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Reliability-constraint energy acquisition strategy for electricity retailers

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ABSTRACT

Electricity retailers desire to specify the energy acquisition strategy and selling prices in a way that maximize the expected profit, and convince consumers to choose them as the energy provider. Reducing selling price decreases retailers' income, and vice versa. Moreover, the higher selling price increases clients' switching probability to rivals that reduces the retailer's expected income. Therefore, the retailer faces a tradeoff between selling prices and clients' consumption. Additionally, fluctuations of wholesale prices, random demand, unexpected failures of self-generation facilities, and risk of rivals' strategies are other difficulties faced by retailers, and these uncertainty resources affect their profits. This paper presents a fuzzy Information Gap Decision Theory (IGDT) based framework for electricity retailers to specify the energy acquisition strategy. Uncertainty of wholesale price is modeled via unknown bounded intervals. Additionally, the Point Estimate Method (PEM) is proposed to cope with the uncertainty of rivals' strategies. Clients' reaction to retail-selling prices is incorporated into the proposed framework via fuzzy numbers. In order to model the availability of generating units, a novel scheduling framework considering the repair time for failed units, in addition to repair cost and forced outage rate (FOR) is presented in this research. Finally, IGDT methodology is applied to determine the retailer's energy acquisition strategy based on financial risk preferences. Performance of proposed model is evaluated via a case study, and the numerical results are discussed.

1. Introduction

Restructuring in electricity distribution networks leads to emerging a new marketplace that is known as the electricity retail market. This market is the final stage of providing the required energy of household consumers. Retailer companies are the point of sale between the generation companies and end-users. They have various options to provide clients' required energy such as the wholesale market, bilateral contracts, and self-generation facilities. Fluctuations of some parameters such as wholesale prices and clients' demand are inevitable, and neglecting uncertainty of these parameters may impose a great financial loss on retailers [1]. In competitive electricity markets, the forward contract is proposed as an effective alternative to hedge the financial risk of random wholesale prices. Self-generating facilities are other source of providing energy. Evidently, these units are not fully reliable and their unexpected outages after acceptance of bids and offers by the market operator enforce retailers to compensate the electricity shortage from the regulation market during committed periods. Moreover, retailers have to pay repair cost to recover failed generating units. Hence, the availability of self-generating units is another uncertainty resource that could imposes additional cost to retailers.

In a competitive electricity market, selling prices play a crucial role in negotiations between retailers and consumers. Evidently, the retailer's business could only be profitable if the income that depends on selling prices is greater than the supply cost. Selling price must be determined in a way that covers the supply cost, leads to an acceptable profit for the retailer, and encourages consumers to purchase energy from the retailer. By increasing selling prices, consumers may change their energy providers and choose another retailer. Hence, the risk of rivals' strategy is another uncertain parameter that must be assessed by the retailer. Impacts of this uncertainty resource depend on rivals' selling prices and clients' tendency to change or switch their energy providers. The switching tendency is affected by many factors such as social, economic, and cultural condition of consumers. Surprisingly, in some countries, even cheaper selling offers do not increase the consumers' motivation to choose another energy provider. For example, Danish households are less willing to switch suppliers compared to their Nordic neighbors. The main reason of this issue is that the electricity bill constitutes a small proportion of Danish end users' monthly income [2]. Therefore, to model the uncertainty of rivals' strategy, their selling prices and customers' switching tendency must be considered, simultaneously.

