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Stochastic Programming Versus Chance-Constrained Optimization for Optimal Rescheduling of Microgrids in Hierarchical Multi-Microgrid Systems

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***Abstract*— Multi-microgrid systems (MMSs) can pave the way for the development of microgrids (MGs) in distribution networks (DNs), contributing to renewable energy exploitation and carbon footprint reduction. Notwithstanding, the emergence of MMSs complicates the day-ahead optimal energy management of DNs since both private MGs and distribution system operators (DSOs) are involved in the decision-making process compared to conventional DNs. Hence, hierarchical structures as practical solutions have attracted the attention of many researchers. Nevertheless, in those structures, MGs have to reschedule their generation and consumption patterns based on the orders received from DSOs. In this paper, two-stage stochastic and chance-constrained models for the rescheduling of an MG in an MMS are deployed and compared to embrace the uncertainties linked to demand and renewable energy generation. Results for the modified IEEE 33-bus test system showed that the proposed chance-constrained model can reduce the total cost by 6.68% compared to the stochastic one. Thus, the proposed model is well-suited for a fair rescheduling of the MG by avoiding excessive costs associated with extreme cases.**

Keywords—chance-constrained optimization, energy management, multi-microgrid systems, renewable energy, stochastic optimization

I. Introduction

A microgrid (MG) can be defined as a small-scale power system with explicit electrical boundaries, consisting of a master controller, flexible and fixed loads, and distributed energy resources (i.e., distributed generation units and distributed energy storage systems), while can function in grid-connected or islanded modes [1]. MGs have enough potential to revolutionize modern distribution networks and accelerate the current transition toward sustainable renewable energy-based power systems [2]. In [3], numerous benefits of MGs for consumers and utilities are mentioned, including, but not limited to, enhancement in reliability, resiliency, power quality, energy efficiency, and sustainability of power systems. Moreover, MGs can contribute to carbon-footprint reduction by paving the way for renewable energy-based distributed generation units (e.g., wind and solar power) and plug-in electric vehicles (EVs) integration [4]. However, indiscriminate and imprecise energy management of MGs may jeopardize their inherent economic merits. In other words, energy management of MGs, including charging and discharging batteries, scheduling of dispatchable distributed generation units, and determining the system's configuration, must be done at the minimum cost. At the same time, all the technical constraints, such as voltage and current limits, should be satisfied [5]. As a result, the energy management of MGs can be modeled as a constrained optimization problem [6].

Despite the aforementioned advantages of MGs, there is still room for maximizing their benefits for power systems by developing multi-microgrid-based distribution networks (DNs). In that way, DNs can host and connect several adjacent microgrids to form a multi-microgrid system (MMS) [7] in which each microgrid may comprise a partial or whole distribution feeder. As MGs belong to the same DN, the distribution system operator (DSO) can centrally manage and coordinate MGs through bidirectional real-time communication. Nevertheless, the intermittence and uncertainty linked to renewable energy sources (RESs) and demand add more complexity to the optimal scheduling of MMSs. Consequently, different methods related to uncertainty modeling in MMSs are proposed in the literature [8]–[13]. In [8], a bilevel model is suggested for the optimal energy management of MMS in which a min-max-min robust optimization is deployed to cope with uncertainty of RES. To embrace uncertainties, in [9], the probability density function of the photovoltaic (PV) and wind turbine (WT) generation, as well as electric vehicle charge and discharge patterns, are modeled as multi-state variables. Stochastic programming has been used to model uncertainties linked to wind speed and solar irradiance via scenario generation, along with a demand response program and the Independence Performance Index [10]. Moreover, a hybrid model based on information gap decision theory (IGDT) and robust optimization was

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presented in [11] to include uncertainties of RES, load demand, and electricity price in the short-term operation of multi-microgrid DNs. In [12], risk-averse- and opportunity-seeker-based IGDT was adopted to cater to uncertainty in the optimal operational planning of isolated MMSs. A bi-level mixed-integer linear programming (MILP) model was proposed in [13] for the optimal energy management of MMSs in which uncertainties linked to RES and demand were modeled via scenario generation; it was shown that using a proper demand response program can considerably decrease the cost of MMSs. It is significant to highlight that the aforementioned references do not focus on the rescheduling of MGs. In addition, more flexible uncertainty handling approaches such as chance-constrained models have not been used in those references.

