Arbitrage Strategy of Renewable-Based Microgrids via Peer-to-Peer Energy-Trading

Hossein Nezamabadi, and Vahid Vahidinasab, *Senior Member, IEEE*

***Abstract*— In this paper, an arbitrage strategy is proposed for renewable-based microgrids (MGs) to overcome the volatile behavior of renewable energy sources (RESs) such as photovoltaic and wind in a newly emerged business space in which peer-to-peer (P2P) energy-trading in transactive energy markets (TEMs) set up between a day-ahead market (DAM) and real-time markets (RTMs). To identify arbitrage opportunities created from the price difference between the P2P and real-time trades, a bi-level risk-constrained stochastic programming with interval coefficients (BRSPIC) is presented. In the first stage of the decision-making, scenarios are employed to deal with the DAM prices uncertainties. In the second stage, P2P energy-trading competition is modelled by a bi-level programming based on non-cooperative leader-follower games. While the social welfare of peers is maximized at the lower level, the MG maximizes its profit at the upper level. By getting closer to real-time, interval coefficients are considered in the third stage to cope with the uncertainties of RESs and loads, as well as RTM prices. The conditional value-at-risk (CVaR) is enforced the model to control the risk of profit variability. By using Karush-Kuhn-Tucker (KKT), the BRSPIC is transformed into a single level optimization. Then, it is linearized and solved by a mixed-integer linear programming (MILP) solver. By evaluating the proposed model on a test system, it is evident that the MG increases more than 3.1% of its profit by the arbitrage strategy. By considering CVaR, a fully risk-averse decision decreases the profit of MG by 27%, although it would be so conservative decision.**

***Index Terms*—Renewable energy, Microgrid, arbitrage strategy, peer-to-peer, Risk control.**

NOMENCLATURE

Indices and sets

t/T	Index/set of time period
dg/S_{DG}	Index/set of DG units
str/S_{STR}	Index/set of ESS units
dr/S_{DR}	Index/set of flexible demands
d/S_{FD}	Index/set of non-flexible demands
r/O	Index/set of opponent peers in the TEM
p/P	Index/set of price scenarios

Parameters

β	Risk-aversion parameter
α	Confidence level
$\lambda_{t,p}^{DA}$	The DAM price forecast (in \$/MWh)
ρ_t^R	Retail price (in \$/MWh)
C^{dg}, C^{dr}, C^{str}	Cost coefficients of DERs (in \$/MWh)
$P^{dg,Min}/P^{dg,Max}$	Min/max capacity of DGs (in MW)
MUT_{dg}/MDT_{dg}	Minimum up/down time of DGs (in hour)
RU^{dg}/RD^{dg}	Ramp up/down rate of DGs (in MW/hr)
$P_t^{dr,Min}/P_t^{dr,Max}$	Min/max capability of DR (in MW)
LDR^{dr}/LPR^{dr}	Pick-up/drop rate of DRs (in MW/hr)
$E^{dr,Max}$	Maximum energy of DRs (in MWh)
$SOC^{str,Init}$	Initial SOC of ESSs (in MWh)
$P_{str}^{ch-Max}/P_{str}^{dch-Max}$	Maximum charging/discharging capability of ESSs (in MW)
$E^{str,Max}/DOD_{str}$	Max/min stored energy in ESSs (in MWh)
$\eta_{str}^{ch}/\eta_{str}^{dch}$	ESSs Charge/discharge energy efficiency
$P^{r,TE-max}/P^{r,TE-min}$	Maximum and minimum bid/offer quantity of rival peers in the TEM (in MWh)
π_p	The probability of scenario p occuring.

Prediction intervals

$[\alpha_{t,p}^{r,TE-LB}, \alpha_{t,p}^{r,TE-UB}]$	Offering and bidding price of rival peers in the TEM (in \$/MWh)
$[\lambda_{t,p}^{RT-LB}, \lambda_{t,p}^{RT-UB}]$	The RTM price forecast (in \$/MWh)
$[D_{d,t}^{LB}, D_{d,t}^{UB}]$	Net Demand (in MWh)

Free variables

$P_{t,p}^{DA}$	Bidding quantity to the DAM (in MWh)
$P_{t,p}^{RT}$	Bidding quantity to the RTM (in MWh)
$P_{t,p}^{TE}$	Bidding quantity to the TEM (in MWh)
$P_{t,p}^{r,TE}$	Bidding quantity of rivals to the TEM (in MWh)
$\lambda_{t,p}^{TE}$	P2P energy-trading price in the TEM (in \$/MWh)
var	Auxiliary variable for calculating CVaR

Positive Variables

$P_{dg,t,p}^{DG}$	Energy production of DGs (in MWh)
$P_{d,t,p}^{DR}$	Energy consumption of DR (in MWh)
$P_{str,t,p}^{ch}/P_{str,t,p}^{dch}$	ESSs charge/discharge rate (in MWh)
$SOC_{str,t,p}^{STR}$	ESSs state of charge (in MWh)
S_p	Auxiliary variable for calculating CVaR in scenario p

Binary variables

$I_{t,p}^{dg}$	Commitment status of DGs
$J_{t,p}^{dg}/K_{t,p}^{dg}$	Start-up/Shut-down status of DGs

The authors are with the Department of Electrical Engineering, Abbaspour School of Engineering, Shahid Beheshti University, Tehran, Iran (e-mail: h_nezamabadi@sbu.ac.ir, v_vahidinasab@sbu.ac.ir)

I. INTRODUCTION

A. Aim and Scope

THE newly emerged transactive energy (TE) technology facilitates the energy-trading in order to improve the competition level in the retail domain, and to increase the rate of uptake of renewable energy sources (RESs) [1]–[3]. The TE establishes a set of control and economic mechanisms to provide the required energy and ancillary services to keep the balance of the demand and supply [4], [5]. Instead of using the traditional tariff-based mechanisms, the TE enables the direct peer-to-peer (P2P) trades between the existing agents at the distribution level, in a decentralized manner [6]. Therefore, the TE changes the business model of distribution systems from a cost-based (or better to say tariff-based) to a value-based (i.e. market-based) [7].

There are three types of transactive energy markets (TEMs) including full P2P, community-based, and hybrid P2P markets

[8]. Under the hybrid P2P market framework, microgrids (MGs) inherit autonomy and scalability from full P2P and community-based models, respectively [8]. In such a new space, MGs can be engaged in both intra-community and inter-community P2P energy-trading with other peers (i.e. producers, consumers, prosumers and other MGs). Since the market clearing of P2P markets is based on consensus on a specified price and quantity [8], price-maker MGs can affect the price of P2P trades.

In this newly emerged business model, the P2P energy-trading sets up between a day-ahead market (DAM) and real-time markets (RTMs) [9]. By the price differences of the P2P energy-trading, prosumers can benefit from arbitrage opportunities [10]. Moreover, based on the arbitrage definition "any activity that tries to buy a commodity under-priced and to sell it over-priced in purpose of gaining profit" [11], MGs can buy/sell energy at a specified price in a P2P manner, and sell/buy it with a higher/lower price of the RTM in purpose of gaining profit. Thus, the existence of different prices between P2P trades and RTMs creates some arbitrage opportunities. Hence, MGs can identify these opportunities in its bidding strategy as an extra income. It should be noted that the other type of arbitrage opportunity is reached by energy storage systems (ESSs), which stores energy during lower-priced hours and releases it during higher-priced hours. Hence, identifying these opportunities, which is called "arbitrage strategy", can affect the bidding strategy of MGs.

In the proposed framework of this paper, while MGs are able to participate in both existing markets (i.e. the DAM and RTM) and P2P TEM, they should optimally operate their DERs (i.e. their community) in order to fulfill their commitments in the aforementioned markets. Also, the MG should deal with all the uncertain parameters associated with the RESs power generation, loads, rivals' bid and offer in TEM, and prices of the RTM and DAM. Although forecasting of uncertain parameters is beyond the scope of this paper, it would be important to consider which types of forecasting (scenario-based or interval-based) in the model. Since the profit of MGs is very sensitive to the types of forecasting, it leads to a hybrid scenario/interval based model. Due to the aforementioned uncertainties, the possibility of experiencing unfavorable profit is increased, which conducts to a risk-constrained model.

This paper is aimed to assist MG's operators to derive arbitrage strategy via P2P energy trades, whereas they can control the risk of experiencing non-desired profit. Noteworthy, the arbitrage opportunity of ESSs is also considered in this work.