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Nomenclature

$Profit_{cr}^{RA}$	critical profit of risk-averse retailer ($)
$Profit_{cr}^{RT}$	critical profit of risk-taker retailer
Inc_t	retailer's income within operation period t ($)
Inc_t^{RET}	income of selling power in retail market within operation period t ($)
Inc_t^{DA}	income of selling power in wholesale day-ahead market within operation period t ($)
$Cost_t$	retailer's supply cost within operation period t ($)
$Cost^{DA}$	cost of purchasing power from the day-ahead wholesale market ($)
	cost of purchasing power from the forward market ($)
$Cost^{SG}$	operational cost of self-generating facilities ($)
FC	fuel cost ($)
RC	repair cost ($)
RGC	cost of purchasing power from the regulation market ($)
SDC	shutdown cost ($)
SUC	startup cost ($)
CC	cooling cost ($)
P_t^L	hourly demand (MW)
$\overline{P}_t^{L,0}$	initial hourly demand without considering the risk of rival retailers (MW)
$\overline{P}_t^{L,k}$	initial hourly demand with considering the risk of rival retailer k th(MW)
$P_t^{DA_S}$	hourly sold power in the day-ahead wholesale market (MW)
$P_t^{DA_B}$	hourly purchased power from the day-ahead wholesale market (MW)
$P_{b,f,t}^{FC}$	hourly purchased power from b-block of forward contract f within operation period t (MW)
$P_{t,f}^{FC}$	total hourly purchased power from forward contract f within operation period t (MW)
P_t^{FC}	total purchased power from the forward market (MW)
$\overline{P}_{b,f,t}^{FC}$	upper bound of b-block of forward contract f (MW)
$P_{i,t}$	hourly generating power of unit i th within operation period t (MW)
$P_i^{\max}$	maximum allowed capacity of unit i (MW)
$P_i^{\min}$	minimum allowed capacity of unit i (MW)
π_t^{RET}	hourly retail-selling price ($/MWh)
π_t^{DA}	hourly energy price of day-ahead wholesale market during operation period t ($/MWh)
$\overline{\pi}_t^{DA}$	estimation of day-ahead hourly price during operation period t ($/MWh)
$\pi_{b,f,t}^{FC}$	price of b-block of forward contract f during operation period t ($/MWh)
π_t^{RG}	hourly regulation price ($/MWh)
π_t^k	retail selling price of rival-retailer k th during operation period t ($/MWh)
N_t^f	number of power blocks of forward contract f during operation period t
N_{SG}	number of self-generating units
N_ϕ^k	set of selling-prices of rival k th
N_{riv}	number of rival-retailers
Ξ	set of available forward contracts
T	set of operation periods
$T_{C_i,t}^{On}$	number of continuous on-time hours of unit i up to hour t (h)
$T_{i,\min}^{On}$	minimum on-time of unit i (h)
$T_{C_i,t}^{Off}$	number of continuous off-time hours of unit i up to hour t (h)
$T_{i,\min}^{Off}$	minimum off-time of unit i (h)
R_i^{Up}	ramp-up rate of unit i (MW/h)
R_i^{Down}	ramp-down rate of unit i (MW/h)
R_i^{SU}	startup ramp-rate of unit i (MW/h)
R_i^{SD}	shutdown ramp-rate of unit i (MW/h)
FOR_i	forced outage rate of unit i th (%)
Pr_r^k	probability of selling price r th of rival k th
a_i,b_i,c_i	coefficients of cost function
λ_t	variation bound of hourly day ahead price
Δ_t^k	hourly difference between selling prices of the retailer and rival k th during operation period t ($/MWh)
A_t^k	fuzzy number of rival-retailer k th during operation period t
$\tau_{A_t^k}$	membership function of A_t^k
$\delta_{b,f,t}$	binary variable of block b of forward contract f during operation period t
$U_{i,t}$	status binary variable of unit i during operation period t
$\mu_{i,t}$	startup decision variable of unit i during operation period t
$\nu_{i,t}$	shutdown decision variable of unit i during operation period t
ρ	ratio of regulation and day-ahead prices
ϑ	profit deviation factor
ζ	ratio of day-head hourly price and its estimation
μ	expected value
σ	standard deviation value
η	standard location
θ	central moment
w	weighting factor

In recent years, various models have been presented in technical literature to specify the electricity retailer's strategy in the wholesale and regulation markets [3], forward contracts [4] as well as handling effects of uncertain parameters. It should be noted that smart control and metering devices enable household clients to adjust their consumption according to energy prices [5]. Therefore, the stochastic framework is addressed in [6–9] to evaluate effects of demand elasticity [6,7] and reward-based demand response programs [8,9] on the retailer's energy acquisition strategy. As mentioned before, retailers could supply the required energy of their consumer by self-generation facilities [10]. In [11], the retailer's strategy is developed in the presence of renewable energy resources. Modeling of uncertain parameters and the risk management methodology are main differences of presented models. The stochastic programming [12–14], game theoretical approach [15], clustering technique [16,17], robust optimization methodology [18,19], and heuristic algorithm [20] are proposed to evaluate the financial risk and behavior of random parameters.

Evidently, increasing the selling price has negative impact on demand of price-sensitive consumers. Hence, retailers face a tradeoff between selling price and clients' demand. In [21], the multi-objective methodology is addressed to determine the retailer's selling price and energy acquisition strategy. The profit maximization and risk minimization are two main objectives of a typical retailer [12–15]. For simultaneous optimization, bi-level programming [22,23] and multi-objective methodology [24] are proposed in some technical references. Moreover, conditional value-at-risk (CVaR) [13,14,16], expected downside risk (EDR) [22], and risk-adjusted recovery on capital (RAROC) [25] are most important methodologies which are used to quantify financial risk.

Although, many researches have evaluated uncertainties of wholesale price and demand, few models can be found that focusing on the uncertainty of rival retailer's strategy and availability of self-generation facilities. Therefore, uncertainties of wholesale price, rivals' strategies, and availability of generating units are modeled in this work, simultaneously. As mentioned before, the risk of rivals' strategies depends on their selling prices and clients' switching behavior. The main difficulty is modeling the switching tendency that depends on many factors. The fuzzy methodology is an effective tool for evaluating

