A Novel Operational Model for Interconnected Microgrids Participation in Transactive Energy Market: A Hybrid IGDT/Stochastic Approach

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***Abstract*—Recently, the decarbonization of the electric power system has led to substantial efforts for designing a pathway toward 100% renewable energy resources (RERs). This paper proposes a novel operational model for the effective participation of the interconnected microgrids with 100% RERs in the transactive energy market. The novelty of the proposed model is mostly related to the use of transactive energy technology for developing the free energy trading environment for the microgrids with 100% RERs as the local energy trading market to establish a dynamic energy balance in the system. To capture the intermittencies in the system, a hybrid version of the stochastic programming and information gap decision theory (IGDT) method with risk-averse and risk-seeker strategies is proposed in the deregulated environment. The proposed model is validated by selecting the modified IEEE 14-bus test system. The results indicate the effectiveness of the proposed model in providing the same percentage of cost-saving for microgrids when they simultaneously participate in the transaction energy market. The cooperative energy interactions of the microgrids in the transactive energy market based on the proposed model leads to 18.34% cost-saving for them in comparison with the base model.**

***Index Terms*—Transactive energy, grid modernization, interconnected microgrids, renewable energy resources.**

NOMENCLATURE

Indices

m	Index of microgrid
s	Index of scenario
t	Index of time
i,j	Index of buses

Parameters

$P_{i,t}^{Load,E}$	Electricity demand (MW).
η^{Bch}, η^{Bdis}	Charging and discharging efficiency of the battery storage.
η^{Tch}, η^{Tdis}	Charging and discharging efficiency of the thermal storage.
$\lambda_t^{DA}, \lambda_t^{Sell}$	The purchasing/selling energy price from/to the day-ahead market and selling energy price to the consumers at time t.
N_t, N_s, N_b	Number of time intervals, scenarios, and buses.
Ω_s	Probability of scenario s.
N_m	Number of microgrids participated in LETM.
$P_{m,t}^{Load,C}$	Cooling energy load.
$\sigma_m^{PV}, \upsilon_m^{PV}$	Conversion unit and array area of PV panel m.
ξ_m^{PV}	Solar irradiation (kW/m^2).
$T_t^{PV,O}$	Outdoor temperature at time t.
$P_m^{W,R}$	Rated power of wind turbine.
$\omega_1, \omega_2, \omega_3$	Coefficients in wind turbine modeling.
V_t, V_m^{Rated}	Forecasted and rated amounts of wind speed.
$V_m^{Cut-In}, V_m^{C-Out}$	Cut-in and cut-out wind speed in microgrid m.
EtC^{RC}	Coefficient for converting electrical energy to cooling one.
$S_m^{Th}, \chi_{\min}^{Th}$	Size of thermal storage and the coefficient that states the minimum amount of cooling energy stored in the thermal storage.
CoI_m^{Th}	Initial amount of energy in the thermal storage.
$\chi_{\min}^{Tch}, \chi_{\max}^{Tch}$ $(\chi_{\min}^{Tdis}, \chi_{\max}^{Tdis})$	Coefficients for the minimum and maximum amount of cooling energy charging (discharging) in the thermal storage.
$P_{i,t}^{Load,Ef}$	Forecasted electricity demand.
$El_{i,t}^{Load}$	The amount of shifted load.
μ^{Max}	Coefficient related to the maximum amount of shiftable load.
$Q_{i,t}^{Load,E}$	Reactive power demand.
$Y_{i,j}, \delta_{i,j}$	Admittance of feeder i-j and its phase angle.

Variables

$P_{m,t,s}^{Bch}, P_{m,t,s}^{Bdis}$	Charging and discharging power of the battery storage.
$P_{m,t,s}^{Tch}, P_{m,t,s}^{Tdis}$	Charging and discharging of the thermal storage.
$P_{m,t,s}^{RC}$	The amount of electricity consumption by the reciprocating chiller.
$P_{m,t,s}^{DA}$	The amount of energy trading in the day-ahead market.
$C_t^{Ba}, C_t^{Te}, Co_t^{RC}$	Operation cost of battery storage, thermal storage, and RC at time t.
$P_{m,t}^{PV}, P_{m,t}^{Wind}$	Output power of PV panel and wind turbine.
$Ee_{m,t}^{LM}, Ee_{m,t}^{ML}$	The electrical energy transmitted from (to) LETM to (from) the microgrid m at time t.
$P_{m,t}^{RC,Co}$	The amount of cooling energy generated by the RC unit.
$Q_{m,t}^{Wind}$	Reactive power of the wind turbine.
$E_{m,t}^{B}$	The electrical energy storage in the battery of microgrid m at time t.
$U_{m,t}^{Bch}, U_{m,t}^{Bdis}$	Binary variables indicating the charging and discharging states of the battery.
$U_{m,t}^{Tch}, U_{m,t}^{Tdis}$	Binary variables denoting the charging and discharging states of the thermal storage.
$P_{m,t}^{Th}$	The amount of cooling energy stored in the thermal storage.
$P_{i,t}^{f}, Q_{i,t}^{f}$ $(P_{i,t}^{Ge,E}, Q_{i,t}^{Ge,E})$	The active and reactive power flows (production) at bus i time t.
$V_{i,t}, \theta_{i,t}$	The voltage magnitude and its phase angle.
$S_{i,j,t}^{Co}$	The complex power in feeder i-j at time t.

$U_{m,t}^{E,Inp}, U_{m,t}^{E,Out}$	Binary variables that indicate the input and output states of electricity in the LETM.
$Ele_{m,t}^{Inp}, Ele_{m,t}^{Out}$	The amount of electrical energy input and output in the LETM.
α^{Ro}, α^{Op}	The optimal horizon of an uncertain variable in the robust and opportunity functions.
F_m^{Ro}, F_m^{Op}	The robust and opportunity cost levels.
F_m^0	The energy cost of microgrids in the deterministic problem.