B. Literature Review and Research Gaps

The bidding problem of MGs in the traditional markets, where P2P trades are not enabled, has been widely studied [1], [12]–[15]. In this regime, MGs are able to integrate the distributed energy resources (DERs) into a centralized DAM. Then, due to the uncertainty of RESs and loads, MGs should balance their supply and demand by participation in an RTM [1]. To solve the bidding strategy of MGs with the prices uncertainty and RESs fluctuations, a hybrid stochastic/interval optimization (HSIO) is proposed in the Ref. [1]. In [12], a hybrid stochastic/robust optimization (HSRO) model is proposed to solve the bidding problem of MGs. In this paper, the robust optimization is deployed to minimize the energy imbalance in the RTM. Optimal offering strategy of an aggregated PV power plant based on a stochastic bi-level model in the day-ahead, intra-day and balancing markets, is presented in [13]. To model the risk averseness of MGs in the DAM, risk-constrained stochastic programming (RSP) is proposed in the [14], [15]. Although the risk-averseness of MGs is considered in these two recent works, P2P trades and arbitrage strategies are not investigated in all of aforementioned papers.

P2P energy-trading can be categorized into two group: 1) intra-community P2P energy-trading (P2P trades inside of an MG, which is called a community MG), 2) inter-community P2P energy-trading (P2P trades between a community like an MG with other peers) . In the first group, the interactions of producers, consumers and prosumers, which are embedded inside of a community MG, are investigated. These interactions can be cooperative or non-cooperative [16].

A cooperative energy management system (EMS) inside of a community is proposed in [10], [17]. A P2P distributed EMS for a single hour-ahead is proposed in [10]. Although the differences between the price of P2P trades make some arbitrage opportunities in this work, the arbitrage opportunities between the real-time prices and P2P trades are not considered. Also, participation of prosumers in the existing markets (i.e. the DAM or the RTM) are not investigated. A synergy framework is presented to integrate a community of houses equipped with battery storage (or better to say a community of prosumers) into the existing day-ahead and intra-day markets in [17]. Using a two-stage stochastic programming approach, P2P trading can integrate prosumers in day-ahead and intra-day markets. Firstly, the community participate in the DAM based on a forecast of the own RESs. Secondly, the prosumers balance their deviation from day-ahead decisions by P2P trades and battery storage systems utilization .Thus, community of prosumers can only benefit from the arbitrage opportunities by the storage. Since the interaction of peers is cooperative, the P2P trade prices are set by the community manager in [10] and [17]. Therefore, the pricing mechanism is not investigated in these two works.

A non-cooperative EMS inside of a community is proposed in [18]–[20]. In all of these work, since the interaction of peers is non-cooperative, the P2P trade prices are obtained by the consensus, which is modelled by game-theoretic approaches. The energy trading interactions between producers and consumers inside of an MG is modeled by a Stackelberg game in which producers lead and consumers follow in [18]. In [19], there are two types of competitions during the trade. The sellers compete on the offered price, and the buyers compete on the selection of the sellers. The price competition among the sellers is modeled as a non-cooperative game. The evolutionary game is used to model the dynamics of the buyers for selecting sellers. In [20], a novel non-cooperative EMS for energy sharing of community prosumers is proposed. In order to consider the uncertainties of household loads and solar generations in the real-time, two-stage dynamic prices (i.e. day-ahead prices and real-time prices) are considered which is proportional to the community net demands in day-ahead stage and real-time stage respectively. Therefore, each prosumer can share energy in the day-ahead stage, and then minimize its energy cost by considering the real-time uncertainties. The risk of solar generation loss takes into account by the RSP model. However, risk of experiencing unfavourable profit is not considered. Although the strategic interactions of the prosumers inside of the community are considered in [18]–[20], the inter-community interactions with existing the DAM and RTM, and with peers outside the community are not investigated simultaneously.

In the second group, the interaction of MGs with other peers are investigated. Like the first group, these interactions can be categorized into cooperative and non-cooperative. A cooperative community of MGs inside a distribution system is proposed in [21]. An optimal operation of multiple MGs is investigated in this paper. Since the interaction of MGs is cooperative, the P2P trade prices are set by the distribution system. Therefore, the pricing mechanism is not considered in this work. A non-cooperative approach based on Stackelberg game is proposed in [2]. By the emergence of the TEM, MGs can balance their deviation from the DAM commitments by the P2P trades, where prices would be more favorable than the RTM [2]. In [2], the bidding strategy of MG is presented in the TEM in which market participants can trade energy in a P2P manner. Although the MG can provide flexible resources for balancing applications in a P2P manner, the arbitrage strategy through P2P energy trades as well as the risk of experiencing non-desired profit are not considered in [2].

According to the above discussion, there is a need for an EMS to consider intra-community and inter-community interactions of MGs ***simultaneously***. In addition to participate in the triple markets (i.e. the DAM, TEM and RTM), the MG should operate DERs in an optimal and reliable fashion. Moreover, the EMS should be able to identify various arbitrage opportunities. especially, lack of identifying the arbitrage between the existing RTM and the P2P energy-trading is felt. Finally, it is required to control the risk of experiencing unfavorable profit in each one of triple markets. In response to these requirements, the arbitrage strategy of MGs via a joint cooperative and non-cooperative P2P energy-trading system is investigated in this paper.

For the sake of clarity, the features of our proposed model are compared with the relevant literature in Table I.

C. Contributions and Approaches

Although the most recent works focus either on intra-community [10], [17]–[20] or inter-community P2P energy-trading [2], [21], this paper presents the arbitrage strategy of MGs via a joint cooperative and non-cooperative EMS, which considers intra-community P2P energy-trading inside the MG in a cooperative manner, and inter-community P2P energy-trading outside the MG in a non-cooperative manner. By the cooperative EMS, the MG operates its DERs in an optimal and reliable fashion. By the non-cooperative EMS based on game-theoretic approach, it can compete with rivals via a Stackelberg game. By enabling arbitrage opportunities of the MG in the newly-established business model, it can simultaneously trade (bid and offer) energy in different markets (i.e. the TEM and RTM) to earn much more profit from differences between the prices of two markets. In confronting profit variability, the degree of risk aversion is measured by the conditional value at risk (CVaR).

To identify the arbitrage opportunities of MGs and oncurrently to control the risk of profit variability on the other, a bi-level risk-constrained stochastic programming with interval coefficient (BRSPIC) is proposed, which considers competitive behaviour of MGs in the level of the TEM by the bi-level programming. In the first stage of decision making, the price uncertainty involved with the DAM is handled by a scenario-based stochastic programming approach. In the second stage, the rivals' offer uncertainty is considered as an interval coefficient. In the third stage, the uncertainties of the RESs, loads and RTM prices are modelled by interval coefficients. Noteworthy, the CVaR is deployed to control the risk of profit variability.

To solve the bi-level problem as a single level problem in the TEM, the lower-level problem is replaced with Karush-Kuhn-Tucker (KKT) conditions. Thus, the bi-level programming is transformed to a mathematical problem with equilibrium constraints (MPEC). Then, the non-linearities of the KKT conditions and the complementary conditions are linearized by the strong duality theorem and the variable substitution, respectively. Hence, the BRSPIC model is transformed to a single level linear model to solve by an MILP solver.

The main contributions of this paper can be summarized by the following:

1) Presenting a joint cooperative and non-cooperative EMS for MGs to manage intra-community and inter-community P2P energy-trading;
2) Proposing arbitrage strategy of MGs through P2P energy-trading to cope with the volatility of the generation of RESs;
3) Deriving MGs decision-making structure based on a bi-level risk-constrained three-stage stochastic programming with an interval coefficients model.

D. Paper Organization

The paper is organized as follows. In section 2, participation of MGs in electricity markets is given. The decision-making frame work of the MG is investigated in section 3. The problem formulation is described in section 4. Finally, numerical analysis is explored in section 5.

II. Participation of Microgrids in Electricity Markets

In the wholesale domain, existing electricity markets including the DAM and the RTM operate in a centralized manner by the independent system operator (ISO) [22]. In the retail domain, the TEM is a decentralized market based on the P2P energy-trading. In contrast with the centralized markets, decentralized TEM is proposed to allow P2P energy-trading without requiring third-party supervision (i.e. ISO) [8]. Blockchain smart contracts facilitate the P2P energy trading in such a decentralized structure, so there is no centralized market operator in the TEM [23].