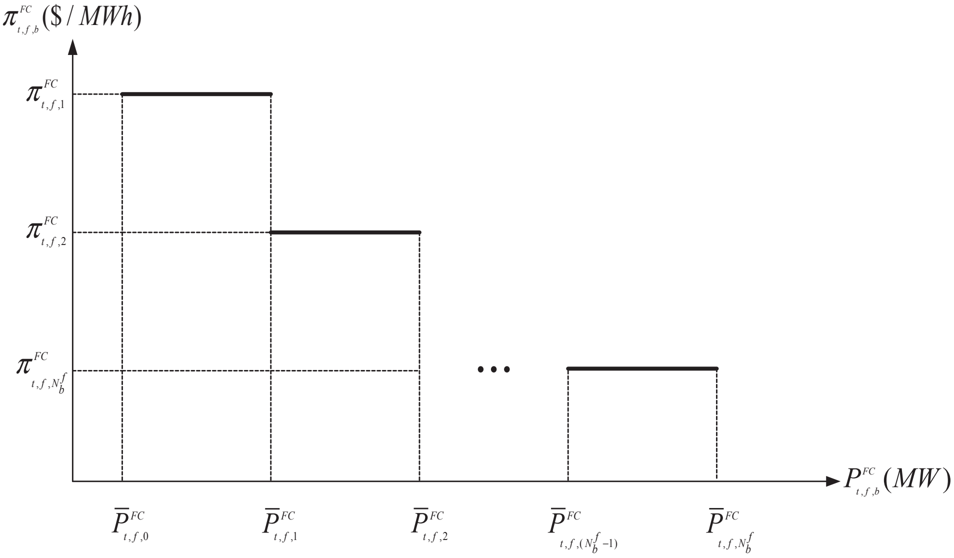

Fig. 1. Price-quota curve of a typical forward contract.

Table 1
Operational cost of generating units in different condition.

Item	$U_{i,t-1}$	$U_{i,t}$	*Health Status*	*Probability*	*Cost*
1	1	1	Available	$1 - FOR_i$	$FC_{i,t}$
2	1	1	Unavailable	FOR_i	$RC_i + CC_i^U + RGC_{i,t}$
3	1	0	Available	$1 - FOR_i$	$SDC_i \times \nu_{i,t}$
4	1	0	Unavailable	FOR_i	$RC_i + CC_i^{SD}$
5	0	1	Available	$1 - FOR_i$	$SUC_i \times \mu_{i,t}$
6	0	1	Unavailable	FOR_i	$RC_i + CC_i^{SU} + RGC_{i,t}$
7	0	0	Available	$1 - FOR_i$	0
8	0	0	Unavailable	FOR_i	$RC_i + CC_i^D$

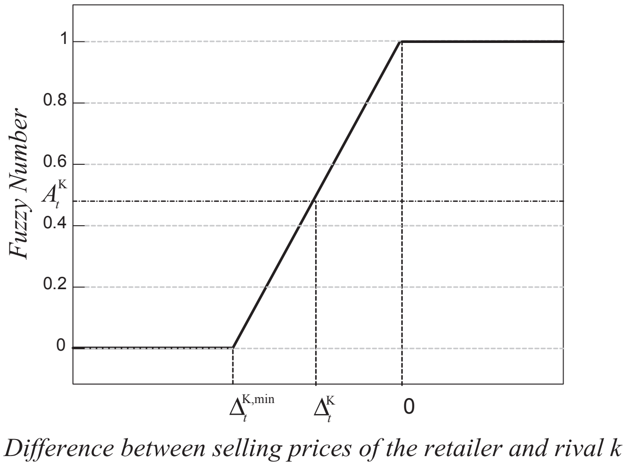

Fig. 2. Membership function $\tau_{A^k_t}(\Delta^k_t)$ based on difference of selling prices.

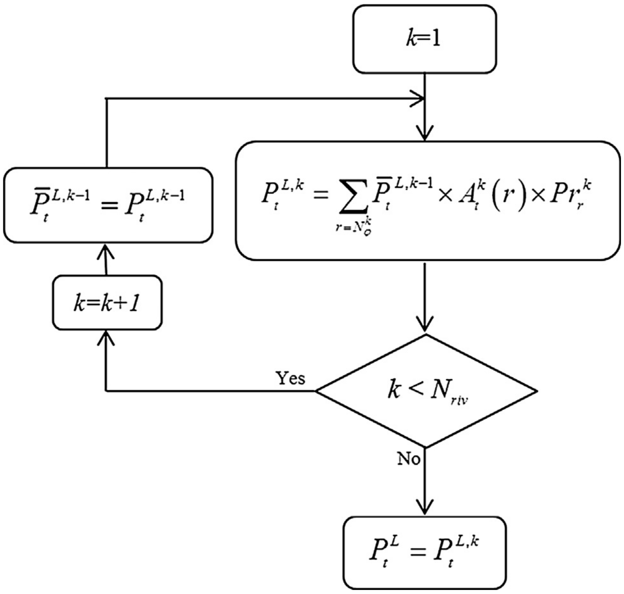

Fig. 3. Procedure of calculating demand based on rivals' selling prices.

uncertain parameters, which are not well understood. It should be noted that these variables are similar to human reasoning. The fundamental difference between traditional risk management theories and fuzzy risk modeling is the nature of inclusion of the uncertain parameter. In traditional methodologies, an element or scenario is either included in the specific condition or not. In fuzzy-based models, a membership degree is defined for an element that determines the degree of truth. The range of membership degree is normally between 0 and 1. In this work, the fuzzy approach is used to model the load based on the relation between customers' switching behavior and retailers' selling prices. Additionally, uncertainty of rivals' selling price is modeled by PEM methodology.