I. Introduction

A. Motivation and Background

In recent decades, the global energy crisis has been intensified due to the significant increase in energy consumption and highly operation of conventional power plants with fossil fuels. In this regard, the depletion of fossil fuels and their disadvantages in terms of economic and environmental aspects have been led to arousing widespread interest in the usage of different technologies of renewable energy resources (RERs) [1]. However, the uncontrollable attribute of RERs such as solar energy and wind turbine manifests the prominent need for effective solutions to enable the power grid for their high level of integration [2]. Despite the existence of intermittency in RERs outputs, the operation of the power system with a full share of renewables is attended as the main step in building a cost-effective and zero-emission system [3]. Due to the remarkable challenges regarding the maximum usage of RERs, the operation of the system with 100% RERs for clean energy production will need a suitable structure not only to handle various types of RERs but also to manage the energy supply and demand in the deregulated environment [4]. In this regard, microgrids are proposed as the small-scale and single controllable entities, which are incorporated with the distributed energy resources (DERs) and controllable loads for significant deployment in the grid modernization process [5]. Indeed, microgrids have an appropriate structure that facilitates the integration of a high level of RERs and provides significant benefits for different participants in the energy market interactions [6]. Given the considerable advantages of microgrids, a large number of them are expected to be integrated by adopting innovative technologies throughout the power system with the aim of meeting the grid modernization goals. Hence, in the power grids with a large number of renewable-based microgrids, the optimal scheduling task will be essential considering the technical, economic, and environmental restrictions. Moreover, such systems not only will need to be incorporated with the capable technologies for maintaining the energy supply and demand in balance but also an appropriate uncertainty modeling mechanism should be applied for the near-reality analysis of the system. Thus, a great need is felt for the holistic models that can simultaneously contain the aforementioned features for the power grids incorporated with the 100 % RERs.

B. Relevant Literature

Optimal scheduling of renewable-based microgrids as the key parts of the modern grids has attracted considerable attention in recent literature. Most of the studies in this field have been carried out using different approaches for achieving diverse objectives. For example, the authors in [7] proposed a novel stochastic energy scheduling scheme for microgrids to overcome the challenges regarding the uncertainties in both the supply and demand sides. The study used the energy trading option between microgrids and utility for the stability of the system where the main objective was to minimize the differences between predicted and real amounts of energy trading in the system. In [8], a bi-level two-stage robust model was proposed for optimal scheduling of the AC/DC hybrid multi-microgrids with the aim of achieving a unified robust dispatch scheme along with realizing the bi-level coordinated scheduling for the microgrids. The optimal scheduling of a self-generation power plant was conducted in [9] for the enterprise microgrids considering the flexibility and economical aspects of the system. The authors in [10] focused on accomplishing practical scheduling by proposing a resource-cost constrained adaptive model based on the robust optimization method. In the same study, the first-stage problem was developed for optimizing the dispatch plan while the minimization of the resource-cost was considered in the second-stage problem. Moreover, the cost-driven strategy was proposed in [11] for optimal energy management of the multi-microgrids by presenting a distributed neuro-dynamic algorithm for solving the non-smooth optimization problem. In addition to these studies, energy trading techniques are also widely used for energy management in the interconnected microgrids in recent years. For instance, a joint energy scheduling and trading strategy was proposed in [12] for energy management of the interconnected autonomous microgrids. In this work, the possibility of optimal scheduling of the local power supply and demand is considered not only for interconnected microgrids but also each of them is empowered for energy trading with other microgrids in the distribution network. In [13], the authors proposed a peer-to-peer transactive multi-resource trading framework with the aim of managing the energy exchanging of the interconnected microgrids. In the proposed framework, each interconnected microgrid can meet its multi-energy demand using the local hybrid biogas-solar-wind renewables while it can proactively exchange its available energy and communication resources with other microgrids aiming to deliver high quality and secured services. Likewise, authors of [14] developed a hierarchical online distributed algorithm for optimal energy management of the interconnected microgrids considering the economic operation of the system, optimal operation of controllable devices, and maximizing the users' utility.

In the systems with a high or full share of the RERs, uncertainty quantification is necessary to realistic analyzing the system for adopting appropriate strategies, especially in the practical problems. For this aim, several effective approaches have been used to model the unpredictable behaviors of the stochastic producers in recent literature including an adaptive robust optimization [15], chance-constrained programming [16], stochastic programming [2], and distributionally robust chance-constrained [6], just to name a few. The stochastic programming contains scenario-based techniques that create high computational burden, complexity, and run time which accordingly makes them unsuitable for practical problems alone. Although the chance-constrained method allows for capturing probabilistic constraints, it cannot provide a certain level of robustness for the renewable-based microgrids as an essential requirement. For this aim, robust optimization is proposed that provides a specific level of robustness for the system in the presence of the high/full level of RERs by considering the worst sate of the uncertain parameters. However, this method only considers the negative effects of the uncertainties while opportunities created by them are ignored. To get realistic modeling of the renewable-based system by effectively modeling both the robustness and opportunistic states of it in the presence of the RERs, the information gap decision theory (IGDT) method with both risk-averse and risk-seeker strategies has been attracted substantial attention in some studies. For example, in [17], the IGDT approach is used for modeling the uncertainties to provide a robust model for the security-constrained unit commitment (SCUC) problem in the presence of uncertainties. In another work [18], the robustness of the multi-objective version of the SCUC problem is considered to be satisfied by the IGDT method. In the self-scheduling problem for the demand response aggregators [19], avoiding the complexity and computational burden caused by the scenario-based methods as well as guaranteeing the achieving of predefined profit for the aggregator are considered as two main reasons for applying the IGDT technique in modeling the system. In spite of significant advantages of the IGDT method in the uncertainty modeling, this approach considers only the worst and best states of the uncertain parameters as the robustness and opportunistic functions. In order to more effectively model the uncertainties in the system, this paper proposes a hybrid IGDT/stochastic technique to simultaneously use the advantages of both the IGDT and stochastic programming methods. Indeed, based on this method, the robustness and opportunistic states of the system are modeled by developing the risk-averse and risk-seeker strategies in the IGDT approach while almost all occurrence states of the uncertain parameters are intended by the stochastic programming using the autoregressive integrated moving average (ARIMA) and fast forward selection (FFS) approaches for scenario production and reduction processes.

For interconnected microgrids with a full level of stochastic producers, transactive energy technology is applied to develop a free energy trading environment in the local area. The capability of this technology is widely used in recent studies for managing energy trading especially to substantially enhance the flexibility of the renewable-based microgrids. For example, authors of [20] have proposed a transactive energy system for interconnected microgrids with electric springs to provide sufficient operational flexibility for the microgrids. A secured distributed energy management system was developed in [21] based on the transactive energy technology with the aim of minimizing the local energy cost of the interconnected microgrids by creating energy trading possibilities among them. Moreover, an agent-based transactive energy management framework was proposed in [22] to effectively address the aggregated complexity induced by microgrids considering their participation in the transactive market interactions.