This paper presents the arbitrage strategy of MGs via a joint cooperative and non-cooperative EMS, which considers intra-community P2P energy-trading inside the MG in a cooperative manner, and inter-community P2P energy-trading outside the MG in a non-cooperative manner. By the cooperative EMS, the MG operates its DERs in an optimal and reliable fashion. By the non-cooperative EMS based on game-theoretic approach, it can compete with rivals via a Stackelberg game. Principally, when two energy markets are cleared with a few minutes' delay, arbitrage opportunities between these two markets can be identified [11]. In terms of optimization, they can be co-optimized in a stage [11]. Thus, it is assumed that the P2P trades can be made near

TABLE I
FEATURES OF THE PROPOSED MODEL AND THE OTHER RELEVANT WORKS

Ref. No	Business objective: Bidding strategy	Business objective: Arbitrage strategy	Business objective: Risk control	Markets: Day-ahead	Markets: Transactive	Markets: Real-time	Intra-com.: Cooperative	Intra-com.: Non-Cooperative	Inter-com.: Cooperative	Inter-com.: Non-Cooperative	Uncertainty model	Approach
[1]	✓	×	×	✓	×	✓	×	×	×	×	Scenario&Interval	Two-stage HSIO
[2]	✓	×	×	×	✓	✓	×	×	×	✓	Interval	BPIC
[12]	✓	×	×	✓	×	✓	×	×	×	×	Scenario&Robust	Two-stage HSRO
[13]	✓	×	×	✓	×	✓	×	×	×	×	Scenario	Three-stage SP
[14]	✓	×	✓	✓	×	✓	×	×	×	×	Scenario	Two-stage RSP
[15]	✓	×	✓	✓	×	✓	×	×	×	×	Scenario	Two-stage CSP
[10]	×	✓	×	×	✓	×	✓	×	×	×	-	Distributed optimization
[17]	×	✓	×	✓	✓	×	✓	×	×	×	Scenario	Two-stage SP
[18]	×	✓	×	×	✓	×	×	✓	×	×	-	game-theoretic
[19]	×	✓	×	×	✓	×	×	✓	×	×	-	game-theoretic
[20]	×	✓	✓	×	✓	×	×	✓	×	×	Scenario	stochastic game-theoretic
[21]	×	✓	✓	×	✓	×	×	×	✓	×	-	SOCP
This paper	✓	✓	✓	✓	✓	✓	✓	×	×	✓	Scenario&Interval	Three-stage BRSPIC

HSIO: Hybrid stochastic/interval optimization; HSRO: Hybrid stochastic/robust optimization; RSP: Risk-constrained stochastic programming BPIC: Bi-level programming with interval coefficient; SOCP: Second order cone programming; BRSPIC: Bi-level risk-constrained stochastic programming with interval coefficient

the RTM. By enabling arbitrage opportunities of the MG in the newly-established business model, it can simultaneously bid and offer energy between the different markets (i.e. the TEM and RTM) to earn much more profit from differences between the prices of two markets.

The settlement mechanism of P2P market is based on consensus. By consensus on a specified price and quantity, a P2P trade is made between two peers. Noteworthy that the P2P market design is based on decentralized structure in which peers directly negotiate with each other on a certain amount of energy and price [8]. Although all involved peers focus only on solving their own local profit maximization (or cost minimization) problem without considering overall social welfare, solving their own local problem will yield maximum social welfare solution by reaching consensus (or better to say by reaching equilibrium point, which is converged on a certain amount of energy and price without centralized supervision). In other words, the equilibrium point of centralized and decentralized approaches are the same in terms of solutions [8]. Since the equilibrium of the decentralized P2P energy-trading in the TEM is converged to the centralized one, the clearing problem of the TEM can be considered as a social welfare maximization problem. In the process of consensus, the strategic interaction between peers (i.e. P2P energy-trading) leading to a leader-follower game-theoretic model [18]–[20]. Thus, a leader-follower game is needed to investigate the strategic interaction of the MG and the other involved peers in the P2P energy trading . Therefore, the MG should maximize its profit while maximizes overall social welfare to consider the consensus problem in a leader-follower approach. Since peers reach a consensus on a certain amount of energy and price during P2P process, the payment balance and the trading fairness are guaranteed by the convergence of negotiation process [24]. By considering decentralized P2P market, trust concerns among market players (including truthfulness, malicious behavior and cyber security) increases, which they affect the payment balance and the trading fairness. These topics open for future works.

In addition to participate in the TEM, an MG can participate in the DAM and RTM. The DAM clears 6 hours before the delivery time for the 24-hour ahead. Although the P2P energy-trading can take place in the DAM and the RTM, the P2P energy-trading (or better to say the TEM) sets up between a DAM and RTMs to provide adjustment opportunities in this paper [22]. Finally, the RTM clears half-hour before the delivery time for the next hour. The settlement mechanism of the DAM and RTM is categorized into the one-price and two-price systems [9]. The two-price system is a common settlement scheme in Europe [25]. The two-price system, in which the stochastic prosumers (like MGs) are settled at unfavorable prices in the RTM, is investigated in this paper. For the sake of clarity, in Fig. 1, the participation of MGs in threefold electricity markets is shown.

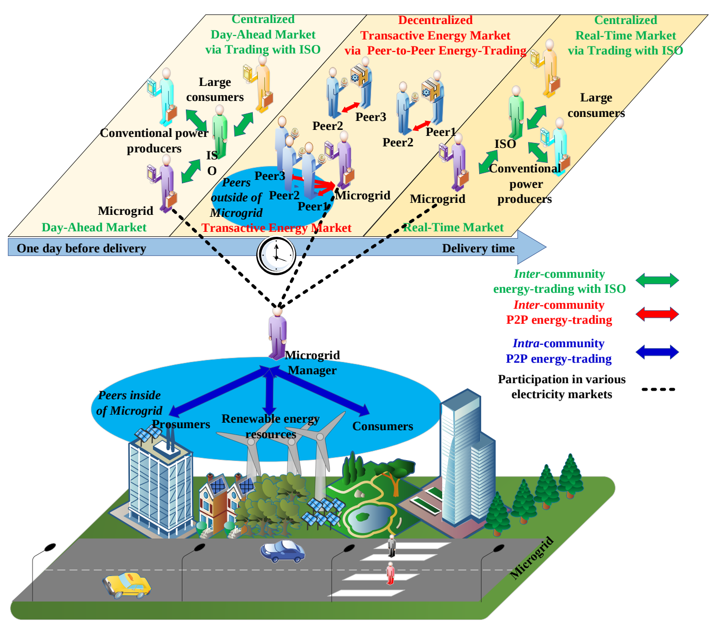

Fig. 1. Participation of microgrids in electricity markets.

III. Uncertainty Management via Three-Stage Hybrid Stochastic-Interval Decision Making Framework

In this paper, the MG is faced with various uncertainties including RESs production, loads consumption, prices of the DAM, Prices of the RTM, and the bidding and offering prices of rival peers in the TEM. Such a large number of uncertainties can be handled by the HSIO, which takes the advantage of the cost-effective solution from the SP, and the reliable solution with computational simplicity from the interval optimization [1]. The HSIO advantages and applicability can be found in the authors' previous work [1].

In the HSIO, the uncertainty of the first-stage is considered by the scenarios. Thus, the DAM price is modeled by scenarios in this paper. Scenario generation process is based on auto regressive models, and then the generated scenarios are reduced by using the probability distance [26]. It should be noted that the MG profit is very sensitive to the DAM price. Therefore, the main benefit of the DAM price scenarios is that it is applied by the SP whose solution is cost-effective from an economic point of view. The other stage uncertainties are considered with prediction intervals. Therefore, interval predictions are considered for RESs production, loads consumption, prices of the DAM, Prices of the RTM, and the bidding and offering prices of rival peers in the TEM. Finally, these interval predictions substitute to the sets of critical scenarios and inter-scenario constraints, which they model the worst-case realization of the uncertainties. This means that the MG will maximize its minimum expected profit, although realizing the worst-case of the uncertainties can be conservative.

It should be noted that the P2P market design is based on peers directly negotiating with each other. Hence, two peers can consensus on a certain amount of energy and price without centralized supervision [8]. In order to consider the impact of the P2P trading on the bidding strategy of MGs in the DAM, MGs should anticipate the bidding and offering prices of rival peers. This anticipation can be provided by prediction intervals. By historical data, Prediction intervals can provide a feeling about the level of price uncertainty for MGs. Generally, prediction intervals define with a central forecast and a coverage rate [22]. As interval prediction is outside the scope of this paper, the central forecast of the P2P price can be simply predicted by the auto-regressive models and, the coverage rate can be estimated by the statistical methods [27].