Fluctuation of wholesale prices is another difficulty faced by a retailer. In the proposed model, IGDT methodology is applied to analyze the risk of wholesale price. IGDT is a non-probabilistic method that characterizes the uncertain parameter via variation interval. In this methodology, instead of profit maximization, the optimal strategy is specified based on the retailer's predefined performance. Evidently, the energy providing strategy depends on retailers' risk preferences. Risk-averse retailers choose the lower risk level to hedge the financial loss, and risk-taker retailers select the higher risk level in the hope that obtain the higher profit. Therefore, two performance functions are used to determine the optimal decisions of risk-averse and risk-taker retailers.

Unplanned outages of self-generation facilities can significantly affect the expected profit of retailers. The availability of generating units depends on *FOR* index and the repair time. In other words, when a unit becomes unavailable, it needs a certain time for repairing and returning to operating condition. Previous works only consider *FOR* index and

Table 2
Operational data of self-generating units.

	$i = 1$	$i = 2$	$i = 3$	$i = 4$
$P_i^{\min}$ (MW)	0.50	0.55	0.55	0.50
$P_i^{\max}$ (MW)	5.00	4.00	3.50	4.50
R_i^{Up} (MW/h)	2.50	2.00	2.00	2.50
R_i^{Down} (MW/h)	2.50	2.00	2.00	2.50
R_i^{SU} (MW/h)	2.50	2.00	2.00	2.50
R_i^{SD} (MW/h)	2.50	2.00	2.00	2.50
a_i ("\$"/MW^2)	5.70	6.80	6.50	6.20
b_i ("\$"/MW)	55.3	53.2	54.0	53.8
c_i ("\$")	34.0	33.5	34.5	32.8
$T_{i,\min}^{Up}$ (h)	1.00	0.50	1.00	0.50
$T_{i,\min}^{Down}$ (h)	1.00	0.50	1.00	0.50
FOR_i (%)	1	2	3	1
$U_{i,0}$	1	0	1	1
$\overline{SUC_i}$ (\$)	15.0	13.0	15.0	13.0
$\overline{SDC_i}$ (\$)	10.0	9.00	10.0	9.00
RT_i (h)	2	2	2	2
RC_i ("\$"/h)	800	600	400	500
CC_i^U ("\$")	400	250	200	300
CC_i^{SU} ("\$")	100	80	80	100
CC_i^{SD} ("\$")	250	150	100	200
CC_i^D ("\$")	50	40	30	50

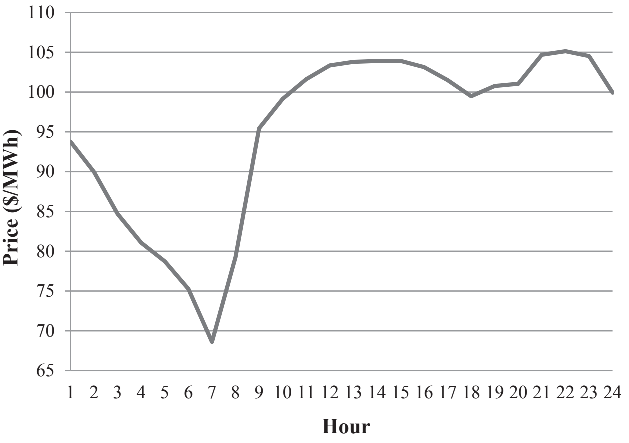

Fig. 4. Expected values of day-ahead prices.

Table 3
Characteristics of forward contracts.

		t = 1–10, 24			t = 11–23		
		$b = 1$	$b = 2$	$b = 3$	$b = 1$	$b = 2$	$b = 3$
$f = 1$	$\overline{P}_{t,1,b}^{FC}$ (MW)	1	2	3	1.5	3	4.5
	$\pi_{t,1,b}^{FC}$ ("\$"/MWh)	95	85	75	107	105	103
$f = 2$	$\overline{P}_{t,2,b}^{FC}$ (MW)	1.5	3	4.5	1	2	3
	$\pi_{t,2,b}^{FC}$ ("\$"/MWh)	90	85	80	100	98	96

neglect effects of repair time. In this work, a new reliability model is presented for scheduling of generating units that considers the repair time and repair cost as well as *FOR* index. The regulation market is predicted as energy resource to compensate the capacity shortage during unexpected outages of generating units.

The main contributions of the presented model can be summarized as follows:

- The fuzzy-robust model is presented to determine the energy procurement strategy of retailers.
- A new reliability model is proposed for scheduling of generating units.
- Different sources of uncertainty such as wholesale price, rivals' strategy, switching behavior of clients, and availability of generating facilities are modeled, simultaneously.