C. Contributions and Organization

Despite several effective studies are carried out regarding the interconnected microgrids, there are some notable research gaps yet, which must be addressed suitably. In recent works, although microgrid scheduling has been done for different objectives using various techniques, the holistic model is not proposed for the microgrids with 100% RERs that can not only provide a reliable way for dynamically meeting the energy demand during a day but also can provide the logical motivation for the microgrids to drive them for participating in the energy market interactions. On the other hand, an effective technique is also not presented for uncertainty modeling of the system with a full share of RERs that can take the robustness and opportunistic aspects of the uncertain parameters together with their occurrence states into account for more realistic evaluating the system. All of these gaps motivated us to propose a holistic model for the optimal operation of the interconnected microgrids under the transactive energy paradigm.

In this study, all microgrids are equipped only with RERs for fully clean energy production in the power grid. In this system with stochastic behaviors, providing appropriate conditions for reliable energy supply is essential for the renewable-based system. For this aim, transactive energy technology is used for developing the local energy trading market (LETM) to create a free energy trading environment for the microgrids that allows them to exchange energy with each other to reliably establish a dynamic energy balance in the renewable-based system. In order to motivate microgrids to participate in the free energy trading interactions, our proposed model is developed to provide the same percentage of cost-saving simultaneously for all microgrids based on their size and scale, which is the first of its kind. On the other hand, in order to use the advantages of both IGDT and stochastic programming approaches, a hybrid version of them is developed to effectively model the stochastic behaviors of the uncertain parameters in the system. Indeed, focusing on both the risk-averse and risk-seeker strategies in the IGDT method along with considering the different effective scenarios in stochastic programming has enabled the proposed model for more realistic analyzing the stochastic behaviors in the renewable-based microgrids.

The remainder of this paper is organized as follows. The problem formulation for the optimal operation of the microgrids is presented in Section II. The uncertainty modeling process is represented in Section III. Section IV describes the simulation results. The results discussion and main achievements of this work are provided in Section V. Finally, Section VI concludes the paper.

II. Problem Formulation

This paper is targeted to propose a novel model for interconnected microgrids with 100% RERs to provide the same percentage of cost-saving for them by creating a free energy trading possibility between them in the LETM under the transactive energy paradigm. The objective function and related constraints for this model are described in the following subsections.

A. Objective Function

Generally, future energy networks are aimed to equip with 100% RERs to fully generate clean energy in the efficient energy network's structures such as microgrids. In this paper, transactive energy technology is used for creating the LETM to provide free energy trading possibility among microgrids to reliably meet their energy demand in the system with a full share of RERs. Indeed, in real-time, all microgrids can use the potential of the LETM to trade energy with each other for maintaining the energy balance in the system. In order to justify and motivate the microgrids to participate in the free energy trading interactions in the LETM, the proposed model should have significant features that can ensure achieving fair economic benefits for all microgrids in the deregulated environment. Therefore, our proposed model is structured to provide the same percentage of cost-saving for all microgrids that participate in the transactive energy market. Indeed, the same percentage of cost-saving is provided simultaneously for all microgrids based on their size and scale. This feature acts as a motivation for microgrids to participate in the free energy trading process and enables a reliable way for meeting energy demand in the presence of the high-level of RERs with a minimum dependency on the power grid. It is assumed that all microgrids of different sizes are agreed to participate in the LETM interactions to achieve the same percentage of cost-saving and they are already aware of this issue. Therefore, the main objective of this work is to maximize the amount of this cost-saving ψ as follows.

$$\text{Max } \psi \tag{1}$$

subject to:

$$F_m^B = \sum_{s=1}^{N_s} \Omega_s . [\sum_{t=1}^{N_t} C_t^{Ba} (\eta^{Bch} . P_{m,t,s}^{Bch} + \frac{P_{m,t,s}^{Bdis}}{\eta^{Bdis}}) + \sum_{t=1}^{N_t} C_t^{Te} (\eta^{Tch} . P_{m,t,s}^{Tch} + \frac{P_{m,t,s}^{Tdis}}{\eta^{Tdis}}) + \sum_{t=1}^{N_t} Co_t^{RC} . P_{m,t,s}^{RC} - \sum_{t=1}^{N_t} \lambda_t^{DA} . P_{m,t,s}^{DA} . \Delta t - \sum_{i=1}^{N_b} \sum_{t=1}^{N_t} \lambda_t^{Sell} . (P_{i,t}^{Load,E}) \Delta t] \quad \forall m \tag{2}$$

$$F_m \le F_m^B . (1-\psi) \qquad \forall m \tag{3}$$

where, F_m is the energy cost of microgrid *m*. For simplicity, the scenario index *s* is removed from the variables below.

B. Constraints

The complete constraints need to be satisfied in the optimal scheduling of renewable-based microgrids to make this problem implementable in the practical cases, which are listed as follows.

1) Electrical and Cooling Energy Balance Constraints

$$\sum_{m=1}^{N_m} [(P_{m,t}^{PV} + P_{m,t}^{Wind} + P_{m,t}^{Bdis} - P_{m,t}^{Bch} - P_{m,t}^{DA} + Ee_{m,t}^{LM}) - (P_{m,t}^{RC} + Ee_{m,t}^{ML})] = \sum_{i=1}^{N_b} P_{i,t}^{Load,E} \quad \forall t \tag{4}$$

$$P_{m,t}^{RC,Co} + P_{m,t}^{Tdis} = P_{m,t}^{Load,C} + P_{m,t}^{Tch} \quad \forall m \ , \ \forall t \tag{5}$$

2) PV Panel Constraint

$$P_{m,t}^{PV} = \sigma_m^{PV} . \xi_m^{PV} . \upsilon_m^{PV} (1 - 0.005(T_t^{PV,O} - 25)) \quad \forall t \tag{6}$$

3) Wind Power Constraints

$$P_{m,t}^{Wind} = \begin{cases} 0 & 0 \le V_t \le V_m^{C-In} \\ (\omega_1 + \omega_2 V_t + \omega_3 V_t^2) P_m^{W,R} & V_m^{C-In} \le V_t \le V_m^{Rated} \\ P_m^{W,R} & V_m^{Rated} \le V_t \le V_m^{C-Out} \\ 0 & V_m^{C-Out} \le V_t \end{cases} \tag{7}$$

$$P_{m,t}^{Wind} / \sqrt{(P_{m,t}^{Wind})^2 + (Q_{m,t}^{Wind})^2} = \text{Constant} \tag{8}$$