In such a market structure mentioned in Section II, the MG should submit its bids appropriate to the gate-closure time of the markets. Therefore, the MG is faced with a three-stage decision-making problem. In the first stage, it is faced with the price uncertainty of the DAM prices. Hence, it should forecast the prices of the DAM by a scenario generation process to make an optimal decision on the bidding problem of the MG in this market. In the second stage, the MG competes with rivals (or better to say other peers) in the TEM. Thus, the MG confronts a bi-level optimization in which it maximizes its profit in the upper level in the TEM, and it models the behaviour of other peers by solving the clearing problem of the TEM in the lower level. After the realization of the net demands and the RTM prices, the MG balances its energy imbalances as a last resort of balancing energy in the third stage. In order to control the risk of experiencing non-desirable profits, CVaR is applied to the model.The risk analysis and risk measures under uncertainty condition have been widely investigated in [22] and [26]. In Fig. 2, the decision-making framework of the MG is given. The nodes indicate decision states (i.e. the decision-making point). In a scenario tree, the branches represent different realizations of the random variables [26].

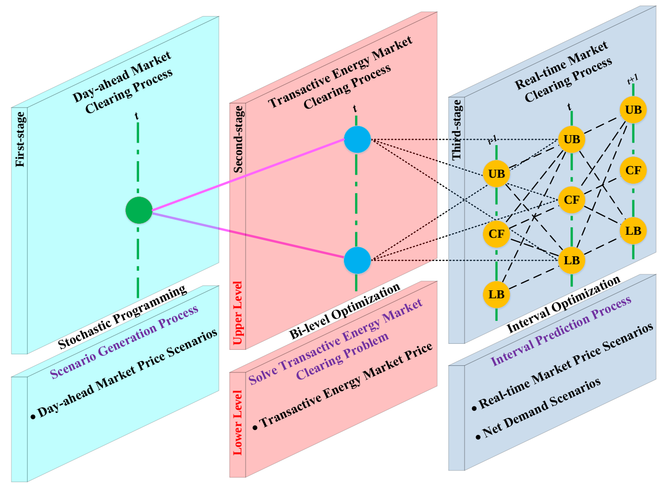

Fig. 2. The decision-making structure of the MG

IV. Model Formulation

A. Risk-Constrained Stochastic Bi-Level Programming with Interval Coefficients

By the following, the mathematical model of bidding problem in the DAM is given.

$$\underbrace{Maximize \quad ULOF}_{Profit_{t,p},\eta,S_p} = (1-\beta)\sum_p \pi_p \sum_t Profit_{t,p} + \beta\left(var - \frac{1}{1-\alpha}\left(\sum_p \pi_p S_p\right)\right) \tag{1}$$

$$Subject\ to:$$

$$Profit_{t,p} = \lambda^{DA}_{t,p} P^{DA}_{t,p} + \lambda^{TE}_{t,p} P^{TE}_{t,p} + \lambda^{RT}_{t,p} P^{RT}_{t,p} + \sum_{d\in S_{FD}} \rho_t D^d_t + \sum_{dr\in S_{DR}} C^{dr} P^{dr}_{t,p} - \sum_{dg\in S_{DG}} C^{dg} P^{dg}_{t,p} - \sum_{str\in S_{STR}} C^{str}\left(P^{str,ch}_{t,p} + P^{str,dch}_{t,p}\right) \tag{2}$$

$$\sum_{dg\in S_{DG}} P^{dg}_{t,p} + \sum_{str\in S_{STR}} \left(P^{dch}_{t,p} - P^{ch}_{t,p}\right) - \sum_{dr\in S_{DR}} P^{dr}_{t,p} - \sum_{d\in S_{FD}} D^d_t - P^{DA}_{t,p} - P^{TE}_{t,p} - P^{RT}_{t,p} = 0, \forall t,p \tag{3}$$

$$|P^{DA}_{t,p} + P^{TE}_{t,p} + P^{RT}_{t,p}| \leq P^{PCC}, \forall t,p \tag{4}$$

$$P^{dg,Min} \leq P_{t,p}^{dg} \leq P^{dg,Max}, \forall dg,t,p \quad (5)$$
$$J_{t,p}^{dg} - K_{t,p}^{dg} = I_{t,p}^{dg} - I_{t-1,p}^{dg}, \forall dg,t,p \quad (6)$$
$$J_{t,p}^{dg} + K_{t,p}^{dg} \leq 1, \forall dg,t,p \quad (7)$$
$$\sum_{l=1}^{MUT^{dg}} I_{t+1,p}^{dg} - 1 \geq MUT_{dg}, \forall J_{t,p}^{dg} = 1, \forall dg,t,p \quad (8)$$
$$\sum_{l=1}^{MDT^{dg}} 1 - I_{t+1,p}^{dg} \geq MDT_{dg}, \forall K_{t,p}^{dg} = 1, \forall dg,t,p \quad (9)$$
$$P_{t-1,p}^{dg} - P_{t,p}^{dg} \leq RD^{dg}, \forall dg,t,p \quad (10)$$
$$P_{t,p}^{dg} - P_{t-1,p}^{dg} \leq RU^{dg}, \forall dg,t,p \quad (11)$$
$$P^{dr,Min} \leq P_{t,p}^{dr} \leq P^{dr,Max}, \forall dr,t,p \quad (12)$$
$$P_{t-1,p}^{dr} - P_{t,p}^{dr} \leq LDR^{dr}, \forall dr,t,p \quad (13)$$
$$P_{t,p}^{dr} - P_{t-1,p}^{dr} \leq LPR^{dr}, \forall dr,t,p \quad (14)$$
$$\sum_{t \in T} \sum_{dr \in S_{DR}} P_{t,p}^{dr} \leq E^{dr,\max}, \forall dr,p \quad (15)$$
$$SOC_{t,p}^{str} = SOC^{str,Init}, \forall str,p,t=0 \quad (16)$$
$$P_{t,p}^{str,ch} \leq P^{str,ch-Max}, \forall str,t,p \quad (17)$$
$$P_{t,p}^{str,dch} \leq P^{str,dch-Max}, \forall str,t,p \quad (18)$$
$$SOC_{t,p}^{str} \leq SOC^{str,Max}, \forall str,t,p \quad (19)$$
$$SOC_{t,p}^{str} \geq DOD^{str}, \forall str,t,p \quad (20)$$
$$SOC_{t,p}^{str} = \quad (21)$$
$$\eta_{str}^{ch} P_{t,p}^{str,ch} - \frac{P_{t,p}^{str,dch}}{\eta_{str}^{dch}} + SOC_{t-1,p}^{str}, \forall str,t,p$$
$$var - \sum_{p} \pi_p \sum_{t} Profit_{t,p} \leq S_p \quad (22)$$
$$\underbrace{Minimize \quad LLOF}_{P_{t,p}^{TE}} = \alpha_{t,p}^{TE} P_{t,p}^{TE} + \sum_{r \in O} \alpha_{t,p}^{r,TE} P_{t,p}^{r,TE} \quad (23)$$
$$Subject\ to:$$
$$P_{t,p}^{TE} + \sum_{r \in O} P_{t,p}^{r,TE} = 0 : \lambda_{t,p}^{TE}, \forall t,p \quad (24)$$
$$P_{t,p}^{TE} \leq P_{t,p}^{TE-\max} : \mu_{t,p}^{\max}, \forall t,p \quad (25)$$
$$P_{t,p}^{TE} \geq P_{t,p}^{TE-\min} : \mu_{t,p}^{\min}, \forall t,p \quad (26)$$
$$P_{t,p}^{r,TE} \leq P^{r,TE-\max} : \mu_{t,p}^{r,\max}, \forall r,t,p \quad (27)$$
$$P_{t,p}^{r,TE} \geq P^{r,TE-\min} : \mu_{t,p}^{r,\min}, \forall r,t,p \quad (28)$$

The upper level objective function (ULOF) is formulated in Equation (1). In the first term of the ULOF, the profit of MG is maximized, which is expanded in detailed in Equation (2). To manage the risk of experiencing unfavourable profit, the CVaR risk measure is maximized in the second part of the OF. Where $\beta \in (0, \infty)$ is a parameter to characterize the tradeoff between the risk-neutral and risk-averse decision making. By neglecting the CVaR in the ULOF (i.e. $\beta = 0$), a risk-neutral decision is made by the MG. By increasing β, the CVaR term becomes more significant with respect to the profit term, which makes the decision risk-averse.