A hierarchical chance-constrained model for the day-ahead scheduling of MMSs consisting of three layers was proposed in [14] and [15]. In the former, a hierarchical structure is proposed whereas the total cost of the MMS and gas emission are minimized as objective functions. In [15], a hierarchical three-stage energy management was designed including the degradation cost of energy storage devices to avoid frequent charging and discharging of batteries. However, in those references, the respective optimization problems are exclusively modeled from DSOs' perspectives. In other words, the main focus of [14] and [15] is on the MMS cost minimization, while the problem is not analyzed from the MGs' point of view. As a result, this research gap is addressed in this research by emphasizing the MGs' functions in the hierarchical structure. To this end, two-stage stochastic optimization and chance-constrained programming models are deployed. The respective results are compared to model the rescheduling of MGs in hierarchical day-ahead scheduling of MMSs. Therefore, the contributions of this paper can be summarized as follows:

- Presenting a two-stage stochastic model for rescheduling of microgrids in the hierarchical day-ahead scheduling of multi-microgrid distribution networks
- Proposing a chance-constrained model for rescheduling of microgrids in the hierarchical day-ahead scheduling of multi-microgrid distribution networks
- Comparing the results between these two methods so as to indicate the superiority of the chance-constrained method over the stochastic approach for this specific application

The rest of the paper is organized as follows: in section II, the hierarchical structure for the optimal energy management of MMSs is briefly explained. The proposed mathematical optimization models are presented in section III. In section IV, case studies and results are presented and discussed. Finally, in section V, conclusions linked to the paper are highlighted and some recommendations for future research are suggested.

II. Hierarchical Scheduling of MMSs

The hierarchical day-ahead scheduling of MMSs consisting of three layers, proposed in [14], [15], is described by a flowchart depicted in Fig. 1. At the first layer, each microgrid solves its optimal day-ahead scheduling to determine the dispatchable distributed generation (DG), charging or discharging of batteries, renewable energy curtailment, and load shedding. Then MGs inform the DSO about their hourly energy shortage or surplus. According to the received data on the shortages and surpluses, the DSO solves the global optimization problem at the second layer to minimize the total cost of the respective MMS. In the last layer, each MG must reschedule based on the commands determined by the DSO. It is noteworthy that the MGs' requirements for energy are satisfied partially since instead of the total cost of each MG, the total cost of the MMS is usually considered the objective function. It is worth noting that the technical constraints of DN are also included in the second layer of the optimization model.

The objective function for the second layer (i.e., cost minimization of MMS) is presented in (1), in which $\widehat{\Theta}^{DER}_{de,t}$ and $\Delta^{DER}_{de,t}$ are the amount of power generated by distributed energy resources in the DN and the respective cost. Decision variables $\widehat{\Theta}^{MG}_{n,t}$ and $\widetilde{\Theta}^{MG}_{n,t}$ are the amount of power injected and absorbed by each microgrid at time interval t. $\Delta^{sell}_{mg,t}$ and $\Delta^{buy}_{mg,t}$ denote the electricity prices that MGs sell and buy the energy. $\widehat{P}^{MG}_{mg,t}$ and $\widetilde{P}^{MG}_{mg,t}$ are parameters representing the amount of power surplus and shortage determined by each MG at the first layer and τ_t is the time interval duration. Ψ^{MG} and Ψ^{DER} are the sets of MGs and DERs in the DN.

$$\min obj_{lay2} = \sum_{mg\in\Psi^{MG}} \sum_{t\in T} \tau_t \left(\widehat{\Theta}^{MG}_{mg,t}\Delta^{sell}_{mg,t} - \widetilde{\Theta}^{MG}_{mg,t}\Delta^{buy}_{mg,t}\right) + \sum_{de\in\Psi^{DER}} \sum_{t\in T} \tau_t \left(\widehat{\Theta}^{DER}_{de,t}\Delta^{DER}_{de,t}\right) \quad (1)$$

$$\widehat{\Theta}^{MG}_{mg,t} \leq \widehat{P}^{MG}_{mg,t} \qquad \forall mg,t \quad (2)$$

$$\widetilde{\Theta}^{MG}_{mg,t} \leq \widetilde{P}^{MG}_{mg,t} \qquad \forall mg,t \quad (3)$$

Constraints (2) and (3) guarantee that the DSO orders do not lead to infeasible solutions for MGs since they should be compatible with their expected generation and consumption capabilities [14], [15].

