Optimal Energy Providing Strategy of Micro-Grid's Operator Based on a Game Theoretical Approach

Shahab Dehghan, Meysam Khojasteh, Mousa Marzband, Gordon Lightbody

Abstract—**Operators of micro-grid as privately-owned sectors try to optimally determine their energy supply strategy aiming at maximizing their profits. Smart grid infrastructures enable residential consumers to modify their electricity consumption in response to energy prices. Clearly, increasing energy tariffs have positive impacts on the operator's profit. Additionally, sensitivity of consumption to selling prices leads to demand reduction by increasing energy tariffs. Therefore, operators of micro-grids retain a tradeoff between energy tariffs and demand. This paper presents a game theoretical approach for operators of micro-grids to supply the required energy of price-sensitive clients. Additionally, the information-gap decision theory (IGDT) is used to handle the financial risk arising from the uncertain wholesale prices. Simulation results justify the performance of the proposed approach.**

I. Introduction

In deregulated electricity distribution networks, the micro-grid operator (MO) functions as an intermediary between the wholesale market and small consumers. In other words, MOs supply the required energy of consumers from competitive markets or their self-generating facilities. MOs as privately-owned sectors try to optimally determine the energy providing strategy and selling prices aiming at maximizing their expected profits. Consequently, the selling price may be set in a manner covering the supply cost and providing an acceptable profit for MOs. Mainly, the wholesale energy price is highly volatile and varies every hour. Accordingly, ignoring the uncertainty pertaining to the wholesale price may impose significant financial losses to energy providers. Also, the fluctuation of clients' demand is another uncertainty source faced by MOs. Since a considerable quantity of electrical energy is not storable in an economical manner, the energy shortage should be resolved in the spot market. Clearly, the spot markets' prices are usually higher than the day-ahead or hour-ahead ones. Therefore, unpredicted demand fluctuations impose additional supply costs to MOs. Accordingly, it is vital to develop a proficient non-deterministic energy procurement strategy for MO hedged against the inherent uncertainty of the wholesale prices.

The optimal energy procurement strategy of MOs is previously analyzed by means of different approaches in the literature. In [1], a stochastic framework is proposed for managing renewable energy resources in a micro-grid. The bidding strategy of MO under uncertainty is evaluated in [2]. In [3], the optimal operation of energy storage in micro-grids is formulated. In [4], the impact of electrical vehicles and load elasticity on operation of micro-grids is modeled. In [5], a stochastic framework is proposed for simultaneously managing both electrical and thermal loads. In [6], a bi-level model is proposed to determine the economical and optimal operation of micro-grids. In [7], the optimal size of renewable energy resources in a micro-grid is determined. In [8], a multi-objective framework is presented to simultaneously optimize the cost and emission of a micro-grid. In summary, previous research works usually either discount the uncertain nature of energy procurement in micro-girds or account them in terms of probability distributions. However, in practice, it is hard to obtain the exact probability distributions for different types of uncertainty sources [9]. Therefore, it is necessary to develop more practical approaches instead of typical probability distribution-based approaches.

The smart metering/measuring facilities enable end-use consumers to monitor selling prices and determine their consumption. Therefore, MO and consumers face a game to specify their optimal strategies. In this game, MO specifies the selling price in a way maximizing profits. According the proposed selling prices, consumers adjust their demands. Hence, offering the higher selling price reduces the demand that may lead to lower profit for MO. In this research work, a game theoretical approach is addressed to evaluate the optimal strategy of MO. Moreover, the information-gap decision theory (IGDT) as a proficient uncertainty handling method is used to characterize the uncertainty of the wholesale prices without requiring any probability distribution [9]. The main contributions of this research work can be summarized as follows:

1) A robust framework is presented to determine the optimal strategy of MO and clients' consumption based on the consumers' sensitivity to selling prices.

2) The game theory methodology is applied to evaluate the clients' response to sale prices.

The rest of this paper is organized as follows. Section II represents the proposed energy providing strategy. The game theoretical approach is introduced in Section III to specify the optimal selling price and demand. The IGDT-based

S. Dehghan is with the Faculty of Electrical, Biomedical, and Mechatronics Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran (e-mail: shahab.dehghan@ieee.org).

M. Khojasteh is with the Department of Electrcial Engineering, Iran University of Scienace and Technology, Tehran, Iran (e-mail: khojasteh@iust.ac.ir).

M. Marzban is with the Department of Maths, Physics and Electrical Engineering, Northumbria University, Newcastle, NE1 8ST, UK (e-mail: mousa.marzband@northumbria.ac.uk).

G. Lightbody is with the Department of Electrical and Electronic Engineering, UCC, College Rd., Cork, Ireland (e-mail: g.lightbody@ucc.ie).

formulations are given in Section IV to evaluate the financial risk of price uncertainty. The performance of the proposed framework is evaluated in Section V using a case study. Finally, concluding remarks are provided in Section VI.