In Equation (2), the first term is involved with the bidding of MG in the DAM. The second and third terms are involved with the offer income and the bid cost in the TEM, respectively. The fourth term is the balancing cost of MG in the RTM. It should be noted that the uncertainty of the RTM price (i.e. $\lambda_{t,p}^{RT}$) is modelled as a prediction interval (i.e. $\left[\lambda_t^{RT-LB}, \lambda_t^{RT-UB}\right]$). It should be noted that $P_{t,p}^{DA}, P_{t,p}^{TE} and P_{t,p}^{RT}$ are free variables. The positive values show selling energy to the markets, and negative values indicates buying energy from the markets. Noteworthy that the uncertainty of net demand appears as an interval coefficient. Since the retail pricing is considered by the net-metering scheme, the 5th term of the Equation (2) shows the real-time revenue of the MG from the net-metering scheme. In this scheme, the differences between the consumption of non-flexible demands and the production of RESs (i.e. net loads) are payed to the MG at retail rates (ρ_t) by the consumers, producers and prosumers. It is worth mentioning that the uncertainty of net load (i.e. D_t^d) appears as an interval coefficient (i.e.$\left[D_t^{d,LB}, D_t^{d,UB}\right]$) in the ULOF. The MG makes energy supply contracts with flexible demands. Thus, the 6th term is the revenue of the MG earned by flexible demands. The 7th and 8th terms are the real-time operation cost of DGs and ESSs, respectively.

The constraints of MG bidding problem are given in Equations (3)-(28). Equation (3) is enforced the supply-demand constraint of MG. The net demand is modelled as an interval prediction (i.e.$\left[D_t^{d,LB}, D_t^{d,UB}\right]$) in this equation. The power exchanged with the upstream network is limited by the point of common coupling (PCC) capacity, which is enforced by Equation (4). Equations (5)-(21) are enforced the constraints of DERs. Equation (22) enforces that the difference between the value-at-risk (var) minus the profit of each scenario realization should be less than the auxiliary continuous non-negative variable (S_p).

In Equations (23)-(28), the clearing problem of the TEM is modelled as the lower level problem, which determines the P2P energy-trading price. As mentioned previously in Section III, the lower level objective function (LLOF), Equation (23), is maximizing the social welfare. In the LLOF, the uncertainty of rivals' offer (i.e. $\alpha_t^{r,TE}$) is considered by the interval coefficient (i.e. $[\alpha_t^{r,TE-LB}, \alpha_t^{r,TE-UB}]$). Equation (24) is the energy balance of the TEM. The Equations (25)-(28) enforce the quantity limits of offering and bidding in the TEM. In the lower level problem, the dual variables of constraints are shown after the colon symbol.

B. Single Level Hybrid Stochastic-Interval Optimization

1) Substitution of Interval coefficients with equivalent scenarios: To solve the risk-constrained stochastic bi-Level programming with interval coefficients, the interval coefficients should be handled by the features of interval optimization provided by [1]. The interval coefficients exist in the ULOF, LLOF and supply-demand constraint of the MG (i.e. Equations (1), (23) and (2), respectively). Generally, an interval prediction is defined by a most probable scenario (i.e. central forecast (CF) and symmetric values around the CF which are called upper bound (UB) and lower bound (LB) [27]. Since the net load in the objective function is not involved with any of the decision variable, this part of the objective function can be replace with the three equi-probable scenarios (i.e. $\omega = \{LB, CF, UB\}$) in interval optimization [1]. Accordingly, an additional dimension is added to the all of decision variables involved with the second and third stages of decision-making (i.e. $\{P_{t,p,\omega}^{dg}, P_{t,p,\omega}^{str,dch}, P_{t,p,\omega}^{str,ch}, P_{t,p,\omega}^{dr}, P_{t,p,\omega}^{RT}, P_{t,p,\omega}^{TE}, P_{t,p,\omega}^{r,TE}, \lambda_{t,p,\omega}^{TE}, \mu_{t,p,\omega}^{\max}, \mu_{t,p,\omega}^{\min}, \mu_{t,p,\omega}^{r,\max}, \mu_{t,p,\omega}^{r,\min}, S_{p,\omega}\}$). So, dimension of ω is added to all of Equations (1)-(28). On the other hand, when the interval coefficient is associated with a positive variable, the worst-case of an interval in the objective function of a maximization problem is resulted by the realization of the LB of the prediction interval, and in the objective function of a minimization problem is resulted by the realization of the UB [1]. The RTM price and the TEM rivals' offer are interval coefficients associated with unrestricted-sign decision variable (i.e. $P_{t,p,\omega}^{RT}$ and $P_{t,p,\omega)}^{TE}$)). To employ the mentioned principle for extracting the worst-case, the power associated with the RTM and the TEM are decomposed into two positive variables (i.e. $P_{t,p,\omega}^{RT} = P_{t,p,\omega}^{RT-buy} - P_{t,p,\omega}^{RT-sell}$ and $P_{t,p,\omega}^{TE} = P_{t,p,\omega}^{TE-buy} - P_{t,p,\omega}^{TE-sell}$). The worst-case of the ULOF and the LLOF can be obtained by this variable decomposition. Therefore, $P_{t,p,\omega}^{RT}$ and $P_{t,p,\omega}^{TE}$ are substituted by $\lambda_{t,p}^{RT-LB} P_{t,p,\omega}^{RT-sell} - \lambda_{t,p}^{RT-UB} P_{t,p,\omega}^{RT-buy}$ and $\alpha_{t,p}^{r,TE-UB} P_{t,p,\omega}^{r,TE-sell} - \alpha_{t,p}^{r,TE-LB} P_{t,p,\omega}^{r,TE-buy}$, respectively.

In addition, interval coefficient exists in supply-demand equality constraint (i.e. Equation (3)). In case of an equality constraint, the worst-case happens when the constraint equals either to the LB or UB [1]. Therefore, the worst-case of the supply-demand equality constraint will happen when the net demand equals either to the LB or the UB. By considering three-fold scenarios and inter-scenario constraints of DERs, it guarantees that the DER outputs of any two critical scenarios in two consecutive time are enforced by the DER constraints, [1]. The critical scenarios are shown by set of $\Omega = \{(CF, CF), (CF, LB), (UB, LB), (CF, UB)\}$. Each one of subsets show a pair of critical scenario which should be considered in DERs constraints. In other words, Therefore, these inter-scenario constraints guarantee that any two critical scenarios (i.e. subsets of the Ω) in two consecutive time are enforced by the ramp up and ramp down of DGs, by the Pick up and drop rate of flexible loads, and by the charge and discharge rate of ESSs, respectively.

2) Mathematical Problem with Equilibrium Constraints: By replacing the KKT conditions of the lower-level problem, the bi-level optimization transforms into a single level problem [28]. Equations (29) and (30) are the stationary conditions. feasibility of the primal problem is enforced by Equation (31). Finally, Equations (32)-(37) are complementary conditions ($0 \leq x \perp y \geq 0$).

$$\alpha_{t,p,\omega}^{TE} - \lambda_{t,p,\omega}^{TE} + \mu_{t,p,\omega}^{-\max} - \mu_{t,p,\omega}^{-\min} = 0, \forall t, p, \omega \tag{29}$$

$$\alpha_{t,p,\omega}^{r,TE} - \lambda_{t,p,\omega}^{TE} + \mu_{t,p,\omega}^{r,\max} - \mu_{t,p,\omega}^{r,\min} = 0, \forall r, t, p, \omega \tag{30}$$

$$P_{t,p,\omega}^{TE} + \sum_{r} (P_{t,p,\omega}^{r,TE} = 0, \forall t, p, \omega \tag{31}$$

$$0 \leq (P_{t,p,\omega}^{TE} - P_{t,p}^{TE-\min}) \perp \mu_{t,p,\omega}^{\min} \geq 0, \forall t, p, \omega \tag{32}$$

$$0 \leq P_{t,p,\omega}^{r,TE-sell} \perp \mu_{t,p,\omega}^{r,sell\min} \geq 0, \forall r, t, p, \omega \tag{33}$$

$$0 \leq P_{t,p,\omega}^{r,TE-buy} \perp \mu_{t,p,\omega}^{r,buy\min} \geq 0, \forall r, t, p, \omega \tag{34}$$

$$0 \leq \left(P_{t}^{TE-\max} - P_{t,p,\omega}^{TE}\right) \perp \mu_{t,p,\omega}^{\max} \geq 0, \forall t, p, \omega \tag{35}$$

$$0 \leq \left(P_{t}^{r,TE-sell-\max} - P_{t,p,\omega}^{r,TE-sell}\right) \perp \mu_{t,p,\omega}^{r,sell-\max} \geq 0, \forall r, t, p, \omega \tag{36}$$

$$0 \leq \left(P_{t}^{r,TE-buy-\max} - P_{t,p,\omega}^{r,TE-buy}\right) \perp \mu_{t,p,\omega}^{r,buy-\max} \geq 0, \forall r, t, p, \omega \tag{37}$$