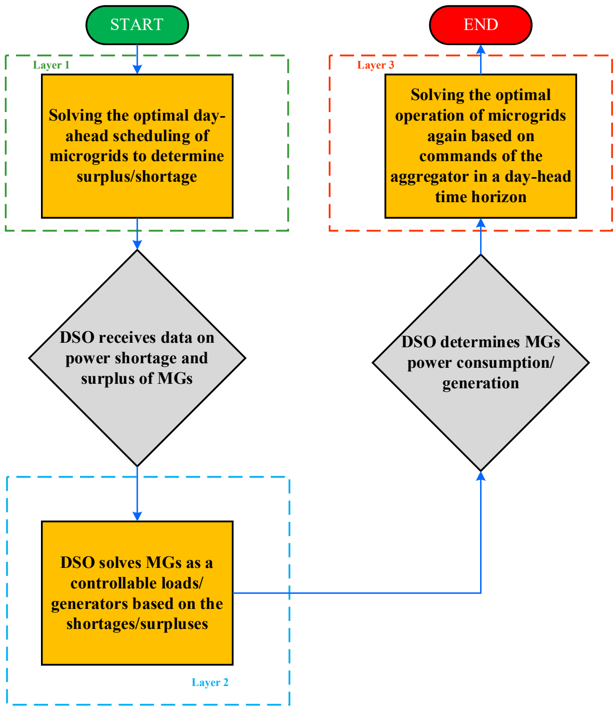

Fig. 1. Block diagram for hierarchical day-ahead scheduling of MMSs.

Other constraints, such as DN power flow, the voltage range of DN buses, and the current range of DN feeders, should be added to (1)–(3) to model the second layer optimization problem completely [14], [15]. However, as this paper focuses on the rescheduling of MGs in the third layer, and for brevity, the formulation of such constraints linked to the second layer is not presented. Consequently, in the next section, the precise and complete formulation for the first and third layers, which are associated with MGs' decision-making procedure (i.e., scheduling and rescheduling), are presented in detail.

III. Mathematical Formulation

A. Stochastic Programming Model for Scheduling of MGs

Stochastic optimization, as a well-known method for modeling uncertainty, has been used widely in the operation and planning of power systems. A comprehensive review regarding the application of this method in studies linked to power systems can be found in [16]. The stochastic model for the scheduling of MGs based on scenarios is presented in (4)–(21). The objective function for the operation cost of the MG is given in (4). Wherein, the first term is the cost linked to power purchased (sold) by MG from (to) the DN, in which P_t^{DN} and $\Gamma_{t,s}^{DN}$ are the power exchanged between the MG and the DN and the electricity price. The cost of dispatchable DG units is modeled via a quadratic function where a_{dg}, b_{dg}, and c_{dg} denote the cost coefficients of dispatchable DG units. The last term in the objective function is associated with the plausible load shedding in the MG; $P_{n,t,s}^{L}$, $\phi_{t,s}^{LSH}$, and Γ^{LSH} represent power demand in MG, the proportion of load shedding, and the load shedding cost.

A mixed-integer nonlinear programming model for power flow is presented in (5)–(8), at which R_{bn}, $P_{bn,t,s}$, and $I_{bn,t,s}$ correspond to the resistance of line bn and the corresponding power and current flowing through line bn. $P_{pv,t,s}^{PV}$, $P_{wt,t,s}^{WT}$, and $P_{bs,t,s}^{BS}$ represent real power of PV systems, WT generation and batteries. $Q_{bn,t,s}$ is the reactive power through line bn and X_{bn} corresponds to its reactance. $Q_{t,s}^{DN}$, $Q_{dg,t,s}^{DG}$, and $Q_{n,t,s}^{L}$ are the reactive power related to DN, dispatchable DG units, and loads. $V_{k,t,s}^{sqr}$ and $V_{b,t,s}^{sqr}$ are the voltage magnitudes of buses k and b. Z_{kb}^{sqr} is the square of impedance of line kb. Furthermore, limits related to voltage and current magnitudes are presented in (9) and (10), where $\underline{V}$ and $\overline{V}$ are the lower and upper bounds for voltage magnitude, while $\overline{I_{kb}}$ is the upper bound for current magnitude in line kb. The restriction linked to the capacity of the transformer at the point of common coupling is considered in (11), in which $\overline{S^{TR}}$ is the maximum apparent power allowed to flow in the transformer. Moreover, technical limits associated with PV systems, WT generation, and DG units are included in (12)–(15), where $\overline{P}_{dg}^{DG}$ and $\underline{P}_{dg}^{DG}$ are upper and lower bounds for generation of DG units and φ_{dg} denotes the corresponding power factors. Moreover, $\ddot{P}_{pv,t,s}^{PV}$ and $\ddot{P}_{wt,t,s}^{WT}$ represent the available power for PV and WT units (before any curtailment). In addition, constraints corresponding to batteries are included in (16)–(21), in which $P_{bs,t,s}^{BS+}$ and $P_{bs,t,s}^{BS-}$ model the charging and discharging of the batteries, P_{bs}^{PEI} denotes the capacity of power electronic interface connecting battery bs to the MG. $E_{bs,t,s}^{BS}$ and E_{bs}^{IBS} represent the state of charge and initial charge of battery bs. Furthermore, η_{bs}^{Ch} and η_{bs}^{Dis} are the charging and discharging efficiency, and β_{bs} is the self-discharge rate of the corresponding battery bs. In (21), $\underline{E}_{bs}^{BS}$ and $\overline{E}_{bs}^{BS}$ denote the lower and upper energy bounds of battery bs.