II. Optimal Framework of MO

To determine the demand, sale prices, and the energy acquisition strategy, objective functions of clients and MO are introduced in this section.

A. Clients' Objective Function

In this work, a linear demand-price model is used to characterize the sensitivity of demand to selling price as follows:

$$d_t = d_t^0\left(1+\varepsilon_t\cdot\left(\Pi_t^M-\Pi_t^0\right)/\Pi_t^0\right);\quad \forall t\in T \tag{1a}$$

$$\varepsilon_t = \left(\Pi_t^0\cdot\Delta d\right)/\left(d_t^0\cdot\Delta\Pi_t^{ret}\right);\quad \forall t\in T \tag{1b}$$

where d_t is the demand at hour t, d_t^0 is the initial demand at hour t, Π_t^0 is the initial selling price at hour t, Π_t^M is the micro-grid's selling price, and ε_t is the elasticity of demand at hour t. Also, T denotes the set of all hours. Equation (1a) can be rewritten as follows:

$$\Pi_t^M = \Pi_t^0\cdot\left(1+\frac{d_t-d_t^0}{\varepsilon_t\cdot d_t^0}\right);\quad \forall t\in T \tag{2}$$

To quantify the benefit of consumption d_t, it is assumed that the sensitivity of the benefit function (i.e., B_t) to the hourly demand is equal to the sale price as given below [11]:

$$\partial B_t/\partial d_t = \Pi_t^M;\quad \forall t\in T \tag{3}$$

By substituting (2) in (3), expression (3) can be rewritten as follows:

$$\frac{\partial B_t}{\partial d_t} = \Pi_t^0\cdot\left(1-\frac{1}{\varepsilon_t}\right)+\frac{\Pi_t^0}{\varepsilon_t\cdot d_t^0}\cdot d_t;\quad \forall t\in T \tag{4}$$

Therefore, the benefit function of clients is calculated as follows:

$$B_t = B_t^0+\Pi_t^0\cdot\left(1-\frac{1}{\varepsilon_t}\right)\cdot d_t+\frac{\Pi_t^0}{2\varepsilon_t d_t^0}\cdot d_t^2;\quad \forall t\in T \tag{5}$$

The profit of clients (i.e., Pr^{cl}) is equal to the benefit of electricity consumption minus the supply cost. Hence, the clients' objective function is derived as follows:

$$\underset{D_t}{Max}\ Pr_t^{cl} = B_t^0+\Pi_t^0\cdot\left(1-\frac{1}{\varepsilon_t}\right)\cdot\Pi_t+\frac{\Pi_t^0}{2\varepsilon_t d_t^0}\cdot d_t^2-\Pi_t^M\cdot d_t \tag{6}$$

$$d_t^{\min}\le d_t\le d_t^{\max};\quad \forall t\in T \tag{7}$$

where $d_t^{\min}/d_t^{\max}$ denotes the minimum/maximum allowable limitation of the consumption at hour t. According to (6), clients can respond to the selling price and can modify the optimal consumption to maximize the profit.

B. MO's Objective Function

MO tries to determine the energy acquisition framework to maximize the profit. According to MO's income (i.e., I_t^M) and supply cost (i.e., C_t^M), the profit function can be calculated as given below:

$$Pr^M = \sum_{t\in T}\left(I_t^M-C_t^M\right) \tag{8}$$

Here, it is assumed that the required energy of clients is provided by distributed generators (DGs), wholesale market, and forward contract. Accordingly, the supply cost at hour t can be obtained as given in (9):

$$C_t^M = C_t^{WS}+C_t^{FC}+C_t^{DG};\quad \forall t\in T \tag{9}$$

where C_t^{WS}, C_t^{FC}, and C_t^{DG} represent the total costs of purchasing electricity from the wholesale market, the forward contract, and the total operation cost of DGs at hour t, respectively. The procured power $P_t^{WS_B}$ and the wholesale price Π_t^{WS} affect the wholesale procurement costs at hour t as given in (10):

$$C_t^{WS} = P_t^{WS_B}\cdot\Pi_t^{WS};\ P_t^{WS_B}\ge 0\quad \forall t\in T \tag{10}$$