By the following, An MPEC casts by using Equations (29)-(37):

$$\begin{aligned} & Maximize \quad \{\sum_{\omega} \pi_{\omega} ULOF\omega\} \\ & Subject \quad to: \\ & Constraints \quad (2)-(28) \quad with \quad adding \quad \omega \quad dimension \\ & Inter-scenario \quad constraints \\ & KKT \quad Conditions \quad (29)-(37) \end{aligned}$$

3) Problem Linearization: The non-linearity, which is imposed on the problem by $\lambda_{t,p,\omega}^{TE} P_{t,p,\omega}^{TE}$, can be linearized by the strong duality theorem [28]. Regarding strong duality, the objective function of the primal and dual problems are equal at the optimal point. Therefore, the non-linear expression in the objective function can be replaced by Equation (38):

$$\begin{aligned} \lambda_{t,p,\omega}^{TE} P_{t,p}^{TE} &= -\sum_{r} \alpha_{t}^{r,TE-sell} P_{t,p,\omega}^{r,TE-sell} \\ &+ \sum_{j} \alpha_{t}^{r,TE-buy} P_{t,p,\omega}^{r,TE-buy} - \sum_{r} \mu_{t,p,\omega}^{r,buy-\max} P_{t}^{r,TE-buy-\max} \\ &- \sum_{j} \mu_{t,p}^{r,sell-\max} P_{t}^{r,TE-sell-\max} \end{aligned} \tag{38}$$

The non-linearity involved with the complementary conditions $0 \leq x \perp y \geq 0$ can be transformed by the equivalent linear equations by Equations (39). Complementary conditions imply that the product between x and y is equal to 0 [22]. Hence, the value of either x or y should be equal to zero. By using binary variable ψ, one of the right-hand sides of $x \leq \psi M_x \; or, y \leq (1-\psi) M_y$ is enforced to zero, and the other one is relaxed to the big value (i.e. M_x or M_y). Noteworthy that M_x and M_y should select big enough to lead the proper solution [28].

$$x, y \geq 0, \psi \in \{0, 1\}, x \leq \psi M_x \; and, y \leq (1-\psi) M_y \tag{39}$$

V. Numerical Analysis

A. Input Data

A modified IEEE 33-bus distribution test system illustrated in Fig. 3 is applied for the MG [29]. The MG test system including one ESS, one DR with the capability of load shifting, and four DGs are considered for testing the proposed model. Technical and economic characteristics of dispatchable and renewable-based intermittent generators are given by Table II. An ESS with 95%

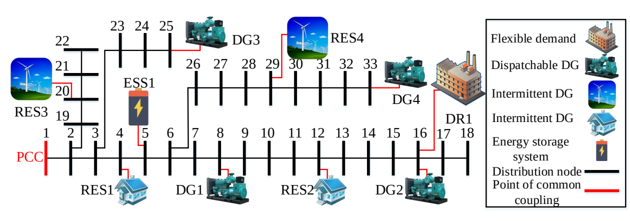

Fig. 3. Test system of the MG

efficiency in energy conversion with a maximum capacity of 2 MWh and charging/discharging rate of 1 MW/h is considered. Noteworthy that the depth of discharge is equal to 0.1 MWh. The

TABLE II
CHARACTERISTICS OF DGS AND RESS

Unit	Type	Cost Coefficients ($/MWh)	Min-Max (MW)	Ramp Rate (MW/h)
DG1	Dispatchable	27.7	1-5	2.5
DG2	Dispatchable	39.1	1-5	2.5
DG3	Dispatchable	61.3	0.2-3	0.5
DG4	Dispatchable	125.6	0.2-3	3
DG5-DG8	Intermittent	-	0-0.6	-

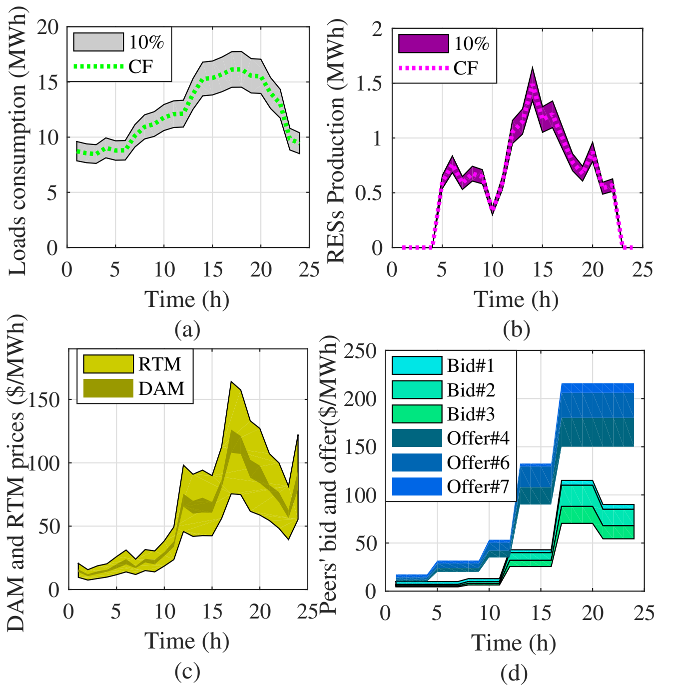

Fig. 4. Input data; (a) Prediction interval of the Loads consumption, (b) Prediction interval of the RESs production, (c) The prediction interval associated with the DAM and RTM prices, (d) Prediction interval of rivals' offer

DR should consume energy minimum of 3 MWh for the 24-hour time horizon. its pick-up and drop rate is equal to 1 MW/h. Also, it can consume energy between 0.5 MW and 2.4 MW in each hour. Moreover, the prediction interval of load consumption and RESs production are given by Fig. 4(a) and (b), respectively. It should be noted that the maximum variability of consumption and production are equal to 10% of the central forecast. The prediction intervals involved with the DAM and RTM prices are given by Fig. 4(c). Noteworthy that all of the generated scenarios of The DAM prices are laying in its prediction interval. It should be noted that 10 scenarios are applied to the proposed model. Finally, the prediction interval of the rivals' offer in TEM is given in Fig. 4(d). It is assumed that the rivals' offer to the TEM for every 4 hours. Also, six rival peers are considered in the numerical analysis, which the first three are buyer and others are seller. The proposed model is simulated and run using CPLEX 12.7 under the GAMS environment [30]. All cases are implemented on a computer with a 3.2 GHz Intel Core i5 processor and 4 GB RAM.

B. Arbitrage Strategy of the MG

To evaluate the arbitrage strategy, the CVaR is not considered in this section. The results are given in Fig. 5. In Fig. 5(a), the standard deviation and the average of the energy traded in the DAM, TEM, and RTM, are given. By considering the DAM, the MG prefers to buy the most of its requirement during the hours 1-10, when the DAM prices are very low (i.e. lower than 30 $/MWh). By increasing the DAM prices to the highest level (i.e. higher than 120 $/MWh), the MG decreases buying energy during the hours 11-23. Finally, when the net demand decreases, it can sell energy during the hour 24.

Since the MCPs of the TEM (see Fig. 5(b)) are lower than that of the RTM (see Fig. 4(c)) during the hours 1-16, the MG play as a buyer in the TEM as it is shown in the Fig. 5(a). Since the MCPs of the TEM are greater than that of the RTM during the hours 17-24 (compare Fig. 5(b) to Fig. 4(c)), the MG play as a seller in the TEM; see Fig. 5(a). As the last resort, the MG buys or sells its energy requirements by the RTM.

