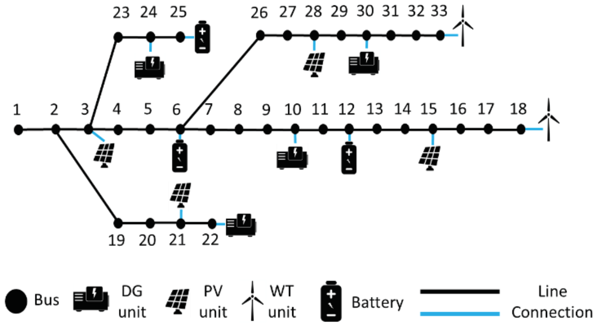

Fig. 2. Microgrid schematic graph.

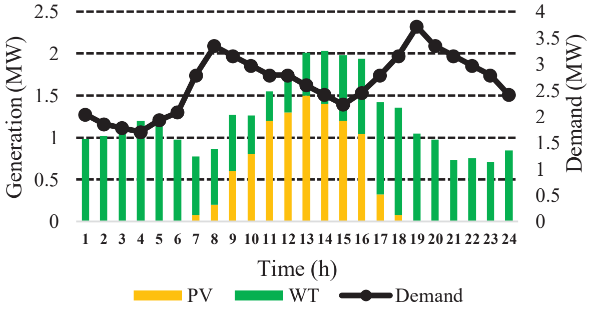

Fig. 3. Renewable energy generation and demand forecast.

TABLE I. DISTRIBUTED GENERATION DATA

Characteristic	**DG 1**	**DG 2**	**DG 3**
Bus	10	22	30
$\overline{P}_{dg}^{DG}$ (kW)	1,200	1,000	1,000
$\underline{P}_{dg}^{DG}$ (kW)	100	100	100
φ_{dg}	0.8	0.8	0.8
a_{dg} ($)	27	25	26
b_{dg} ($/MWh)	87	87	81
c_{dg} ($/MWh^2)	0.0025	0.0035	0.184

TABLE II. BATTERY DATA

Characteristic	**BS 1**	**BS 2**	**BS 3**
Bus	6	12	25
$\overline{S}_{bs}^{BS}$ (kW)	200	200	200
$\overline{E}_{bs}^{BS}$ (kWh)	1200	900	900
$\underline{E}_{bs}^{BS}$ (kWh)	200	150	150
η_{bs}^{Ch} & η_{bs}^{Dis}	0.95	0.94	0.96
β_{bs}	0.002	0.002	0.004

A. Case I: Deterministic Model

The deterministic model was implemented and solved in the first case study. This model assumes that the exact forecast related to PV and WT generation is available. The total cost was $3,517.45. The power generation by dispatchable DG units and the charging and discharging of batteries are illustrated in Fig. 4. The range of voltage magnitude during the period is depicted in Fig. 5. showing the satisfaction of power quality constraints (voltage profile). DG 1 did not commit generation, while DG 2 and DG 3 generated power almost at their maximum capacity in specific hours.

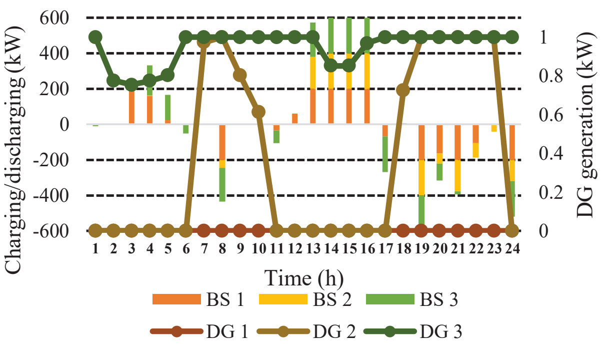

Fig. 4. Optimal scheduling of the MG in the Case I.

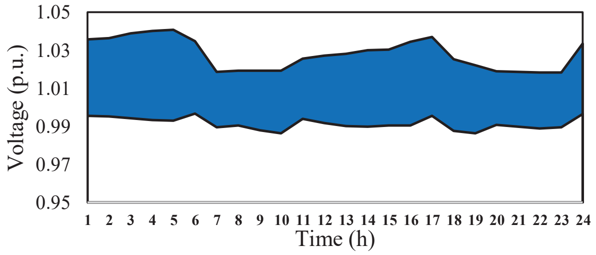

Fig. 5. Voltage range in the MG based on the deterministic model.