$$\min obj_{lay1} = \sum_{t\in T}\sum_{s\in S}\tau_t\pi_s P_t^{DN}\Gamma_{t,s}^{DN} + \sum_{dg\in DG}\sum_{t\in T} a_{dg}\omega_{dg,t} + \sum_{dg\in DG}\sum_{t\in T}\sum_{s\in S}\tau_t\pi_s\left(b_{dg}P_{dg,t,s}^{DG} + c_{dg}{P_{dg,t,s}^{DG}}^2\right) + \sum_{b\in B}\sum_{t\in T}\sum_{s\in S}\tau_t\pi_s P_{b,t,s}^{L}\phi_{t,s}^{LSH}\Gamma^{LSH} \tag{4}$$

$$\sum_{kb} P_{kb,t,s} - \sum_{bn}\left(P_{bn,t,s} + R_{bn}I_{bn,t,s}^{sqr}\right) + P_t^{DN} + \sum_{pv|b_{pv}=b} P_{pv,t,s}^{PV} + \sum_{wt|b_{wt}=b} P_{wt,t,s}^{WT} + \sum_{dg|b_{dg}=b} P_{dg,t,s}^{DG} = P_{b,t,s}^{L}\left(1-\phi_{t,s}^{LSH}\right) + \sum_{bs|b_{bs}=b} P_{bs,t,s}^{BS};\ \forall b,t,s \tag{5}$$

$$\sum_{kb} Q_{kb,t,s} - \sum_{bn}\left(Q_{bn,t,s} + X_{bn}I_{bn,t,s}^{sqr}\right) + Q_{t,s}^{DN} + \sum_{dg|b_{dg}=b} Q_{dg,t,s}^{DG} = Q_{b,t,s}^{L}\left(1-\phi_{t,s}^{LSH}\right);\quad \forall b,t,s \tag{6}$$

$$V_{k,t,s}^{sqr} - V_{b,t,s}^{sqr} = 2\left(P_{kb,t,s}R_{kb} + Q_{kb,t,s}X_{kb}\right) + I_{kb,t,s}^{sqr}Z_{kb}^{sqr}\quad \forall kb,t,s \tag{7}$$

$$V_{b,t,s}^{sqr}I_{kb,t,s}^{sqr} = \left({P_{kb,t,s}}^2 + {Q_{kb,t,s}}^2\right);\qquad \forall kb,t,s \tag{8}$$

$$\underline{V}^2 \le V_{b,t,s}^{sqr} \le \overline{V}^2;\qquad \forall b,t,s \tag{9}$$

$$0 \le I_{kb,t,s}^{sqr} \le \overline{I_{kb}}^2;\qquad \forall kb,t,s \tag{10}$$

$$\left({P_t^{DN}}^2 + {Q_{t,s}^{DN}}^2\right) \le \overline{S^{TR}}^2;\qquad \forall t,s \tag{11}$$

$$\underline{P}_{dg}^{DG}\omega_{dg,t} \le P_{dg,t,s}^{DG} \le \overline{P}_{dg}^{DG}\omega_{dg,t};\qquad \forall t,s \tag{12}$$

$$\left|Q_{dg,t,s}^{DG}\right| \le P_{dg,t,s}^{DG}\tan\left(\cos^{-1}\left(\varphi_{dg}\right)\right);\qquad \forall t,s \tag{13}$$

$$0 \le P_{pv,t,s}^{PV} \le \ddot{P}_{pv,t,s}^{PV};\qquad \forall pv,t,s \tag{14}$$

$$0 \le P_{wt,t,s}^{WT} \le \ddot{P}_{wt,t,s}^{WT};\qquad \forall wt,t,s \tag{15}$$