The rest of this work is organized as follows: the proposed risk-based framework to specify the retailer's energy acquisition strategy is introduced in Section 2. In order to illustrate the performance of the proposed model, numerical studies are provided and discussed in Section 3. Finally, this work is concluded in Section 4.

2. Energy acquisition strategy of retailer

This section introduces mathematical formulation of retailer's energy acquisition strategy. As a private sector, the profit maximization is the main goal of an electricity retailer. Total profit within the operation period T is represented as follows:

$$Profit = \sum_{t \in T} Inc_t - Cost_t \tag{1}$$

where

Inc_t is the retailer's income within operation period t (\$),
$Cost_t$ is the retailer's supply cost within operation period t (\$),
T is the set of operation periods.

2.1. Income of selling energy

A retailer can sell the provided energy in retail and day-ahead markets. Hence, Inc_t is formulated as follows:

$$Inc_t = Inc_t^{RET} + Inc_t^{DA}\ ; \quad \forall\, t \in T \tag{2}$$

The income of selling power in the retail market depends on the hourly demand (P_t^L) and retail-selling price (π_t^{RET}):

$$Inc_t^{RET} = P_t^L \times \pi_t^{RET}\ ; \quad \forall\, t \in T \tag{3}$$

Additionally, the day-ahead income is calculated as follows:

$$Inc_t^{DA} = P_t^{DAs} \times \pi_t^{DA}\ ; \quad \forall\, t \in T \tag{4a}$$

$$P_t^{DAs} \geqslant 0\ , \quad \forall\, t \in T \tag{4b}$$

where π_t^{DA} and P_t^{DAs} are hourly price and amount of sold power in the day-ahead market, respectively.

2.2. Cost of providing energy

In this work, we suppose that the retailer can provide the required energy via day-ahead wholesale market, forward contracts, and self-generation facilities. Hence, Cost$_t$ is formulated as follows:

$$Cost_t = Cost_t^{DA} + Cost_t^{FC} + Cost_t^{SG}\ ; \quad \forall\, t \in T \tag{5}$$

where $Cost^{DA}$, , and $Cost^{SG}$ are cost of purchasing power from the day-ahead market, forward contracts, and operational cost of generating units.

2.2.1. Day-ahead cost

Cost$_t^{DA}$ depends on amount of hourly purchased power from the wholesale market ($P_t^{DA_B}$) and π_t^{DA}:

$$Cost_t^{DA} = P_t^{DA_B} \times \pi_t^{DA}\ ; \quad \forall\, t \in T \tag{6a}$$

$$P_t^{DA_B} \geqslant 0\ , \quad \forall\, t \in T \tag{6b}$$

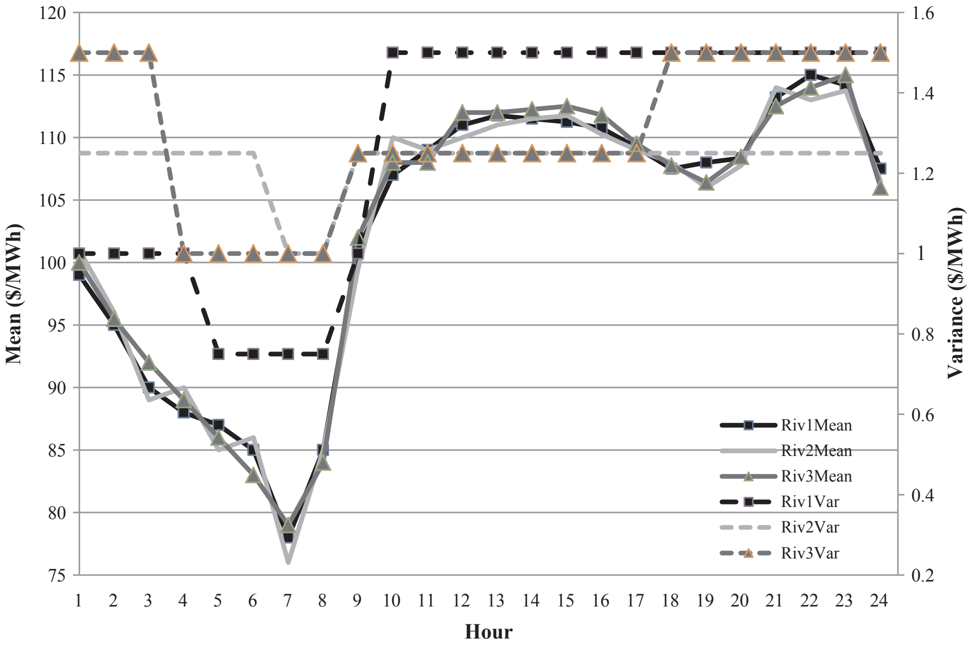

Fig. 5. Characteristics (Mean value & Variance) of rival retailers' prices.