The entire procedure of modeling C_t^{FC} is provided in [11]. According to [11], the cost of procuring power from the forward contract is formulated as given below:

$$C_t^{FC} = \sum_{c\in\Xi}\sum_{s=1}^{N_t^c}P_{t,c,s}^{FC}\cdot\Pi_{t,c,s}^{FC}\cdot\theta_{t,c,s};\quad \forall t\in T \tag{11}$$

where $P_{t,c,s}^{FC}$ denotes the procured power from segment s in forward contract c at hour t, $\Pi_{t,c,s}^{FC}$ denotes the price of segment s in forward contract c at hour t (\$/MWh), N_t^c denotes the total number of power segments in forward contract c, and $\theta_{t,c,s}$ denotes a binary variable, where this binary variable is equal to 1 if the procured power from forward contract c pertains to segment s and it is equal to 0 otherwise. Also, Ξ represents the set of all available forward contracts. The operation-related costs of DG units including fuel costs ($C_{i,t}^{Fu}$), startup costs ($SU_{i,t}$), and shutdown costs ($SD_{i,t}$) are considered as:

$$C_t^{DG} = \sum_{i=1}^{N_{DG}}C_{i,t}^{Fu}+SU_{i,t}+SD_{i,t};\quad \forall t\in T \tag{12}$$

The fuel-related costs of the thermal DG units can be represented as given below:

$$C_{i,t}^{Fu} = (a_i\cdot P_{i,t}^2+b_i\cdot P_{i,t}+c_i)\cdot X_{i,t};\quad \forall t\in T, i=1,...,N_{DG} \tag{13}$$

where X_i represents a binary status variable indicating up/down status of DG i ($X_{i,t}=1$ if the DG is up, and $X_{i,t}=0$ otherwise) and a_i, b_i, and c_i represent the coefficients of the cost function for DG i. Also, the startup and shutdown costs can be calculated as given in (14) and (15), respectively:

$$C_{i,t}^{SU} = \overline{SU_i}\cdot\gamma_{i,t};\quad \forall t\in T, i=1,...,N_{DG} \tag{14}$$

$$C_{i,t}^{SD} = \overline{SD_i}\cdot\eta_{i,t};\quad \forall t\in T, i=1,...,N_{DG} \tag{15}$$

where $\gamma_{i,t}$ in (14) and $\eta_{i,t}$ (15) are binary variables indicating the startup and shutdown status of DG i at hour t, respectively. Also, the following relations hold between $\gamma_{i,t}$, $\eta_{i,t}$, and $X_{i,t}$:

$$\gamma_{i,t} + \eta_{i,t} \le 1; \quad \forall t \in T, i = 1,...,N_{DG} \qquad (16)$$

$$\gamma_{i,t} - \eta_{i,t} = X_{i,t} - X_{i,t-1}; \quad \forall t \in T, i = 1,...,N_{DG} \qquad (17)$$

In the proposed framework, it is assumed that MO can resell the energy to the wholesale market as well as the final clients. Consequently, MO's income can be calculated as given below:

$$I_t^M = \sum_{t=1}^{T} d_t \cdot \Pi_t^M + P_t^{WS_S} \cdot \Pi_t^{WS}; \; P_t^{WS_S} \ge 0 \quad \forall t \in T \qquad (18)$$

where $P_t^{WS_S}$ represents the sold power in the wholesale market. Also, the operation-related constraints of DGs are given below [11]:

- Minimum Up-time Constraint

$$\left(T_{C_i,t-1}^{up} - T_{i,\min}^{up}\right)\cdot\left(X_{i,t-1} - X_{i,t}\right) \ge 0; \quad \forall t \in T, i = 1,...,N_{DG} \; (19)$$

where $T_{C_i,t}^{up}$ denotes the up-time hours for DG i before hour t, $T_{i,\min}^{up}$ denotes the minimum up-time of DG i.

-Minimum Down-time Constraint

$$\left(T_{C_i,t-1}^{down} - T_{i,\min}^{down}\right)\cdot\left(X_{i,t} - X_{i,t-1}\right) \ge 0; \quad \forall t \in T, i = 1,...,N_{DG} \; (20)$$

where $T_{C_i,t}^{down}$ denotes the down-time hours for DG i before hour t, $T_{i,\min}^{down}$ denotes the minimum down-time of DG i.

- Ramp-rate Constraint

$$P_{i,t} - P_{i,t-1} \le R_i^{up} \cdot X_{i,t} + R_i^{su} \cdot \gamma_{i,t}; \forall t \in T, i = 1,...,N_{DG} \qquad (21)$$

$$P_{i,t-1} - P_{i,t} \le R_i^{down} \cdot X_{i,t-1} + R_i^{sd} \cdot \eta_{i,t}; \forall t \in T, i = 1,...,N_{DG} \qquad (22)$$

where R_i^{up} , R_i^{su} , R_i^{down} , and R_i^{sd} stand for ramp-up rate, startup ramp-rate, ramp-down rate, and shutdown ramp-rate limits for DG i, respectively.