$$0 \le P_{bs,t,s}^{BS+} \le P_{bs}^{PEI};\qquad \forall bs,t,s \tag{16}$$

$$0 \le P_{bs,t,s}^{BS-} \le P_{bs}^{PEI};\qquad \forall bs,t,s \tag{17}$$

$$P_{bs,t,s}^{BS} = P_{bs,t,s}^{BS+} - P_{bs,t,s}^{BS-}\qquad \forall bs,t,s \tag{18}$$

$$E_{bs,t,s}^{BS} = E_{bs}^{IBS} + \tau_t\left(P_{bs,t,s}^{BS+}\eta_{bs}^{Ch} - P_{bs,t,s}^{BS-}/\eta_{bs}^{Dis} - E_{bs,t,s}^{BS}\beta_{bs}\right)\ \forall bs,t,s|t=1 \tag{19}$$

$$E_{bs,t}^{BS} = E_{bs,t-1}^{BS} + \tau_t\left(P_{bs,t}^{BS+}\eta_{bs}^{Ch} - P_{bs,t}^{BS-}/\eta_{bs}^{Dis} - E_{bs,t}^{BS}\beta_{bs}\right)\forall bs,t|t\ge 1 \tag{20}$$

$$\underline{E}_{bs}^{BS} \le E_{bs,t}^{BS} \le \overline{E}_{bs}^{BS};\qquad \forall bs,t \tag{21}$$

The objective function and constraint (8) are nonlinear, being linearized effortlessly via a piecewise linearization approach [17]. Constraint (8) can be rewritten using linear constraints (22) and (23), in which $V_{b,t,s}^{est}$ and $m_{kb,\omega}$ denote the estimated voltage at bus b and the slope of the lines in the linearization procedure. Moreover, $\Delta_{kb,t,s,\omega}^{P}$ and $\Delta_{kb,t,s,\omega}^{Q}$ are non-negative auxiliary variables associated with active and reactive power [17].

$$V_{b,t,s}^{est} = \left(\overline{V}^2 + \underline{V}^2\right)/2\qquad \forall b,t,s \tag{22}$$

$$V_{b,t,s}^{est}I_{kb,t,s}^{sqr} = \sum_{\omega} m_{kb,\omega}\left(\Delta_{kb,t,s,\omega}^{P} + \Delta_{kb,t,s,\omega}^{Q}\right)\quad \forall kb,t,s \tag{23}$$

B. Stochastic Programming Model for Rescheduling of MGs in the Third Layer

The proposed stochastic model presented above for scheduling MGs is also valid for the rescheduling. Nonetheless, contrary to the first layer, the amount of active power the MG can exchange with the DN is no longer a first-stage decision variable. In other words, the amount of power imported to or exported from the MG must be fixed according to the value determined by the DSO in the second layer. As a result, (24) must be added to (4)–(21) for modeling the stochastic rescheduling problem.

$$P_t^{DN} = \widetilde{\Theta}_t^{MG} - \hat{\Theta}_t^{MG} \qquad \forall t, s \qquad (24)$$

C. Chance-Constrained Programming Model for Rescheduling of MGs in the Third Layer

The linearized version of the two-stage stochastic model presented in (4)–(21) can be rewritten in a compact form as shown in (25)–(29), in which X is the set of decision variables at the first stage (here-and-now), and Y is the set of decision variables at the second stage (wait-and-see). C_1 and C_2 are the respective cost coefficients in the first and second stages. A_1, B_1, A_2, B_2, D_s, E_s, B_3, F_s, G_s, and B_4 are the set of coefficients corresponding to equality and inequality constraints in the first and second stages.

$$\min C_1 X + \sum_{s \in S} \pi_s C_2 Y \qquad (25)$$

$$A_1 X = B_1; \qquad (26)$$

$$A_2 X \leq B_2; \qquad (27)$$

$$D_s X + E_s Y = B_3; \qquad \forall s \qquad (28)$$

$$F_s X + G_s Y \leq B_4; \qquad \forall s \qquad (29)$$

There are two approaches to solving a chance-constrained optimization problem: reformulating it as its equivalent deterministic model or approximating it through samples. In the sample-based approach, constraints can be violated for a limited number of samples depending on the respective confidence level. Therefore, the two-stage stochastic model can be reformulated as an equivalent chance-constrained model in the same way as explained in [18]. The chance-constrained model for rescheduling the MG is presented in (30)–(36), where σ_s is an auxiliary binary variable. On one hand, for scenario s, if $\sigma_s = 1$, then all the constraints linked to scenario s can be neglected. On the other hand, if $\sigma_s = 0$, then all the constraints linked to scenario s must be satisfied. It is worth mentioning that, in this approach, the confidence level is usually considered between 0.9 and 0.99.