4) Reciprocating Chiller Constraint

$$P_{m,t}^{RC,Co} = EtC^{RC} . P_{m,t}^{RC} \quad \forall m \ , \ \forall t \tag{9}$$

5) Electrical Energy Storage Constraints

$$E_{m,t+1}^B = E_{m,t}^B + \eta^{Bch} P_{m,t}^{Bch} - \frac{P_{m,t}^{Bdis}}{\eta^{Bdis}} \quad \forall t \ , \forall m \tag{10}$$

$$\bar{E}_m^B \le E_{m,t}^B \le \underline{E}_m^B \quad \forall m \ , \ \forall t \tag{11}$$

$$0 \le P_{m,t}^{Bch} \le U_{m,t}^{Bch} . \bar{P}_m^{Bch} \quad \forall m \ , \ \forall t \tag{12}$$

$$0 \le P_{m,t}^{Bdis} \le U_{m,t}^{Bdis} . \bar{P}_m^{Bdis} \quad \forall m \ , \ \forall t \tag{13}$$

$$U_{m,t}^{Bch} + U_{m,t}^{Bdis} \le 1 \quad \forall m \ , \ \forall t \tag{14}$$

Equation (11) indicates the limitation of the energy stored in the battery. Equations (12) and (13) state the upper and lower bounds for charging and discharging of the battery, respectively. Equation (14) models that the battery cannot charge and discharge at the same time.

6) Thermal Energy Storage Constraints

$$U_{m,t}^{Tch} + U_{m,t}^{Tdis} \le 1 \quad \forall m \ , \ \forall t \tag{15}$$

$$S_m^{Th} . \chi_{\min}^{Th} \le P_{m,t}^{Th} \le S_m^{Th} \quad \forall m \ , \ \forall t \tag{16}$$

$$P_{m,1}^{Th} = CoI_m^{Th} + (P_{m,1}^{Tch} - P_{m,1}^{Tdis}) . \Delta t \quad \forall m \ , \ t = 1 \tag{17}$$

$$P_{m,t}^{Th} - P_{m,t-1}^{Th} = (P_{m,t}^{Tch} - P_{m,t}^{Tdis}) . \Delta t \quad \forall m \ , \ \forall t \ge 2 \tag{18}$$

$$S_m^{Th} . \chi_{\min}^{Tch} . U_{m,t}^{Tch} \le P_{m,t}^{Tch} \le S_m^{Th} . \chi_{\max}^{Tch} . U_{m,t}^{Tch} \quad \forall m \ , \ \forall t \tag{19}$$

$$S_m^{Th} . \chi_{\min}^{Tdis} . U_{m,t}^{Tdis} \le P_{m,t}^{Tdis} \le S_m^{Th} . \chi_{\max}^{Tdis} . U_{m,t}^{Tdis} \quad \forall m \ , \ \forall t \tag{20}$$

Equation (15) indicates the thermal storage cannot be charged and discharged at the same time. Equation (16) limits the amount of thermal energy stored in the storage system in the allowable range. Equations (17) and (18) model the thermal energy balance in the storage. Equations (19) and (20) are used for keeping the amount of thermal energy charging and discharging in the permissible range.

7) Day-ahead Energy Trading Constraint

$$\underline{P}_t^{DA} \le P_t^{DA} \le \bar{P}_t^{DA} \quad \forall t \tag{21}$$

Equation (21) presents the limitation for energy trading between microgrids and the power grid in the day-ahead market.

8) Elastic Loads Constraints

$$P_{i,t}^{Load,E} = P_{i,t}^{Load,Ef} + El_{i,t}^{Load} \quad \forall t \ , \ \forall i \tag{22}$$

$$-\mu^{Max}.P_{i,t}^{Load,Ef} \le El_{i,t}^{Load} \le \mu^{Max}.P_{i,t}^{Load,Ef} \tag{23}$$

$$\sum_{t=1}^{N_t} El_{i,t}^{Load} = 0 \tag{24}$$

Equation (22) is used for considering the role of the elastic loads in the energy demand. Equation (23) denotes the amount of shifted load should be kept in the allowable range. Equation (24) states the sum of elastic load during a day should be equal to zero due to the avoid of load shedding in the system.

9) Electricity Network Constraints

$$P_{i,t}^{f} + P_{i,t}^{Load,E} = P_{i,t}^{Ge,E} \quad \forall t, \ \forall i \tag{25}$$

$$Q_{i,t}^{f} + Q_{i,t}^{Load,E} = Q_{i,t}^{Ge,E} \quad \forall t, \ \forall i \tag{26}$$

$$P_{i,t}^{f} = \sum_{j=1}^{N_b} V_{i,t}.V_{j,t}.Y_{i,j}.\mathrm{Cos}(\delta_{i,j} + \theta_{j,t} - \theta_{i,t}) \ \forall t, \ \forall i \tag{27}$$

$$Q_{i,t}^{f} = -\sum_{j=1}^{N_b} V_{i,t}.V_{j,t}.Y_{i,j}.\mathrm{Sin}(\delta_{i,j} + \theta_{j,t} - \theta_{i,t}) \ \forall t, \ \forall i \tag{28}$$

$$\underline{S}_{i,j}^{Co} \le S_{i,j,t}^{Co} \le \overline{S}_{i,j}^{Co} \quad \forall t, \ \forall i, \ \forall j \tag{29}$$

$$\underline{V}_i \le V_{i,t} \le \overline{V}_i \quad \forall t, \ \forall i \tag{30}$$

$$\underline{\theta}_i \le \theta_{i,t} \le \overline{\theta}_i \quad \forall t, \ \forall i \tag{31}$$

10) LETM Constraints

$$U_{m,t}^{E,Inp} + U_{m,t}^{E,Out} \le 1 \quad \forall m \ , \ \forall t \tag{32}$$

$$Ee_{m,t}^{LM} \le M.U_{m,t}^{E,Out} \quad \forall m \ , \ \forall t \tag{33}$$

$$Ee_{m,t}^{ML} \le M.U_{m,t}^{E,Inp} \quad \forall m \ , \ \forall t \tag{34}$$

$$\sum_{m} Ee_{m,t}^{ML} = \sum_{m} Ee_{m,t}^{LM} \tag{35}$$

where, *M* is a big number. Equation (32) denotes that although each microgrid can participate in the LETM interactions by receiving or transmitting energy but none of them can receive/transmit energy from/to the LETM at the same time. Equations (33) and (34) limits the amount of electrical energy traded between microgrids with the LETM. Equation (35) models the energy balance in the energy interactions of the LETM.