- Capacity Constraint

$$P_i^{\min} \cdot X_{i,t} \le P_{i,t} \le P_i^{\max} \cdot X_{i,t}; \quad \forall t \in T, i = 1,...,N_{DG} \quad (23)$$

- Supply-Demand Constraint

The total procured power from the wholesale market and the forward contract as well as the power production of DGs should be equal to the amount of sold power in the wholesale and the clients' demand:

$$P_t^{WS_B} + \sum_{i=1}^{N_{DG}} P_{i,t} + P_t^{FC} = P_t^{WS_S} + d_t; \;\; \forall t \in T \qquad (24)$$

By substituting (10), (11), (13), (14), (15), and (18) in (8), the profit function of MO can be rewritten as follows:

$$\underset{\substack{\Pi_t^M, P_t^{WS_S}, P_t^{WS_B}, P_{i,t}, P_{t,c,s}^{FC} \\ \forall t\in T, \forall c\in\Xi, \forall i=0,...,N_{DG}, \forall s=1,...,N_t^c}}{Pr^M} = \sum_{t\in T}\left(\begin{array}{l} d_t \cdot \Pi_t^M + \left(P_t^{WS_S} - P_t^{WS_B}\right)\cdot \Pi_t^{WS} \\ -\sum_{c\in\Xi}\sum_{b=1}^{N_t^c} P_{t,c,s}^{FC} \cdot \Pi_{t,c,s}^{FC} \cdot \theta_{t,c,s} \\ -\sum_{i=1}^{N_{DG}}\left(\begin{array}{l}(a_i \cdot P_{i,t}^2 + b_i \cdot P_{i,t} + c_i)\cdot X_{i,t} \\ + \overline{SU}_i \cdot \gamma_{i,t} + \overline{SD}_i \cdot \eta_{i,t}\end{array}\right)\end{array}\right)$$

(25)

subject to (16), (17), (19)-(24).

III. Game Theory Framework

The game theory is a mathematical decision-making tool to find the optimal strategy in cooperative or non-cooperative optimization problems between players. In the game theory-based models, the equilibrium of the game refers to a strategy where no player can profit via unilaterally changing their strategies. As mentioned before, the energy trading between MO and price-sensitive clients can be characterized as a game. Although MO can obtain the maximum profit in a particular selling price, it does not mean that clients can obtain their maximum profit at the same selling price. The higher selling price increases MOs' profit and decreases the clients' consumption.

In the proposed game theory-based model, the optimal strategy (i.e., $\bar{\Pi}^M$ and $\bar{d}$) is a Nash Equilibrium (NE) if no unilateral deviation in the strategy (i.e., selling price for MO and consumption for clients) by any single player (i.e., MO and clients) is profitable for that player as given below:

$$Client: \forall d \in D, d \ne \bar{d} : Pr^{cl}(\bar{\Pi}^M, \bar{d}) \ge Pr^{MO}(\bar{\Pi}^M, d) \quad (26)$$

$$MO: \forall \Pi^M \in \Theta, \Pi^M \ne \bar{\Pi}^M : Pr^{MO}(\bar{\Pi}^M, \bar{d}) \ge Pr^{MO}(\Pi^M, \bar{d}) \quad (27)$$

where d denotes the consumption of clients (i.e., $d = \{d_1, d_2, ..., d_T\}$), D denotes the set of feasible consumption (i.e., $D = \{D_1, D_2, ..., D_T\}$), Π^M denotes the micro-grid's price (i.e., $\Pi^M = \{\Pi_1^M, \Pi_2^M, ..., \Pi_T^M\}$), and Θ denotes the set of feasible selling price (i.e., $\Theta = \{\Theta_1, \Theta_2, ..., \Theta_T\}$).

The IGDT-based risk-management approach is presented in the next section.

IV. Information-Gap Decision Theory

The IGDT methodology is a non-probabilistic risk-management approach to determine a robust solution under different uncertainty sources [9], [10]. The information-gap models quantify the variation interval of the uncertain variable as the gap between what is known and what is unknown. The variation interval, which is designated as the robustness region, can be represented as follows:

$$\left|\frac{\Pi_t^{WS} - \bar{\Pi}_t^{WS}}{\bar{\Pi}_t^{WS}}\right| \le \lambda \,,\; \lambda \ge 0; \quad \forall t \in T \qquad (28)$$

where $\bar{\Pi}_t^{WS}$ denotes the expected values of the hourly energy prices. The gap between the known and unknown values of uncertain price is modeled by λ . In the IGDT-based models, the robustness region or λ and the optimal decision can be obtained by means of the desired *performance function*. Two types of performance functions are presented in the IGDT methodology: robustness and opportunity. The robustness function determines the maximum variation interval of the uncertain parameter that ensuring the minimum profit is within the robustness region. The opportunity function determines the minimum variation interval that ensuring the maximum desired profit is achievable for at least one price belonging to the robustness region. The risk-averse MOs select the lower risk level. Consequently, they choose the robustness function. The risk-taker MOs select the higher risk level to obtain the desired performance. Consequently, they choose the opportunity function and specify the optimal strategy based on the best condition up to the horizon of uncertainty. These functions can be written as follows:

$$Robustness\ Function^{Risk-Averse} = \max \lambda \quad s.t.$$

$$\min_{\substack{\Pi_t^M, P_t^{WS_S}, P_t^{WS_B}, P_{i,t}, P_{t,c,s}^{FC} \\ \forall t \in T, \forall c \in \Xi, \forall i=0,\dots,N_{DG}, \forall s=1,\dots,N_t^f}} Pr^{MO} \geq Pr_{cr}^{RA}; \Pi_t^{WS} \in \left[(1-\lambda)\bar{\Pi}_t^{WS}, (1+\lambda)\bar{\Pi}_t^{WS}\right] \quad (29)$$

$$Pr_{cr}^{RA} = (1-\rho^{RA}) \times Pr_{Exp}$$

$$Opportunity\ Function^{Risk-Taker} = \min \lambda \quad s.t.$$

$$\max_{\substack{\Pi_t^M, P_t^{WS_S}, P_t^{WS_B}, P_{i,t}, P_{t,c,s}^{FC} \\ \forall t \in T, \forall c \in \Xi, \forall i=0,\dots,N_{DG}, \forall s=1,\dots,N_t^f}} Pr^{MO} \geq Pr_{cr}^{RT}; \Pi_t^{WS} \in \left[(1-\lambda)\bar{\Pi}_t^{WS}, (1+\lambda)\bar{\Pi}_t^{WS}\right] \quad (30)$$

$$Pr_{cr}^{RT} = (1+\rho^{RT}) \times Pr_{Exp}$$

where Pr_{Exp} denotes the expected profit, ρ^{RA} and ρ^{RT} denote the profit deviation factors of risk-averse and risk-taker MOs, respectively. It is worthwhile to note that MO's profit can be obtained by means of (25).

V. SIMULATION RESULTS

In this work, the presented energy acquisition strategy is implemented on a price-taker supplier who has four thermal DGs [11]. The characteristics of DGs as well as available stepwise forward contracts are similar to [11]. The initial selling prices (i.e., Π_t^0), the initial demands (i.e., d_t^0), and the expected values of wholesale prices (i.e., $\bar{\Pi}_t^{WS}$) at every hour are illustrated in Fig. 1. Moreover, the elasticity coefficients within low-load (i.e., hours 1-6), mid-load (i.e., hours 7-18), and peak-load hours (i.e., hours 19-24) are equal to -4, -4.8, and -5.2, respectively. In this research work, it is assumed that MO can offer the selling price based on a time-of-use pricing. Therefore, Π_t^M is considered as:

$$\Pi_t^M = \begin{cases} \Pi_L^M & ; \ t = 1-6 \\ \Pi_M^M & ; \ t = 7-18 \\ \Pi_P^M & ; \ t = 19-24 \end{cases}$$

The optimal framework of MO to provide the required energy of the price-sensitive clients and the demand at every hour are illustrated in Fig. 2. It is worthwhile to note that the wholesale prices in this case study are equal to the expected values, as depicted in Fig. 1. Simulation results demonstrate that the maximum profits of MO and clients are equal to \$7416 and \$2389.9, respectively. The optimal selling prices for low-load, mid-load, and peak-load hours (i.e., Π_L^M, Π_M^M, and Π_P^M) are equal to \$90.5, \$108, and \$114, respectively. The profits of MO for different average selling prices ($\bar{\Pi}^M = \frac{1}{T}\sum_{t=1}^{T}\Pi_t^M$) are provided in Fig. 3. As mentioned, a higher selling price leads to a higher profit for MO. However, the intelligent clients reduce their consumption by increasing the selling price. As depicted in Fig. 3, increasing the selling price has a negative impact on MO's profit for $\bar{\Pi}^M > 104.167\ (\$/MWh)$. Also, Fig. 4 depicts the sensitivity of clients' demand and profit to the average selling price. The sensitivity of the clients' profit to the selling price is not linear. Table I and Table II demonstrate the effects of the variations of the wholesale prices on the optimal selling price and the MO's profit, respectively.

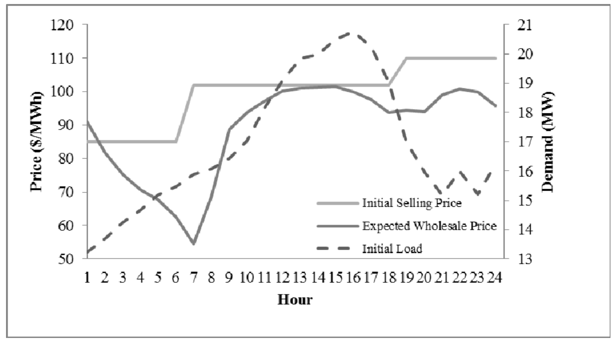

Fig. 1. Initial selling prices, initial demands, and expected wholesale prices.