$$\min C_1 X + \sum_{s \in S} \pi_s C_2 Y (1 - \sigma_s) \qquad (30)$$

$$(A_1 X - B_1) = 0; \qquad (31)$$

$$(A_2 X - B_2) \leq 0; \qquad (32)$$

$$(D_s X + E_s Y - B_3)(1 - \sigma_s) = 0; \qquad \forall s \qquad (33)$$

$$(F_s X + G_s Y - B_4)(1 - \sigma_s) \leq 0; \qquad \forall s \qquad (34)$$

$$\sigma_s \in \{0,1\} \qquad \forall s \qquad (35)$$

$$\sum_{s \in S} 100 \left(\frac{\sigma_s}{S}\right) \leq \varepsilon \qquad \forall s \qquad (36)$$

In this study, the same approach is adopted, yet the probabilistic constraints can only be violated in less than 1% of the scenarios (i.e., $\varepsilon = 1$ and confidence level is 0.99). This approach can help the MG to avoid costly operation under extreme scenarios.

IV. Test and Results

To evaluate the effectiveness of the proposed method in rescheduling MGs in the hierarchical day-ahead scheduling of MMSs. A modified IEEE 33-bus test system is selected as a test MG. As illustrated in Fig. 2. the MG consists of 2 WT units, 2 PV units, 2 dispatchable DG units, and 3 batteries. The capacities of PV and WT units are 600 kW and 1500 kW, respectively. The data linked to the dispatchable DG units and batteries are presented in Table I and Table II. It is worth noting that the mathematical modeling is carried out in AMPL and solved by using CPLEX [19]. In this research, it is assumed that the forecasted values for electricity price and renewable energy generation (i.e., WT and PV units) are available for MGs, as depicted in Fig. 3. In addition, the scenarios are generated for the two-stage stochastic model considering up to 30% errors in forecasted values, as adopted in [2].

A. The Two-Stage Stochastic Scheduling of the MG

In this case study, two-stage stochastic model is solved to determine the optimal scheduling of the MG in the first layer. The total cost of the MG, calculated according to (4), is \$2779.53. Results linked to the first stage decision variables involving charging and discharging batteries and the amount of power to be exchanged between MG and DN, as well as the second stage decision variables, including the average of power generated by dispatchable DG units (among all scenarios) are visualized in Fig. 4.

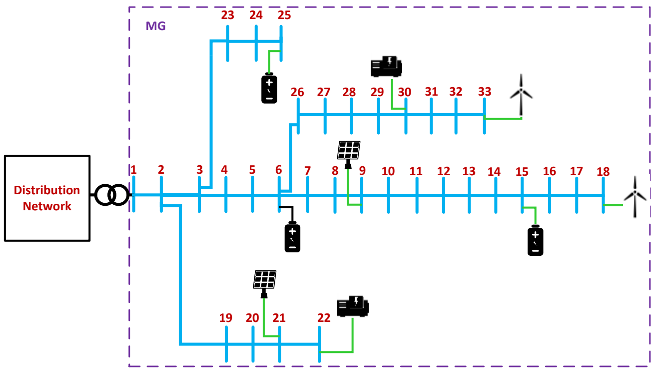

Fig. 2. Modified IEEE 33-bus test system.

TABLE I. Data of DG Units

Characteristic	Dispatchable DG unit 1	Dispatchable DG unit 2
Bus	22	30
$\overline{P}_{dg}^{DG}$(MW)	1.00	1.20
$\underline{P}_{dg}^{DG}$(MW)	0.15	0.10
a_{dg}(\$)	30	35
b_{dg}(\$/MW)	87	81
c_{dg}(\$/MW2)	0.0025	0.184

TABLE II. Data of Batteries

Characteristic	BS 1	BS 2	BS 3
Bus	6	15	25
P_{bs}^{PEI}(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	0.002