To evaluate the arbitrage opportunities of MG, the results without considering the TEM is given in Fig.4 (a). By comparing both curves (i.e. 'DAM' and 'DAM-WO-TEM'), the MG buys less energy in the DAM in case of considering TEM during the hours 1-16, when the MG buys energy from the TEM. Conversely, the MG buys more energy in the DAM in case of considering TEM during the hours 17-24, when the MG sells energy to the TEM. Thus, during the hours 17-24, the MG buys energy in the DAM with the prices (i.e. in the range of [56.29,126.25] $/MWh; see Fig. 4(c)) lower than that of the TEM, and then it sells energy by the prices (i.e. in the range of [85, 110] $/MWh; see Fig. 5(b)) higher than that of the DAM. Hence, the MG can decrease its cost from $6309.6 to 6112.2$ (i.e. increase more than 3.1% in the MG profit) by the arbitrage opportunity through P2P energy-tradings.

In Fig. 4(c), the production of DGs are illustrated. During the hours 1-9, the lowest production cost of DGs (i.e. DG1=27.7 $/MWh) is lower than the DAM prices. Therefore, none of the DGs produces energy during these hours. By increasing DAM prices, the production of DGs is increased based on the production cost of each DG (i.e. DG1, DG2, DG3 and DG4 have the lowest production cost, respectively).

The energy consumption of DR is given in Fig. 5(d). When the cost of DR (i.e. 95 $/MWh) is greater than DAM prices (i.e. during the hours 1-15 and 23), the DR consumes its maximum capability (i.e. 2.4 MWh). However, by increasing the DAM prices, the DR decreases its energy consumption during the hours 16-22 and 24.

The SOC of the ESS is shown in Fig. 5(e). During the hours 1-5,7-11, 15-16, and 23, the prices of DAM are lower than the prices during hours 6, 12-14, 17-22, and 24, respectively. when the prices of DAM are low (i.e. during the hours 1-5,7-11, 15-16, and 23), the energy is stored in the ESS. In contrast, when the prices of DAM are high (i.e. during hours 6, 12-14, 17-22, and 24), the stored energy is released to the MG.

Without considering transition between two critical scenarios (i.e. LB to UB, CF to CF, UB to UB, LB to LB, UB to LB, CF to LB and CF to UB), the operation costs of the MG are 6069.79$, 6103.63$, 6110.72$, 6111.87$, 6111.99$, 6111.99$, 6112.17$ and 6112.14$, respectively. Without considering the most critical scenario (i.e. LB to UB), the profit of the MG can be increased by 0.7%. Although the cost of the MG decreases without considering each one of critical scenarios, the risk of exposure to uncertainty increases in the RTM.

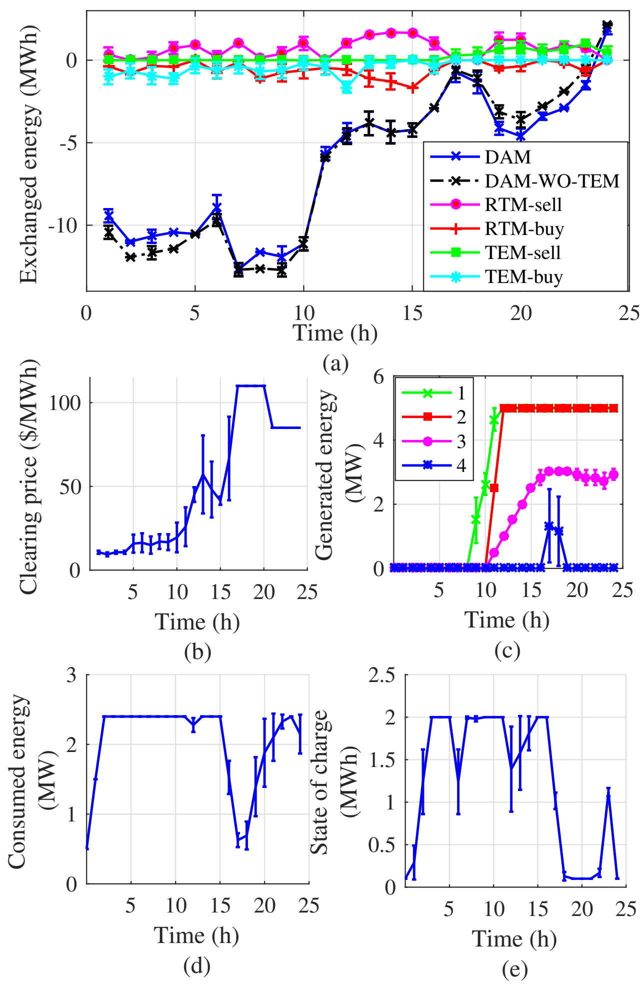

Fig. 5. The proposed model Results; (a) Traded energy in the DAM, TEM, and RTM, (b) Market clearing prices of TEM, (c) The production of DGs, (d) The consumption of DR, (e) The SOC of ESS

C. Risk Analysis

In order to analyse the risk involved with the given decision, the CVaR is investigated in this section. The results of the risk analysis are given by Fig. 6. The bidding strategy of MG is evaluated, both for the risk-neutral solution (i.e. setting $\beta = 0$) and risk-averse solution (i.e. increasing β to ∞). The range of effective β in changing the profit and CVaR is varied case by case. In Fig. 6(b), it can be seen in our case study (i.e. modified IEEE 33-bus) that the efficient frontier curve of the MG is saturated by increasing β more than 1. Therefore, the solution associated to the $\beta = 1$ is called the risk-averse solution here. Noteworthy, the positive and negative values show that the MG offers and bids energy in the market in Fig. 6(a), respectively. the traded energy in the DAM as well as the traded energy of the TEM plus the RTM (i.e. TEM+RTM) for the $\beta = 0$ and $\beta = 1$ are shown by the solid and dashed line. By comparing two curves corresponding to the DAM, the bidding energy associated with the risk-neutral solution (i.e. $\beta = 0$) is less than that of the risk-averse one (i.e. $\beta = 1$) during the hours 1-23. Also, the offering energy associated with the risk-neutral solution (i.e. $\beta = 0$) is more than that of the risk-averse one (i.e. $\beta = 1$) during the hour 24.

By comparing two curves corresponding to the TEM+RTM, the bidding energy associated with the risk-neutral solution (i.e. $\beta = 0$) is more than that of the risk-averse solution (i.e. $\beta = 1$) during the hours 1-3, 6, 8-9 and 11-12. Also, the offering energy associated with the risk-neutral solution (i.e. $\beta = 0$) is less than that of the risk-averse solution (i.e. $\beta = 1$) during the hours 5, 7, 10 and 13-24. Totally, by considering CVaR, the MG prefers to bid/offer more/less energy in the DAM, and to bid/offer less/more energy in the TEM+RTM. In Fig. 6(b), the expected profit in terms

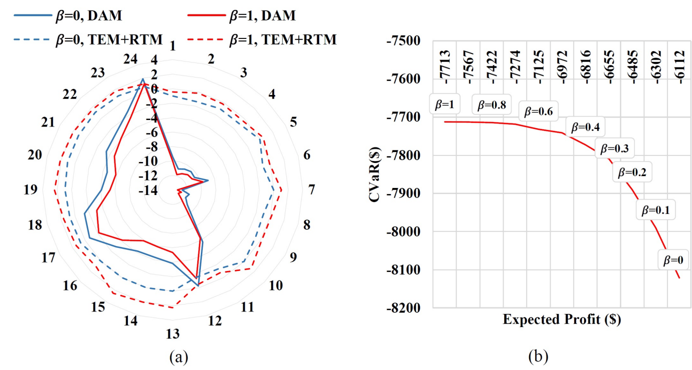

Fig. 6. The risk analysis of the proposed model; (a) Traded energy in the DAM, TEM and RTM, (b) The efficient frontier

of the CVaR, which is called the efficient frontier, is provided. Since the MG is an energy buyer during the 1-23 hours (see Fig. 5(c)), the total expected profit and CVaR are negative values. By the efficient frontier, the MG can select the degree of conservatism in decision making. By comparing the fully risk-averse with the risk-neutral decision, the profit of MG can be increased by 27%, although it would be risky to make a risk-neutral decision.