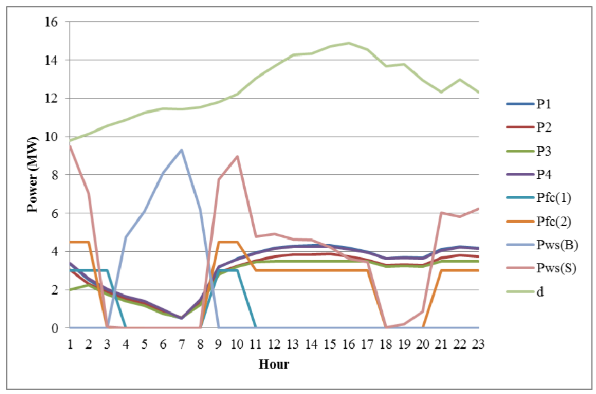

Fig. 2. Optimal strategy of MO based on the expected wholesale prices (MW).

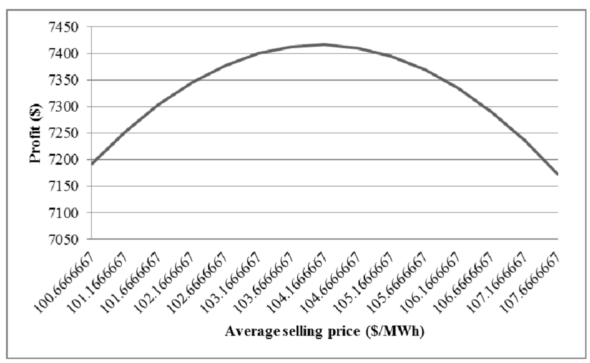

Fig. 3. MO's profit versus average selling price.

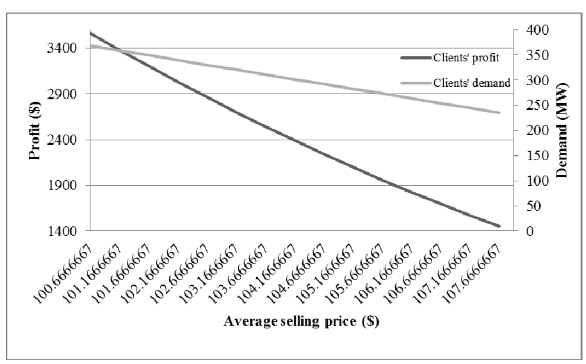

Fig. 4. Impact of average selling price on the clients' profit and consumption.

Table I. Optimal selling price for different variation intervals of wholesale prices ($/MWh).

λ	Low-Load		Mid-Load		Peak-Load	
	$(1-\lambda)$	$(1+\lambda)$	$(1-\lambda)$	$(1+\lambda)$	$(1-\lambda)$	$(1+\lambda)$
0	90.5	90.5	108	108	114	114
0.05	88.5	92	105.5	110	111.5	116.5
0.1	86.5	94	103.5	112.5	109.5	119
0.15	84.5	96	101	115	107	121.5
0.2	83	97.5	98.5	117	104.5	124
0.25	81	99.5	96.5	119.5	102	126.5
0.3	79	101.5	94	122	99.5	129

Table II. MO's maximum and minimum profits for different variation intervals of wholesale prices ($).

λ	Low-Load		Mid-Load		Peak-Load	
	$(1-\lambda)$	$(1+\lambda)$	$(1-\lambda)$	$(1+\lambda)$	$(1-\lambda)$	$(1+\lambda)$
0	829.53	829.53	4156.23	4156.23	2430.28	2430.28
0.05	892.66	842.4	4157.91	4441.52	2380.09	2630.79
0.1	1019.09	929.59	4426.77	5001.89	2463.83	2983.44
0.15	1214.28	1092.65	4911.23	5751.68	2646.09	3451.9
0.2	1470.58	1327.58	5614.23	6643.8	2942.38	3980.76
0.25	1775.08	1631.38	6520.12	7664.82	3352.95	4563.32
0.3	2117.18	1989.2	7614.54	8804.52	3866.75	5199.2

Table III. Clients' maximum and minimum profits for different variation intervals of wholesale prices ($).