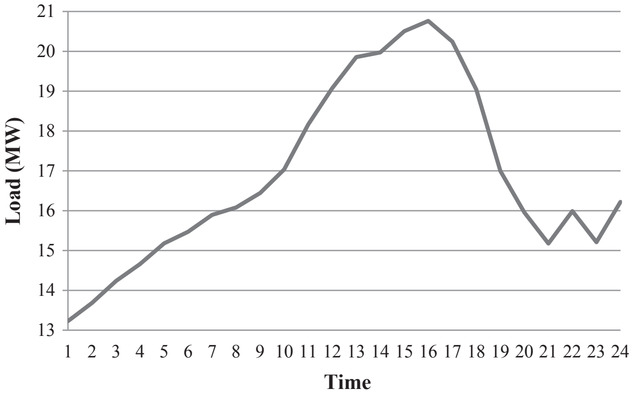

Fig. 6. Initial hourly load without considering the risk of rivals' strategy ($\overline{P}_t^{L,0}$).

2.2.2. Forward cost

According to [10], usually stepwise format is used for selling offers of forward contracts. Additionally, in order to encourage buyers to have more participation in this market, sellers propose the lower price as the amount of traded power is increased. The price-quota curve for a typical forward contract is demonstrated in Fig. 1.

According to Fig. 1, is formulated as follows [10]:

$$\delta_{t,f,b} \in \{0,1\}\ ; \quad \forall\ t \in T\ , \quad \forall\ f \in \Xi, \quad b = 1,\ldots,N_t^f \tag{7}$$

$$0 \leqslant \sum_{b=1}^{N_t^f} \delta_{t,f,b} \leqslant 1\ ; \quad \forall\ t \in T\ , \quad \forall\ f \in \Xi \tag{8}$$

$$\overline{P}_{t,f,b-1}^{FC} \times \delta_{t,f,b} \leqslant P_{t,f,b}^{FC} \leqslant \overline{P}_{t,f,b}^{FC} \times \delta_{t,f,b}\ ; \quad \forall\ t \in T\ , \quad \forall\ f \in \Xi, b = 1,\ldots,N_t^f \tag{9}$$

$$P_f^{FC} = \sum_{t=1}^{T} \sum_{b=1}^{N_t^f} \overline{P}_{t,f,b}^{FC} \times \delta_{t,f,b}\ ; \quad \forall\ t \in T\ , \quad \forall\ f \in \Xi \tag{10}$$

Table 4
Retailer's energy providing strategy without considering load uncertainty (MW).

t	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	$P_{t,1}^{FC}$	$P_{t,2}^{FC}$	P_t^{DAB}	P_t^{DAS}
1	3.37	2.00	3.04	3.22	3.00	4.50	0.00	6.91
2	3.03	2.69	2.74	2.91	3.00	4.50	0.00	7.66
3	2.57	2.3	2.34	2.48	3.00	4.50	0.00	5.72
4	2.25	2.04	2.06	2.19	3.00	4.50	0.00	1.39
5	2.05	1.86	1.88	2.00	3.00	0.00	4.38	0.00
6	1.74	1.61	1.62	1.72	3.00	0.00	5.77	0.00
7	1.16	1.12	1.11	1.19	0.00	0.00	11.31	0.00
8	2.10	1.91	1.92	2.05	3.00	0.00	3.06	0.00
9	3.51	3.09	3.16	3.35	3.00	4.50	0.00	7.78
10	3.84	3.36	3.45	3.65	3.00	4.50	0.00	4.77
11	4.05	3.55	3.50	3.85	0.00	3.00	0.22	0.00
12	4.21	3.67	3.50	3.99	4.50	3.00	0.00	3.79
13	4.25	3.71	3.50	4.02	4.50	3.00	0.00	3.12
14	4.25	3.71	3.50	4.03	4.50	3.00	0.00	3.03
15	4.26	3.71	3.50	4.03	4.50	3.00	0.00	2.50
16	4.19	3.66	3.50	3.97	4.50	3.00	0.00	2.05
17	4.04	3.54	3.50	3.84	0.00	3.00	2.33	0.00
18	3.87	3.39	3.47	3.68	0.00	3.00	1.64	0.00
19	3.98	3.48	3.50	3.78	0.00	3.00	0.00	3.54
20	4.00	3.50	3.50	3.80	0.00	3.00	0.00	1.85
21	4.32	3.77	3.50	4.10	4.50	3.00	0.00	8.01
22	4.36	3.80	3.50	4.13	4.50	3.00	0.00	7.31
23	4.31	3.76	3.50	4.08	4.50	3.00	0.00	7.94
24	3.91	3.42	3.50	3.71	3.00	4.50	0.00	6.52

$$Cost_t^{FC} = \sum_{f \in \Xi} \sum_{b=1}^{N_t^f} \overline{P}_{t,f,b}^{FC} \times \pi_{t,f,b}^{FC} \times \delta_{t,f,b}\ ; \quad \forall\ t \in T \tag{11}$$