D. Applicability and Scalability of the Proposed Model

The average of expected costs (ECs), the standard deviation (SD) of ECs, and the average of computational times are given in Table III for implementing the models 10 times, in order to compare the fully SP (FSP) and fully IO (FIO) models (i.e. existing models) with the BRSPIC model. Since some critical scenarios would be removed in the scenario reduction process, the EC of the FSP are the lowest optimistic one ($5956.6). By considering the whole of interval predictions, the EC of the FIO is the highest pessimistic one ($6216.6). However, the EC of the BRSPIC is a middle one, which it shows the advantages of inheritance from the both FSP and FIO models. The EC of the BRSPIC is increased in comparison with the FSP to improve the security of the MG dealing with uncertainties. The SD shows the sensitivity of the solutions to the scenario generation and reduction process. Therefore, the sensitivity of the BRSPIC is decreased in comparison with the FSP (i.e. $89.2 decreases to $28.1). By comparing the computational time (i.e. 169.6 s against 2.4 s), it is evident that the BRSPIC model significantly decreases the computational burden of the problem.

To evaluate the scalability of the proposed model, three modified IEEE 33-bus distribution system are considered as a large MG, which they are connected at the PCC to each other. The profit and computational time of the three times larger MG are $18354.2 and 15.6 s, respectively.

TABLE III
COMPARISON OF THE COST AND PERFORMANCE WITH EXISTING WORKS

	Expected Cost ($)	Standard Deviation ($)	Time (s)
FSP	5956.6	89.2	169.6
BRSPIC	6088.1	28.1	2.4
FIO	6216.6	0	0.9

VI. CONCLUSION

In this paper, the arbitrage strategy of a MG via P2P energy-tradings is investigated. To this end, a three-stage decision-making framework has been developed. In the first stage, a scenario-based stochastic programming approach has been employed to deal with the DAM prices uncertainties. In the second stage, the uncertainty of rivals' offer has been handled using the interval coefficients in a leader-follower game-theoretic approach. Finally, in the third stage, the uncertainties of RESs and loads have been investigated by the interval optimization. A three-stage single-level optimization has been proposed by using the KKT conditions in order to be able to identify the existing arbitrage opportunities. The results of the presented model prove that:

- In case of considering TEM, an MG is able to buy more energy in the DAM for selling in the TEM and use the arbitrage opportunity between DAM and TEM.
- By the realization of excess production or consumption deficit, the MG tends to sell energy cheaper than the DAM price in the TEM, instead of selling energy in the RTM with the lower price.
- An MG can increase its profit by at least 3.1% by using the arbitrage opportunity between DAM and TEM.
- By comparing the fully risk-averse with the risk-neutral decision, the profit of MG can be increased by 27%, although it would be risky to make a risk-neutral decision.

The future research direction can be focused on the grid cost allocation in such a transactive environment.

REFERENCES

[1] H. Nezamabadi and V. Vahidinasab, "Market bidding strategy of the micro-grids considering demand response and energy storage potential flexibilities," *IET Generation, Transmission & Distribution*, vol. 13, no. 8, pp. 1346–1357, 2019.

[2] H. Nezamabadi and V. Vahidinasab., "Micro-grids bidding strategy in a transactive energy market," *Scientia Iranica*, vol. 26, no. 1, pp. 3622–3634, 2019.

[3] M. Andoni, V. Robu, D. Flynn, S. Abram, D. Geach, D. Jenkins, P. McCallum, and A. Peacock, "Blockchain technology in the energy sector: A systematic review of challenges and opportunities," *Renewable and Sustainable Energy Reviews*, vol. 100, pp. 143–174, 2019.

[4] F. Rahimi, A. Ipakchi, and F. Fletcher, "The changing electrical landscape: end-to-end power system operation under the transactive energy paradigm," *IEEE Power and Energy Magazine*, vol. 14, no. 3, pp. 52–62, 2016.

[5] H. Gharibpour and F. Aminifar, "Multi-stage equilibrium in electricity pool with flexible ramp market," *International Journal of Electrical Power & Energy Systems*, vol. 109, pp. 661–671, 2019.

[6] J. Kim and Y. Dvorkin, "A p2p-dominant distribution system architecture," *IEEE Transactions on Power Systems*, 2019.

[7] E. Vaahedi, K. Nodehi, D. Heim, F. Rahimi, and A. Ipakchi, "The emerging transactive microgrid controller: illustrating its concept, functionality, and business case," *IEEE Power and Energy Magazine*, vol. 15, no. 4, pp. 80–87, 2017.

[8] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, and E. Sorin, "Peer-to-peer and community-based markets: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 104, pp. 367–378, 2019.

[9] Í. Munné-Collado, E. Bullich-Massagué, M. Aragüés-Peñalba, and P. Olivella-Rosell, "Local and micro power markets," *Micro and Local Power Markets*, 2019.

[10] M. H. Ullah and J.-D. Park, "Peer-to-peer energy arbitrage in prosumer-based smart residential distribution system," in *2019 IEEE Energy Conversion Congress and Exposition (ECCE)*. IEEE, pp. 508–514.

[11] M. Shahidehpour, H. Yamin, and Z. Li, *Market operations in electric power systems: forecasting, scheduling, and risk management*. John Wiley & Sons, 2003.

[12] G. Liu, Y. Xu, and K. Tomsovic, "Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 227–237, 2015.

[13] X. Han, E. G. Kardakos, and G. Hug, "Offering strategy of a price-maker pv power plant: multi-stage stochastic programming with probabilistic constraints," in *2018 Power Systems Computation Conference (PSCC)*. IEEE, 2018, pp. 1–7.

[14] D. T. Nguyen and L. B. Le, "Risk-constrained profit maximization for microgrid aggregators with demand response," *IEEE Transactions on smart grid*, vol. 6, no. 1, pp. 135–146, 2014.

[15] T. Zhao, X. Pan, S. Yao, C. Ju, and L. Li, "Strategic bidding of hybrid ac/dc microgrid embedded energy hubs: A two-stage chance constrained stochastic programming approach," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 1, pp. 116–125, 2020.

[16] M. Fathi and H. Bevrani, "Statistical cooperative power dispatching in interconnected microgrids," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 3, pp. 586–593, 2013.

[17] J. M. Zepter, A. Lüth, P. C. Del Granado, and R. Egging, "Prosumer integration in wholesale electricity markets: Synergies of peer-to-peer trade and residential storage," *Energy and Buildings*, vol. 184, pp. 163–176, 2019.

[18] K. Anoh, S. Maharjan, A. Ikpehai, Y. Zhang, and B. Adebisi, "Energy peer-to-peer trading in virtual microgrids in smart grids: a game-theoretic approach," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1264–1275, 2019.

[19] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 8, pp. 6087–6097, 2018.

[20] S. Cui, Y.-W. Wang, C. Li, and J.-W. Xiao, "Prosumer community: A risk aversion energy sharing model," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 2, pp. 828–838, 2019.

[21] T. Liu, X. Tan, B. Sun, Y. Wu, X. Guan, and D. H. Tsang, "Energy management of cooperative microgrids with p2p energy sharing in distribution networks," in *2015 IEEE international conference on smart grid communications (SmartGridComm)*. IEEE, 2015, pp. 410–415.

[22] J. M. Morales, A. J. Conejo, H. Madsen, P. Pinson, and M. Zugno, *Integrating renewables in electricity markets: operational problems*. Springer Science & Business Media, 2013, vol. 205.

[23] T. Morstyn, N. Farrell, S. J. Darby, and M. D. McCulloch, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants," *Nature Energy*, vol. 3, no. 2, pp. 94–101, 2018.

[24] E. Sorin, L. Bobo, and P. Pinson, "Consensus-based approach to peer-to-peer electricity markets with product differentiation," *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 994–1004, 2018.

[25] M. H. Bashi, G. R. Yousefi, M. A. Latify, and C. L. Bak, "Impacts of intraday risky power trades on the high wind penetrated electricity markets," *IET Generation, Transmission & Distribution*, vol. 13, no. 17, pp. 3836–3846, 2019.

[26] A. J. Conejo, M. Carrión, J. M. Morales *et al.*, *Decision making under uncertainty in electricity markets*. Springer, 2010, vol. 1.

[27] Y. Liu, C. Jiang, J. Shen, and J. Hu, "Coordination of hydro units with wind power generation using interval optimization," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 2, pp. 443–453, 2015.

[28] S. J. Kazempour and H. Zareipour, "Equilibria in an oligopolistic market with wind power production," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 686–697, 2013.

[29] A. Gholami, T. Shekari, F. Aminifar, and M. Shahidehpour, "Microgrid scheduling with uncertainty: The quest for resilience," *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2849–2858, 2016.

[30] GAMS Development Corporation. (2015) General algebraic modeling system (gams). [Online]. Available: http://www.gams.com