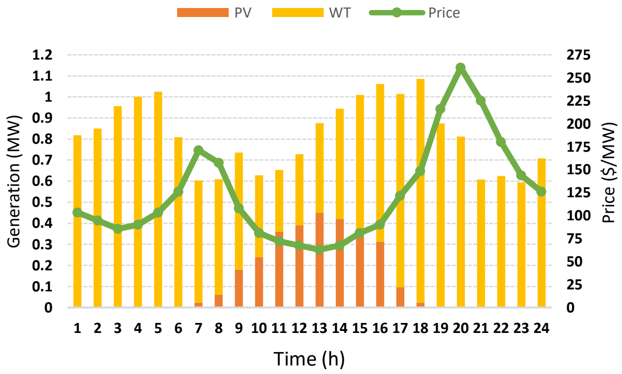

Fig. 3. Renewable generation and electricity price forecast

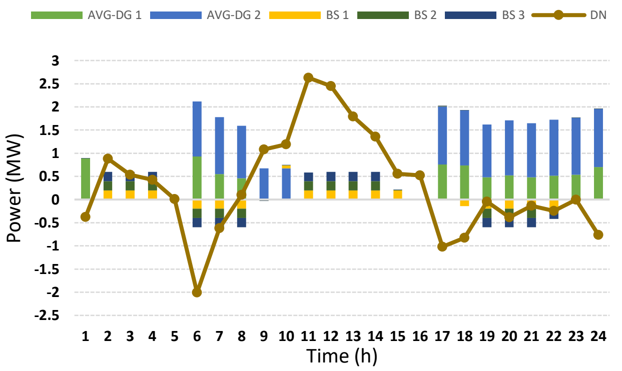

Fig. 4. Optimal scheduling of the MG in the first layer based on the two-stage stochastic optimization model

According to Fig. 4. the dispatchable DG units can play a key role in providing energy in the morning (from 6 am to 8 am) and in the evening (from 5 pm to 12 am). A considerable amount of power is imported from the MG during noon (from 11 am to 1 pm). In addition, batteries are mainly charged after midnight (between 2 am and 4 am) and around noon (from 1 am to 2 pm). Furthermore, they are discharged in the morning (between 6 am and 8 am) and evening (between 7 pm and 10 pm).

B. *The Two-Stage Stochastic Rescheduling of the MG*

To artificially model the effect of the second layer solutions (i.e., DSO commands) on the rescheduling problem, the results for P_t^{DN} in the first layer (determined by the MG) are multiplied to a set of random numbers drawn from the uniform distribution in the interval (0,1) as shown in Fig. 5 to simply model the uncertainty linked to the second layer decision making process, in which "Pgrid" corresponds to the optimal solution related to the power exchanged between MG and the DN when scheduling each MG individually, whereas "PgridX" is associated with the optimal solution obtained by DSO while solving the MMS scheduling in the second layer (i.e., commands for MGs in the third layer). The cost of rescheduling the MG based on the two-stage stochastic programming model is acquired at $2962.05, showing an increase in the total cost of MG by 6.56% compared to the cost in the first layer. The results related to the rescheduling of MG are depicted in Fig. 6. The voltage range of MG is demonstrated in Fig. 7. It can be seen that the voltages of buses remain in the acceptable range (i.e., between 0.9 p.u. and 1.1 p.u.) in all scenarios and time intervals.

C. *The Chance-Constrained Rescheduling of the MG*

The cost of rescheduling of the MG based on the chance-constrained programming model is obtained as $2764.28, showing a decrease of 6.68% in the total cost in comparison with rescheduling of MG using the two-stage stochastic programming method. The results associated with the rescheduling of MG based on this approach are demonstrated in Fig. 8. which is slightly different from Fig. 6. The voltage range of MG is shown in Fig. 9. It can be seen that the voltages of buses lie in the acceptable range (i.e., between 0.9 p.u. and 1.1 p.u.) through all scenarios and time intervals.

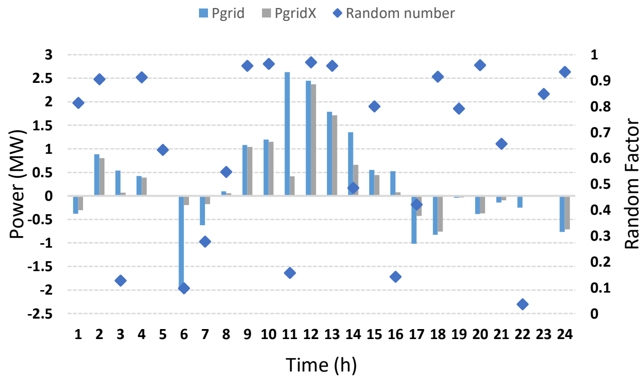

Fig. 5. Visualization of the DSO effect on the power exchanged between MG and DN in the second layer