III. Uncertainty Modeling

In this paper, a hybrid of IGDT and stochastic programming method is applied to model uncertainties of RERs and electricity price in the day-ahead market. The main goal for proposing the hybrid version of the two capable uncertainty modeling methods is to simultaneously use the advantages of them for effectively and near realistic modeling of the system with a full share of the RERs.

A. Information Gap Decision Theory (IGDT) Method

In general, IGDT is a non-fuzzy and non-probabilistic method [23] that does not require any information regarding the probability distribution of uncertain parameters [9]. Uncertainty modeling using the IGDT method has been done considering the risk-averse and risk-seeker strategies. Here, the uncertainty modeling of the electricity price is conducted based on the aforementioned strategies due to suitableness of the IGDT method for modeling the stochastic behaviors of those uncertain parameters that have a certain behavioral pattern during a day such as electricity price.

1) Risk-averse Strategy

From the viewpoint of risk-averse, the IGDT approach seeks to maximize the horizon of uncertainty with the aim of guaranteeing the achievement of a certain amount of expectation for the objective function [24]. This mode of IGDT is referred to as the robustness function and can be defined as follows for this problem.

$$\mathrm{Max} \ \alpha^{Ro} \tag{36}$$

subject to:

$$F_m \le F_m^{Ro} = (1+\vartheta)F_m^0 \tag{37}$$

(4) - (35)

$$F_m = \max_{\Delta\lambda_t^{DA}} \left\{ A_m - \sum_{t=1}^{N_t} (\hat{\lambda}_t^{DA} + \Delta\lambda_t^{DA}).P_{m,t}^{DA}.\Delta t \right\} \quad \forall m \tag{38}$$

subject to:

$$-\alpha^{Ro}\hat{\lambda}_t^{DA} \le \Delta\lambda_t^{DA} \le \alpha^{Ro}\hat{\lambda}_t^{DA} \tag{39}$$

where, $\hat{\lambda}_t^{DA}$ and $\Delta\lambda_t^{DA}$ present the amount of forecasted day-ahead market price and deviation from it. A_m is the remaining part of the objective function in (2), which is used for simple evaluation. As seen in the mentioned formulation, the single-level scheduling problem is converted to the bi-level one by applying the IGDT method. In order to convert the bi-level problem to the single-one, the worst cases of the energy price will be one of the following states due to the negative or positive amount of $P_{m,t}^{DA}$:

$$\Delta\lambda_t^{DA} = \begin{cases} \alpha^{Ro}\hat{\lambda}_t^{DA} & P_{m,t}^{DA} \le 0 \\ -\alpha^{Ro}\hat{\lambda}_t^{DA} & P_{m,t}^{DA} \ge 0 \end{cases} \tag{40}$$

Given the worst states of energy price in (40), the two terms of this equation can be defined as follows for converting the bi-level problem to the single one.

$$(\Delta\lambda_t^{DA} + \alpha^{Ro}\hat{\lambda}_t^{DA}).P_{m,t}^{DA} \le 0 \tag{41}$$

$$(\Delta\lambda_t^{DA} - \alpha^{Ro}\hat{\lambda}_t^{DA}).P_{m,t}^{DA} \le 0 \tag{42}$$

In (41), when the microgrid *m* is a seller ($P_{m,t}^{DA} \ge 0$) in the day-ahead market, considering the (39) and (41), the amount of price deviation $\Delta\lambda_t^{DA}$ is equal to $-\alpha^{Ro}\hat{\lambda}_t^{DA}$, which describes the worst state of price in this condition. On the other hand, when the microgrid *m* is a purchaser ($P_{m,t}^{DA} \le 0$), the positive deviation $\alpha^{Ro}\hat{\lambda}_t^{DA}$ will be reached for $\Delta\lambda_t^{DA}$ based on (39) and (42).

2) Risk-seeker Strategy

From the risk-seeker perspective, the IGDT approach seeks to minimize the horizon of uncertainty with the aim of using an opportunity of obtaining more benefits caused by uncertainties in the system [24]. This mode of IGDT is referred to as opportunity function and can be defined as follows for this problem.

$$\text{Min } \alpha^{Op} \tag{43}$$

subject to:

$$F_m \le F_m^{Op} = (1-\vartheta)F_m^0 \tag{44}$$

(4) - (35)

$$F_m = \min_{\Delta\lambda_t^{DA}} \left\{ A_m - \sum_{t=1}^{N_t} (\hat{\lambda}_t^{DA} + \Delta\lambda_t^{DA}).P_{m,t}^{DA}.\Delta t \right\} \quad \forall m \tag{45}$$

subject to:

$$-\alpha^{Op}\hat{\lambda}_t^{DA} \le \Delta\lambda_t^{DA} \le \alpha^{Op}\hat{\lambda}_t^{DA} \tag{46}$$

Similar to the risk-averse strategy, the problem from the risk-seeker viewpoint is also bi-level, which needs to be converted to the single-one problem. The best occurrence states for the energy price based on the opportunity function can be realized as follows.

$$\Delta\lambda_t^{DA} = \begin{cases} -\alpha^{Op}\hat{\lambda}_t^{DA} & P_{m,t}^{DA} \le 0 \\ \alpha^{Op}\hat{\lambda}_t^{DA} & P_{m,t}^{DA} \ge 0 \end{cases} \tag{47}$$

Given the favorable states of energy price in (47), the two terms of this equation can be expressed as follows.

$$(\Delta\lambda_t^{DA} + \alpha^{Op}\hat{\lambda}_t^{DA}).P_{m,t}^{DA} \ge 0 \tag{48}$$

$$(\Delta\lambda_t^{DA} - \alpha^{Op}\hat{\lambda}_t^{DA}).P_{m,t}^{DA} \ge 0 \tag{49}$$

Given the (39) and (48), when the microgrid m is a purchaser ($P_{m,t}^{DA} \le 0$) in the day-ahead market, the amount of price deviation $\Delta\lambda_t^{DA}$ is equal to $-\alpha^{Op}\hat{\lambda}_t^{DA}$, which describes the favorable sate of price in this condition. On the other hand, when the microgrid m is a seller ($P_{m,t}^{DA} \ge 0$), the positive deviation i.e. $\alpha^{Op}\hat{\lambda}_t^{DA}$ will be reached for $\Delta\lambda_t^{DA}$ based on (39) and (49).