λ	Low-Load		Mid-Load		Peak-Load	
	$(1-\lambda)$	$(1+\lambda)$	$(1-\lambda)$	$(1+\lambda)$	$(1-\lambda)$	$(1+\lambda)$
0	504.64	504.64	1220.69	1220.69	664.57	664.57
0.05	640.94	413.1	1653.72	921.5	872.39	484.98
0.1	793.51	305.28	2047.39	606.57	1058.98	333.61
0.15	962.36	213.73	2598.52	357.25	1317.62	210.48
0.2	1099.68	155.75	3215.26	205.03	1604.49	115.58
0.25	1297.01	92.69	3755.9	73.81	1919.59	48.91
0.3	1510.62	45.9	4490.74	8.2	2262.92	10.48

Simulation results demonstrate that the minimum and maximum selling prices within the variation interval $\left[(1-\lambda)\bar{\Pi}_t^{WS},(1+\lambda)\bar{\Pi}_t^{WS}\right]$ are obtained at the minimum and maximum wholesale prices, which are equal to $(1-\lambda)\bar{\Pi}_t^{WS}$ and $(1+\lambda)\bar{\Pi}_t^{WS}$, respectively. In other words, by increasing wholesale prices, MO has to offer the higher selling price to cover the supply cost. Table II demonstrates that increasing the wholesale price uncertainty (i.e., variation interval) increases the minimum and maximum profits of MO. It is worthwhile to note that MO provides a major portion of the required energy of the clients at the low-price hours using the wholesale market. As mentioned above, MO has to offer the higher selling price within the high-price hours, which results in a lower consumption. Consequently, MO is capable of selling the surplus energy at the higher price in the wholesale market. Evidently, DGs and forward contracts enable MO to obtain a higher profit in all circumstances. The clients' profit for different variation intervals of the wholesale prices is presented in Table III. According to the provided results, the maximum and minimum profits are obtained for the minimum and the maximum prices identified by the uncertainty horizon, which are equal to $(1-\lambda)\bar{\Pi}_t^{WS}$ and $(1+\lambda)\bar{\Pi}_t^{WS}$, respectively.

MO's maximum profit versus the wholesale price deviation factor (i.e., $k=\Pi_t^{WS}/\bar{\Pi}_t^{WS}$) is depicted in Fig. 5. The minimum profit $7391 is obtained at $k = 0.9711$.

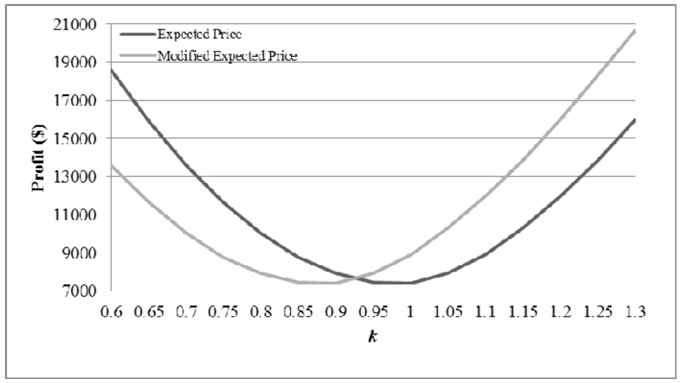

Fig. 5. MO's maximum profit versus k for the expected and the modified expected wholesale prices ($).

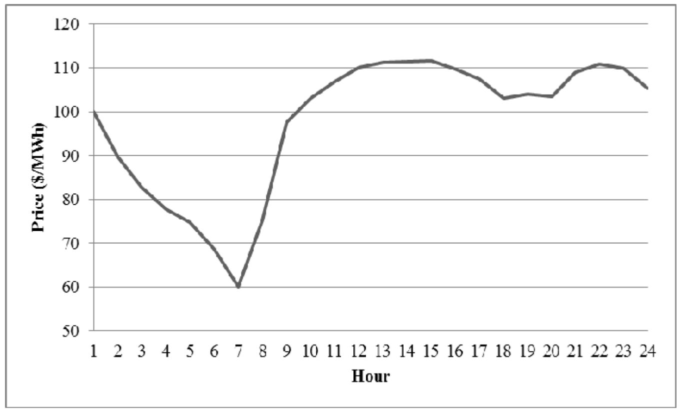

Fig. 6. Modified expected wholesale prices.

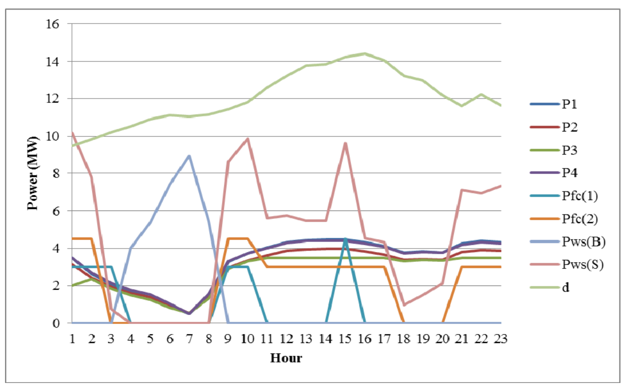

Fig. 7. Optimal strategy of the risk-averse MO (MW).