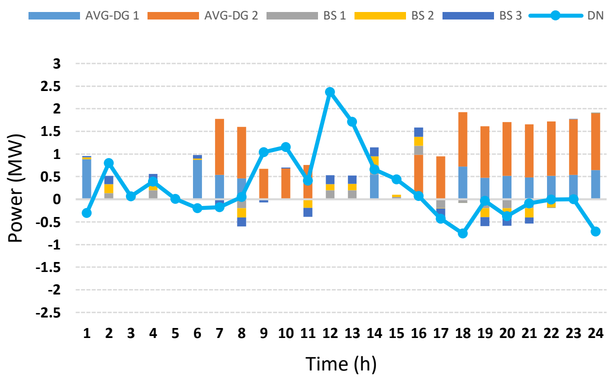

Fig. 6. Optimal rescheduling of the MG in the third layer based on the two-stage stochastic optimization

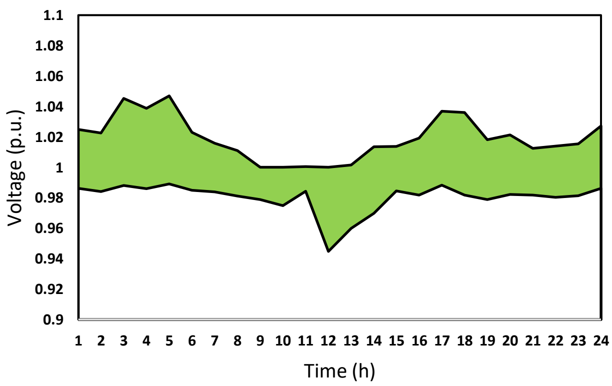

Fig. 7. Voltage range in the MG is based on the two-stage stochastic optimization

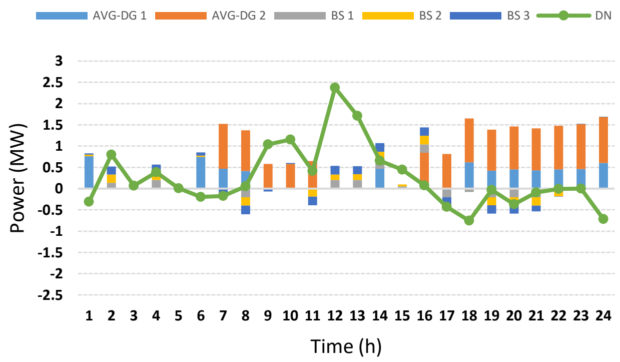

Fig. 8. Optimal rescheduling of the MG in the third layer based on the chance-constrained model

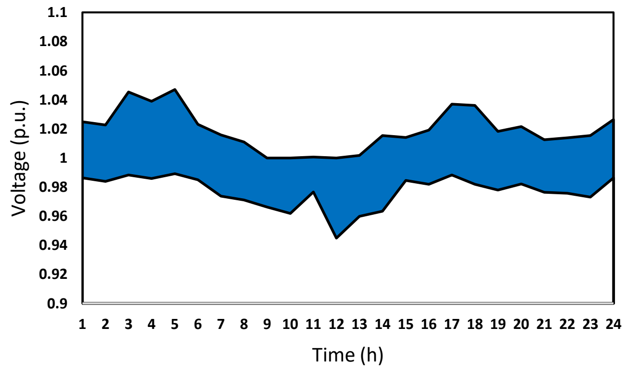

Fig. 9. Voltage range in the MG based on the chance-constrained

V. CONCLUSION

Multi-microgrid-based distribution networks have captivated the attention of many researchers due to the distinct advantages they can offer to smart power systems, including but not limited to enhancing the resiliency, flexibility, and reliability of distribution networks. Nevertheless, due to complexity and elaborate structures, deploying a proper method for the energy management of multi-microgrid systems is essential to guarantee the applicability and optimality of solutions. As a result, hierarchical structures for the energy management of multi-microgrid systems are proposed in the literature. Yet, to the best of the authors' knowledge, the problem is mostly addressed from the distribution system operator perspective, and the research gap corresponding to coping with the problem from MGs' points of view has still needed further analyses. Hence, in this study, to fill this research gap, two-stage stochastic programming and chance-constrained optimization methods for modeling uncertainties in the rescheduling of microgrids in multi-microgrid systems were modeled, implemented, and compared. The results showed that using the proposed chance-constrained method can reduce the total cost of microgrids by 6.68% in comparison to two-stage stochastic programming.

This research was carried out assuming that the distribution network and microgrids are balanced. In addition, it was assumed that all microgrids in the multi-microgrid system can benefit from this hierarchical price-based centralized energy management structure since the distribution system operators try to minimize the cost of the distribution network considering all microgrids' shortages and surpluses of energy. Hence, unbalanced distribution networks and microgrids can be considered for future research. Moreover, the applicability of the proposed models in decentralized decision-making procedures can also be evaluated.

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