B. Stochastic Programming Technique

The stochastic programming method is recognized as one of the effective approaches for considering almost all occurrence states of the uncertain parameters along with the corresponding probabilities. Hence, this approach is more suitable for modeling the fluctuations of those uncertain parameters that have high-level variations during a day such as wind speed. In this regard, the Monte Carlo simulation method is one of the effective ways of modeling the fluctuation of uncertain parameters by generating numerous scenarios. However, this method is not suitable for practical problems due to taking a long time for convergence, complexity, and high computational burden caused by generating a large number of scenarios [25]. Thus, in the stochastic process, the autoregressive integrated moving average (ARIMA) and fast forward selection (FFS) methods are respectively applied for scenario generation and reduction processes and described as follows.

1) Autoregressive Integrated Moving Average (ARIMA) Method

An autoregressive moving average (ARMA) method is a class of stochastic processes that is taken into account as one of the effective techniques for scenario generation. This method belongs to the group of path-based techniques that is intended for evaluating the time series [26]. The distribution of the ARMA method is Gaussian with a stationary stochastic process that is recognized as two major concerns in the ARMA models. The following equation presents the mathematical model of the ARMA (m, n) process Ψ.

$$\Psi_t = \sum_{\ell=1}^{m} \xi_\ell \Psi_{t-\ell} + \varphi_t - \sum_{\ell=1}^{n} \Pi_\ell \varphi_{t-\ell} \tag{50}$$

In (50), the first and second terms denote the autoregressive and moving average parts, respectively. m and n state the number of parameters in the autoregressive and moving average parts. φ_t presents the error term. In order to achieve the stationery for the mean, the ARMA model is developed to the ARIMA one by employing the differencing procedure. An ARIMA model with three parameters (m, z, n) can be formulated as follows [27].

$$\left(1 - \sum_{\ell=1}^{m} \xi_\ell B^\ell\right)(1-B)^z \Psi_t = \left(1 - \sum_{\ell=1}^{n} \Pi_\ell B^\ell\right)\varphi_t \tag{51}$$

where, z and B denote the differentiating order and the backshift operator, respectively.

2) Fast Forward Selection (FFS) Method

In the stochastic programming techniques, scenario generation is a typical step for analyzing the different states of the uncertain parameters. Although generating a large number of scenarios is an applicable way for more realistic modeling of the system by considering most occurrence states of the scenarios, this work has created some significant challenges for practical problems. A large number of scenarios have led to an increase in the complexity, computational burden, and running-time of the problem, which are not acceptable for practical problems [28]. In this respect, scenario reduction methods are proposed to overcome these challenges by reducing the number of generated scenarios to the logical number. The FFS approach is one of the capable scenario reduction approaches, which works based on the Kantorovich distant theory [29]. More information and the flowchart of the scenario reduction process by the FFS technique can be fully accessed in [30].

IV. Simulation Results

In this paper, a novel operational model is proposed for the effective participation of the interconnected microgrids in the transactive energy market interactions. The modified IEEE 14-bus test system is selected for analyzing the goals of this research by considering full clean energy production in the system. The schematic of this test system is illustrated in Fig. 1 and related data for this case study can be fully reached from [31]. Also, the amount of electrical data as well as the wind speed can be found in the Appendix section of [28]. Each microgrid is equipped with PV panel and wind turbine for clean electrical energy production [32, 33], electrical and thermal storages for increasing the reliability of continues energy supplying in the presence of stochastic producers [34], and the RC unit for meeting the cooling load in the system [35]. The amount of solar radiation along with the efficiency of the different devices are tabulated in Table I.

TABLE I
SOLAR RADIATION AND EFFICIENCY OF VARIOUS DEVICES

Parameter	PV panel	Electrical energy storage		Thermal energy storage	
		Charging	Discharging	Charging	Discharging
Efficiency	0.22	0.9	0.9	0.95	0.95
Time (Hour)	1	2	3	4	5	6
Solar radiation ($kW\ /m^2$)	0	0	0	0	0.041	0.249
Time (Hour)	7	8	9	10	11	12
Solar radiation	0.48	0.708	0.909	1.072	1.186	1.242
Time (Hour)	13	14	15	16	17	18
Solar radiation	1.24	1.172	1.051	0.881	0.676	0.448
Time (Hour)	19	20	21	22	23	24
Solar radiation	0.21	0.024	0	0	0	0

The existence of nonlinear equations along with the binary variables has made the optimal scheduling problem as a mixed-integer nonlinear problem (MINLP). Due to this, the general algebraic modeling system (GAMS) with the SBB [36] and DICOPT [37] solvers are used for solving this problem. The run time of this problem is 34.651 second carried out on a PC with Intel Core i76700HQ CPU @ 2.60 GHz with 16.00 GB RAM. After solving the problem, the same results are obtained, which indicates the acceptable level of optimality for the MINLP problem.

After solving the problem, the energy cost of the renewable-based microgrids in the base (Case I) and the proposed (Case II) models are reported in Table II. Microgrids can only participate in the day-ahead market for energy trading in the base model while they can operate to have energy exchanging in both the day-ahead market and LETM in the proposed model. In other words, in the base model, all microgrids can only have energy trading with the main grid and they are not considered to participate in the LETM interactions. However, participation in the LETM interactions is intended for microgrids in the proposed model that allows them to exchange energy in the local area. Mathematical modeling is the same for both the base and proposed models and the only difference is that the LETM constraints (equations (32) to (35)) are not considered in modeling of the base model (the possibility of local energy trading in the LETM is not considered for microgrids in the base model). Given the obtained results, all microgrids have gained the same amount of cost-saving by participating in the transactive energy market interactions. The achieved percentage of cost-saving for microgrids is equal to 18.34%. Indeed, each microgrid can gain an 18.34% amount of cost-saving in comparison with the base model when they participate in the LETM for performing the appropriate energy interactions. The proposed transactive energy-based model gives the same percentage of cost-saving for microgrids based on their size and interactions in the LETM with the aim of motivating them to participate in the local energy-trading environment. The energy trading possibility between microgrids with each other in the LETM provides a proper way for establishing a dynamic energy balance especially in the systems with a full share of RERs. In this paper, the behaviors of the electrical energy devices in the microgrids are illustrated in Fig. 2. To keep simplicity in representing the simulation results, the charging and discharging states of the storage systems are aggregated in one profile where the negative and positive amounts indicate the charging and discharging states of the storage systems, respectively.