$P_{b,f,t}^{FC}$ is the purchased power from b-block of forward contract f (MW),
$P_{t,f}^{FC}$ is the total purchased power from forward contract f (MW),
P_t^{FC} is the total purchased power from the forward market (MW),
$\overline{P}_{b,f,t}^{FC}$ is the upper bound of b-block of forward contract f (MW),
$\pi_{b,f,t}^{FC}$ is the price of b-block of forward contract f ($/MWh),

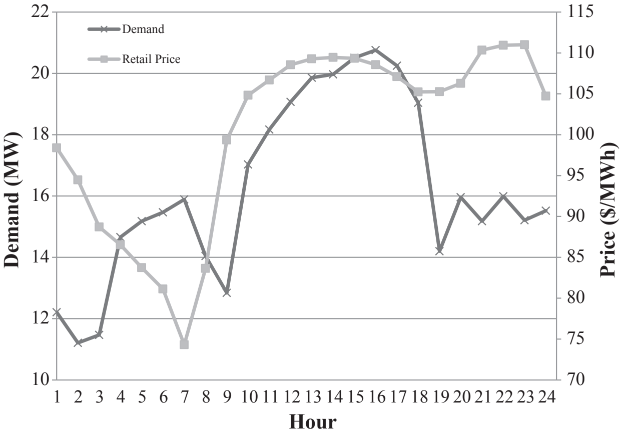

Fig. 7. Clients' demand and retail-selling price without considering load uncertainty.

Table 5
Retailer's energy providing strategy for $FOR_1 = 5\%$, $FOR_2 = 10\%$, $FOR_3 = 15\%$, and $FOR_4 = 5\%$ (MW).

t	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	$P_{t,1}^{FC}$	$P_{t,2}^{FC}$	P_t^{DAB}	P_t^{DAS}
1	3.33	2.00	2.93	3.18	3.00	4.50	0.00	6.74
2	3.00	2.63	2.64	2.88	3.00	4.50	0.00	7.44
3	2.54	2.25	2.25	2.46	3.00	4.50	0.00	5.51
4	2.22	1.98	1.97	2.16	3.00	4.50	0.00	1.18
5	2.02	1.81	1.79	1.98	3.00	0.00	4.58	0.00
6	1.72	1.56	1.53	1.70	3.00	0.00	5.96	0.00
7	1.14	1.08	1.03	1.17	0.00	0.00	11.49	0.00
8	2.07	1.85	1.84	2.02	3.00	0.00	3.26	0.00
9	3.48	3.03	3.06	3.32	3.00	4.50	0.00	7.54
10	3.80	3.30	3.34	3.62	3.00	4.50	0.00	4.52
11	4.02	3.48	3.50	3.81	0.00	3.00	0.36	0.00
12	4.17	3.60	3.50	3.95	4.50	3.00	0.00	3.65
13	4.21	3.64	3.50	3.99	4.50	3.00	0.00	2.97
14	4.22	3.64	3.50	4.00	4.50	3.00	0.00	2.88
15	4.22	3.64	3.50	4.00	4.50	3.00	0.00	2.35
16	4.15	3.59	3.50	3.94	4.50	3.00	0.00	1.91
17	4.01	3.47	3.50	3.80	0.00	3.00	2.47	0.00
18	3.83	3.32	3.36	3.64	0.00	3.00	1.88	0.00
19	3.94	3.41	3.50	3.74	0.00	3.00	0.00	3.40
20	3.97	3.44	3.50	3.77	0.00	3.00	0.00	1.71
21	4.28	3.70	3.50	4.06	4.50	3.00	0.00	7.87
22	4.32	3.73	3.50	4.09	4.50	3.00	0.00	7.16
23	4.27	3.69	3.50	4.05	4.50	3.00	0.00	7.79
24	3.87	3.35	3.50	3.68	3.00	4.50	0.00	6.38

N_t^f is the number of power blocks of forward contract f,
$\delta_{b,f,t}$ is a binary variable, which is equal to 1 if the purchased power from forward contract f belongs to block b, and is 0 otherwise,
Ξ is the set of available forward contracts.

2.2.3. Operational cost of self-generating units

Self-generation facilities are another source of supplying the required energy. This energy resource is not fully reliable, and its unexpected outages may impose additional cost to the retailer. As mentioned before, the regulation market is predicted to compensate energy shortage. Table 1 demonstrates operational cost ($Cost_i^{SG}$) of generating unit i th in different condition. As seen in this table, the availability (*Up*) and unavailability (*Down*) probabilities are represented by 1-*FOR* and *FOR*, respectively. When the generating unit is committed and the unexpected outage happens, the retailer has to compensate the electricity shortage via regulation market. Additionally, an unexpected failure

Table 6
Retailer's energy providing strategy for $\rho_t = 1.25\ ;\quad \forall\ t \in T$ (MW).