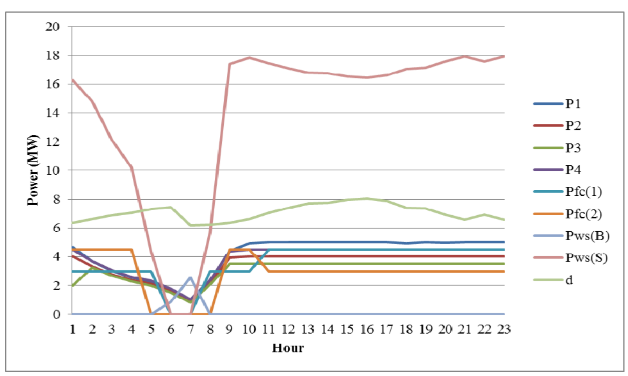

Fig. 8. Optimal strategy of the risk-taker MO (MW).

This figure justifies that the clients' price sensitivity, DGs, and forward contracts enable MO to obtain a higher profit at low-price and high-price hours. According to Fig. 5, for $\lambda \geq 0.0289$, the minimum profit is equal to \$7391 (the expected profit is equal to \$7416). Therefore, the profit deviation factor of the risk-averse MO (i.e., ρ^{RA}) in expression (29) cannot be higher than 0.0034. It is worthwhile to note that these results depend on $\bar{\Pi}_t^{WS}$. Therefore, to evaluate the performance of the proposed robustness and opportunity functions, the expected values of the wholesale prices are modified according to Fig. 6. Also, to evaluate the optimal framework of the risk-averse and the risk-taker MOs based on the proposed robustness and opportunity functions, the desired profit level, denoted by Pr_{cr}^{RA} and Pr_{cr}^{RT} in (29) and (30), are considered as \$7500 ($\rho^{RA} = 0.159$) and \$10500 ($\rho^{RT} = 0.178$), respectively. The optimal framework of the risk-averse MO is depicted in Fig. 7. Simulation results demonstrate that the proposed strategy within the maximum variation interval 0.0766 or $\left[0.9234\bar{\Pi}_t^{WS}, 1.0766\bar{\Pi}_t^{WS}\right]$ guarantees the minimum profit \$7500, which is obtained at $\Pi_t^{WS} = 0.9234\bar{\Pi}_t^{WS}$. Moreover, the selling prices Π_L^M, Π_M^M, and Π_P^M are equal to \$91, \$108.5 and \$115, respectively. The maximum profit of clients based on the proposed strategy is equal to \$2204.4. Fig. 8 demonstrates that the optimal framework of the risk-taker MO. The minimum variation interval of the wholesale price, which ensures the maximum profit \$10500, is equal to 0.05148 ($\Pi_t^{WS} \in \left[0.94852\bar{\Pi}_t^{WS}, 1.05148\bar{\Pi}_t^{WS}\right]$). The selling prices π_L^M, π_M^M, and π_P^M are equal to \$96, \$115 and \$122, respectively. Moreover, the maximum profit is achieved at $\Pi_t^{WS} = 1.05148\bar{\Pi}_t^{WS}$. According to the proposed strategy for the risk-taker MO, the clients' maximum profit is equal to \$760.23. Comparing the results of Figs. 7 and 8 demonstrates that the risk-averse and risk-taker MOs prefer to determine their optimal strategies based on the minimum and maximum wholesale prices, respectively. Therefore, risk-taker MOs have to offer the higher selling prices to their clients. According to (1a), increasing the selling price reduces the clients' consumption. Hence, the risk-taker MO has more surplus energy for selling in the wholesale market. Additionally, the optimal power production of DGs in the risk-taker strategy is higher than the risk-averse one.

VI. Conclusion

This paper presents a robust energy acquisition framework for micro-grid operators to determine the optimal energy procurement strategy based on the price uncertainty and demand sensitivity to the selling prices. MO's profit depends on the selling price and demand, which are determined by MO and clients, respectively. Accordingly, by the game theoretical approach, the optimal selling prices are specified to simultaneously optimize the profits of the MO and clients. During the low-price hours, MO provides a major portion of the required energy of clients using the wholesale market. Additionally, by increasing the wholesale price, the selling price is increased, which results in the lower demand. Therefore, MO has more surplus energy for selling in the wholesale market. In other words, DGs, clients' sensitivity to selling prices, and forward contracts enable MO to obtain a higher profit in all circumstances. To evaluate the optimal strategy based on the MO's risk preferences, the robustness and opportunity performance functions are developed for the risk-averse and risk-taker MOs, respectively. Simulation results demonstrate that the risk-averse and risk-taker MOs prefer to determine their optimal strategies based on the minimum and maximum wholesale prices, respectively. According to the proposed framework, MO has to offers the higher selling prices within high-price hours to cover the supply cost. Therefore, the selling price of the risk-taker MO is higher than the risk-averse MO. Moreover, the risk-taker MO prefers to participate in the wholesale market as a seller. The optimal power production of DGs in the risk-taker strategy is higher than the risk-averse one.

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