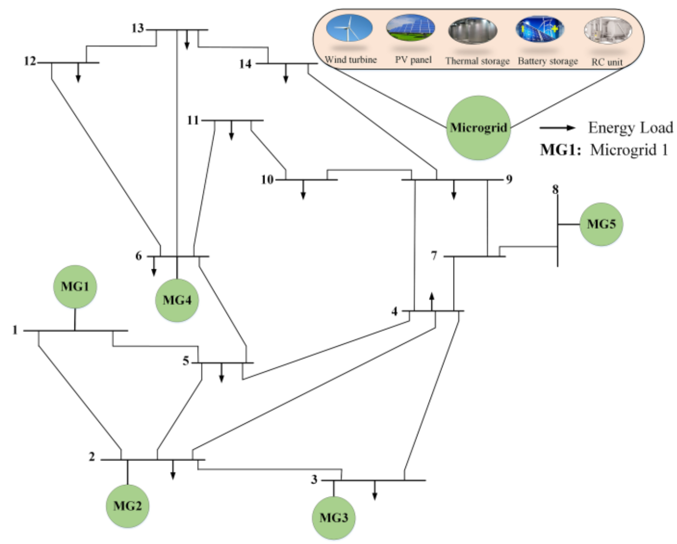

Fig. 1. The schematic of the modified IEEE 14-bus test system.

TABLE II
ENERGY COST OF MICROGRIDS

Microgrid index	Energy cost in the base model ($)	Energy cost in the proposed model ($)
Microgrid 1	3539.611	2890.199
Microgrid 2	10242.823	8363.573
Microgrid 3	21715.452	17731.318
Microgrid 4	6053.093	4942.534
Microgrid 5	7291.749	5953.933
Total cost	48842.735	39881.564

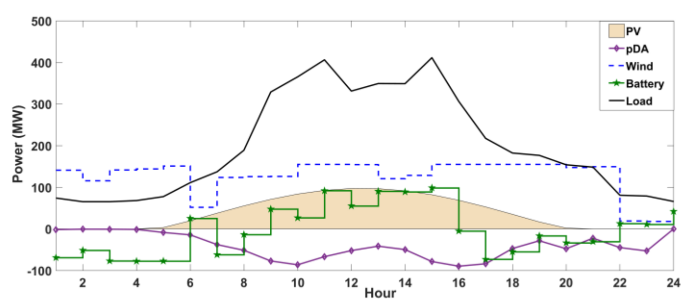

Fig. 2. The outputs of the electrical energy devices during a day.

As obvious from Fig. 2, wind power generation is greater than the electrical energy consumption in the early morning (1-6 am), which leads to the use of surplus energy production for charging the battery storage. In these hours, because of more energy generation in the system, receiving energy from the day-ahead market is not required. However, by rapidly growing the energy demand from 7 am and a relative decline in the wind turbines production, the system has faced with a reduction in the energy generation, so the battery storage system is discharged to compensate the power shortages. In addition to the storage system, microgrids have received more energy from the day-ahead market to create a dynamic energy balance during peak times. This is while the PV system as another clean energy production unit has the maximum energy generation at peak hours and is used for supporting the system to easily meet the electricity demand of the peak times. Moreover, at night (9-12 pm), the amount of power production of generation units in the system is less than the energy consumption. As seen in Fig. 2, this is concluded in the discharging of the battery as well as purchasing energy from the day-ahead market for balancing energy. In addition to the electrical devices, this paper proposes a transactive energy-based mechanism as another reliable way for supporting the renewable-based system in dynamically meeting the energy demand. Indeed, transactive energy technology is applied for developing the LETM to enable the interconnected microgrids for freely energy exchanging with each other in the local area. The amount of energy trading in the LETM is illustrated in Fig. 3 during a day.

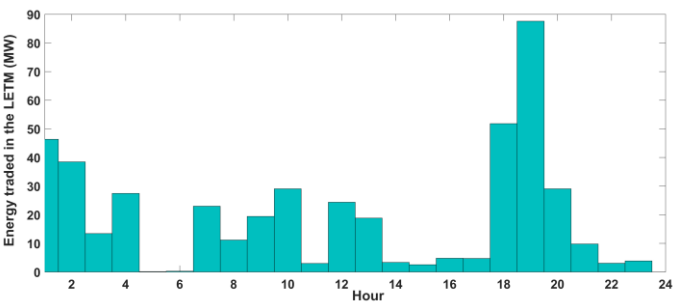

Fig. 3. The amount of energy traded in the LETM.

Given Fig. 3, in the early morning (1 to 4 am), the amount of energy traded in the LETM is high due to the high energy generation by the wind turbines. Indeed, microgrids have used the energy trading possibility not only for meeting energy demand but also for charging their energy storage system and minimizing their dependency on the main grid. However, when the energy demand rises from 5 am, no energy exchange is observed for two consecutive hours. This is because microgrids have used their energy generation capacity for accommodating their energy demand without participating in the LETM interactions. From 7 to 12 am, energy trading is established between the microgrids due to increasing the outputs of the PV panels. At peak times (2 to 5 pm) with a high amount of energy consumption, a large portion of the produced energy in the microgrids is used for meeting the energy demands that have led to weak participation of them in the LETM interactions. This is while a high amount of clean energy produced by the wind turbines in the evening (6 to 8 pm) has led to an increment in the level of LETM interactions. In this paper, the RC unit and thermal storage are used to meet the thermal load as demonstrated in Fig. 4.

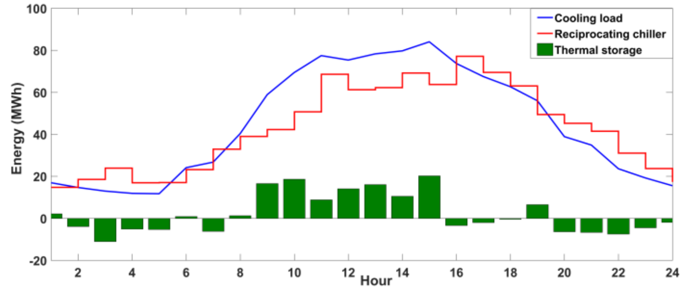

Fig. 4. The outputs of the RC unit and thermal storage during a day.