B. Case II: Fuzzy Programming Model

In this case study, the uncertainty linked to WT and PV units was considered using the fuzzy programming model and fuzzy numbers. The total cost of MG was $3,202.18, showing a 9% cost reduction compared to the deterministic approach. The scheduling of DG units as well as charging and discharging of batteries are shown in Fig. 6. Both DG 2 and DG 3 contributed to power generation. However due to quadratic cost function, DG 3 operated with its maximum capacity, while DG 2 functioned partially. The voltage profile is depicted in Fig. 7. indicating the voltage limit satisfaction.

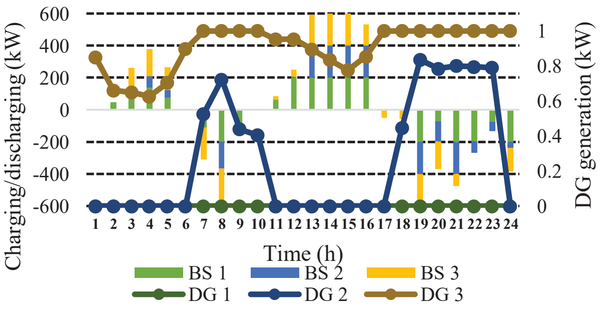

Fig. 6. Optimal scheduling of the MG in Case II.

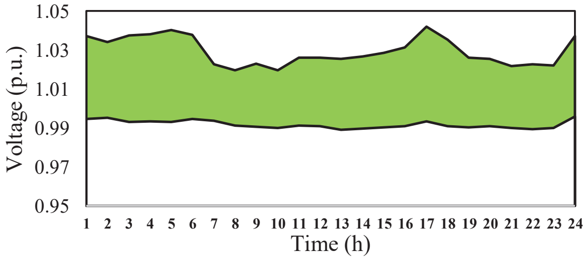

Fig. 7. Voltage range in the MG based on fuzzy programming model.

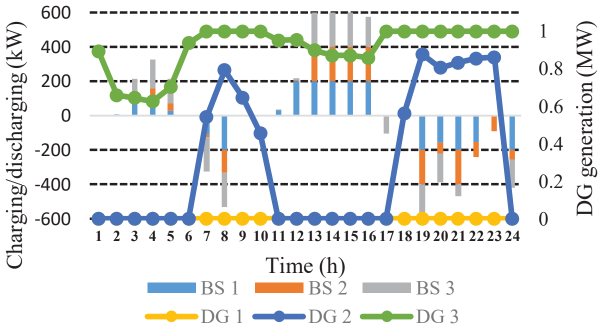

Fig. 8. Optimal scheduling of the MG in Case III.

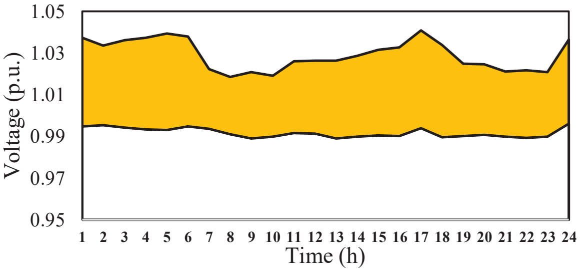

Fig. 9. Voltage range in the MG based on hybrid fuzzy-stochastic model.

C. Case III: Hybrid Fuzzy-stochastic Model

In this case the proposed hybrid fuzzy-stochastic model was implemented. Total cost was $3,277.9, which is a slight increase compared to fuzzy approach. The scheduling of distributed energy resources is visualized in Fig. 8. This figure is slightly different from Fig. 6. indicating marginal modification in the scheduling. The voltage range is depicted in Fig. 9. showing that, like previous cases, the voltage of buses stayed within the acceptable ±5% range.

V. CONCLUSION

Microgrids can lead the transition from centralized fuel-based toward decentralized renewable energy-based power systems by accommodating renewable energy distributed generation units, distributed energy resources, and electric vehicles. However, because of intermittent generation of clean resources such as photovoltaic and wind turbine and their dependency on weather conditions, the optimal operation of microgrids involves uncertainties. Fuzzy programming is one of the methods used in the literature for addressing uncertainties by taking advantage of fuzzy numbers. Nevertheless, results and solutions depend on the value of the α-cut considered. Therefore, this paper presented a new hybrid fuzzy-stochastic model to address the uncertainties linked to photovoltaic and wind power generation and mitigate the dependency of the fuzzy approach on the α-cut by including different scenarios. The proposed model takes advantage of stochastic and fuzzy models to handle uncertainties. A case study compared the deterministic, fuzzy programming, and the proposed methods. The results showed that fuzzy programming reduced the total cost compared to the deterministic approach by 9%. In addition, the results indicated that the proposed hybrid method enhanced the fuzzy programming model and guaranteed the robustness of the solutions against the α-cut value by slightly increasing the total cost of the microgrid by 2.3%.

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