According to Fig. 4, the output of the RC unit in the early morning (1-7 am) is not only used for meeting the cooling energy but also utilized for charging the thermal storage. In the peak times (10-12 am and 1-6 pm) with high energy demand, the RC unit production has not been sufficient for fully covering the cooling energy demand, which is led to discharging of the thermal storage to establish a dynamic balance between cooling energy supply and consumption. However, thermal storage has worked on the charging mode at night due to the larger cooling energy production by the RC unit in comparison with cooling energy demand at these hours. One of the main objectives of this research is to propose a novel model that considers the robustness and opportunistic states caused by the uncertainties in the system. For this aim, the IGDT method is applied by considering the strategies of both risk-averse and risk-seeker. In this regard, the microgrids' energy cost for various amounts of the horizon of an uncertain variable in the robust and opportunity functions is shown in Fig. 5.

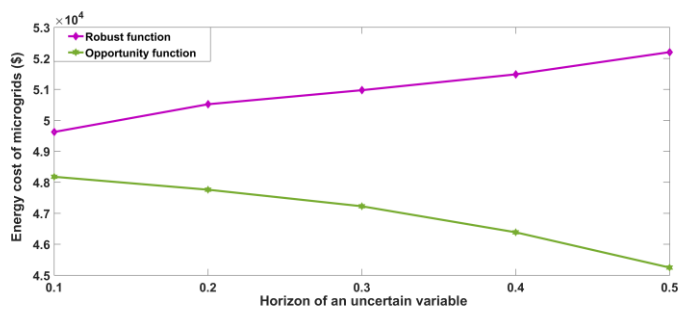

Fig. 5. The microgrids energy cost in robust and opportunity functions.

As obvious from Fig. 5, the microgrids' energy cost is increased proportionally with the increase of the horizon of an uncertain variable in the robust function. In another word, more energy costs will be imposed on the microgrids if they want to have a condition in the more deviation of an uncertain variable. On the other hand, lower energy costs are reached for the microgrids when they operate from the risk-seeker viewpoint. In this strategy, microgrids use the opportunities caused by the uncertainties in the system for minimizing their energy costs. In other words, desirable deviations of the uncertain parameters can create the opportunity of achieving more economic benefits in the system. Hence, by decreasing the horizon of an uncertain variable in the opportunity function, the amount of microgrids' energy cost is also reduced.

V. Results Discussion and Main Achievements

This paper proposes a novel operational model for optimal scheduling of the interconnected microgrids with 100% RERs. Transactive energy technology is used for empowering the proposed model by developing the LETM to make free energy trading among the microgrids possible. Given the extracted results, in comparison with Case I (base model) that all microgrids have not worked based on the proposed model, they have achieved 18.34% cost-saving in Case II (proposed model) when they have participated in the LETM interactions. According to the results, all microgrids have used their clean energy production capacity along with the energy storage systems for meeting their energy demands in the first priority. This is while given Fig. 3, microgrids have effectively used the free energy trading possibility for establishing a dynamic energy balance by participating in the LETM interactions. Indeed, the real-time energy trading possibility created among the interconnected microgrids has enabled them to use the LETM potential for dynamically balancing energy in real-time. Moreover, the costly energy exchanging with the power grid is considered as the last option for balancing energy in the system. In addition to the electrical energy, microgrids have used the RC unit and thermal storage system for reliably meeting their cooling energy demand according to Fig. 4. Because each microgrid is equipped only with RERs, realistic analysis of the system by considering the stochastic behaviors of the uncertain parameters along with providing the robust condition for ensuring the continuous energy supply is essential in this deregulated environment. Thus, the hybrid version of the stochastic programming and the IGDT method with risk-averse and risk-seeker strategies are employed for uncertainty modeling. According to Fig. 5, both the robust and opportunity functions are provided for the microgrids in the different horizons of an uncertain variable. Given the simulation results, the significant achievements of this research are as follows. 1) Providing an appropriate condition for optimal operation of the interconnected microgrids equipped with 100% RERs by proposing a novel operational model. The proposed model can be effectively used for the future modern grids that are aimed to be equipped with 100% RERs. 2) Developing the proposed model based on the transactive energy technology for creating the LETM to enable the microgrids for free energy sharing with each other in real-time with the aim of reliably meeting their energy demand in the deregulated environment. This energy trading environment is necessary for ensuring the continuous energy supply in the systems with a full share of RERs. 3) Realistic modeling of the renewable-based system by applying a hybrid IGDT/stochastic approach for uncertainty modeling along with providing a robust condition for the system in the deregulated environment.

VI. Conclusion

This paper proposed a novel operational model for the interconnected microgrids in the transactive energy market. The full clean energy production goal was realized by equipping each microgrid only to the RERs for energy generation and energy storage systems for mitigating the stochastic behaviors of the RERs. For the systems with 100% RERs, adopting the innovative technologies as well as the reliable ways is necessary for maintaining the continuous energy supply condition. Thus, the proposed model was developed by employing state-of-the-art transactive energy technology for creating the LETM to provide a free energy exchanging possibility for microgrids that enables them to reliably and economically meet their energy demand in the system with a full share of the RERs. For uncertainty quantification, a hybrid IGDT/stochastic technique was developed in a way that the IGDT method was exerted for modeling the fluctuations of the energy price in the day-ahead market considering the risk-averse and risk-seeker strategies. Moreover, the stochastic programming was employed for taking into account the intermittences of the RERs by applying the ARIMA and FFS methods for scenario generation and reduction. The problem was solved in the two models. Model I evaluates the optimal scheduling problem in the base state without considering the same percentage of cost-saving for the microgrids (the possibility of local energy trading in the LETM is not considered for microgrids in this model). This is while Model II was developed based on transactive energy technology to focus on providing the same percentage of cost-saving for the interconnected microgrids. After solving the problem, the effectiveness of Model II was proved by achieving an 18.34% cost-saving for all microgrids than Model I in the deregulated environment.

As the proposed model provides the proper conditions for optimal operation of the microgrids with 100% RERs, adapting it with other control strategies can give a suitable opportunity for developing a comprehensive control scheme for the renewable-based microgrids. In this regard, the hierarchical droop-based control strategies can be integrated with the proposed model using the transactive energy systems to make the controlling process of the system easier. On the other hand, as RERs' outputs and energy price are assumed as the uncertain parameters for uncertainty modeling of the system in this research, there are some other uncertain parameters such as the energy load that can be used as the uncertain parameters for special purposes in the stochastic modeling of the system. All of these issues can be considered as future trends for this work.

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