t	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	$P_{t,1}^{FC}$	$P_{t,2}^{FC}$	P_t^{DAB}	P_t^{DAS}
1	3.35	2.00	3.00	3.20	3.00	4.50	0.00	6.85
2	3.02	2.67	2.71	2.90	3.00	4.50	0.00	7.59
3	2.56	2.28	2.31	2.47	3.00	4.50	0.00	5.65
4	2.24	2.02	2.03	2.18	3.00	4.50	0.00	1.32
5	2.04	1.85	1.85	1.99	3.00	0.00	4.45	0.00
6	1.73	1.59	1.59	1.72	3.00	0.00	5.84	0.00
7	1.15	1.11	1.08	1.18	0.00	0.00	11.37	0.00
8	2.09	1.89	1.90	2.04	3.00	0.00	3.13	0.00
9	3.50	3.07	3.13	3.34	3.00	4.50	0.00	7.70
10	3.82	3.34	3.41	3.64	3.00	4.50	0.00	4.68
11	4.04	3.52	3.50	3.84	0.00	3.00	0.27	0.00
12	4.19	3.65	3.50	3.97	4.50	3.00	0.00	3.74
13	4.23	3.68	3.50	4.01	4.50	3.00	0.00	3.07
14	4.24	3.69	3.50	4.02	4.50	3.00	0.00	2.98
15	4.24	3.69	3.50	4.02	4.50	3.00	0.00	2.45
16	4.17	3.63	3.50	3.96	4.50	3.00	0.00	2.00
17	4.03	3.51	3.50	3.83	0.00	3.00	2.38	0.00
18	3.85	3.37	3.44	3.66	0.00	3.00	1.72	0.00
19	3.97	3.46	3.50	3.77	0.00	3.00	0.00	3.50
20	3.99	3.48	3.50	3.79	0.00	3.00	0.00	1.81
21	4.31	3.75	3.50	4.08	4.50	3.00	0.00	7.96
22	4.35	3.78	3.50	4.12	4.50	3.00	0.00	7.25
23	4.29	3.73	3.50	4.07	4.50	3.00	0.00	7.89
24	3.89	3.40	3.47	3.70	3.00	4.50	0.00	6.44

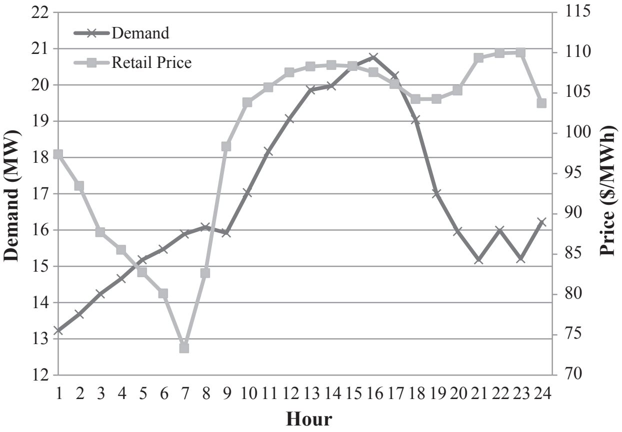

Fig. 8. Clients' demand and retail-selling price for $\Delta_t^{\min} = -3\ ;\quad \forall\ t \in T$.

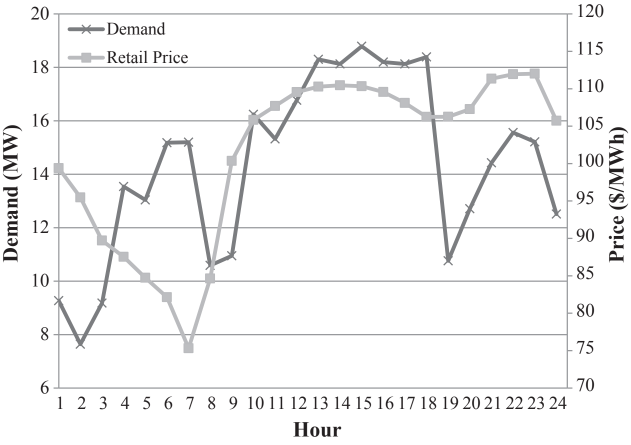

Fig. 9. Clients' demand and retail-selling price for $\Delta_t^{\min} = -7\ ;\quad \forall\ t \in T$.

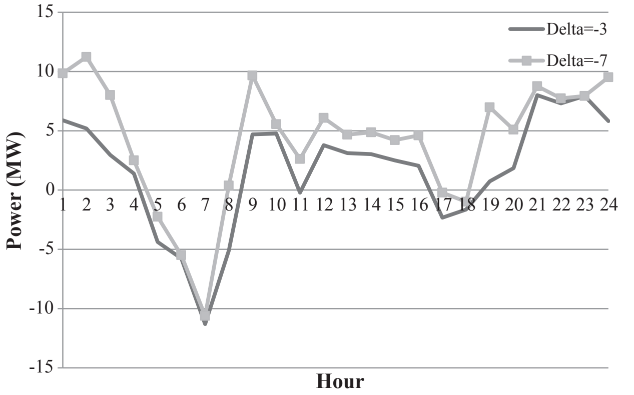

Fig. 10. Retailer's sold power in the wholesale market for $\Delta^{\min} = -3$ and $\Delta^{\min} = -7$ (Purchased power is shown by negative value).

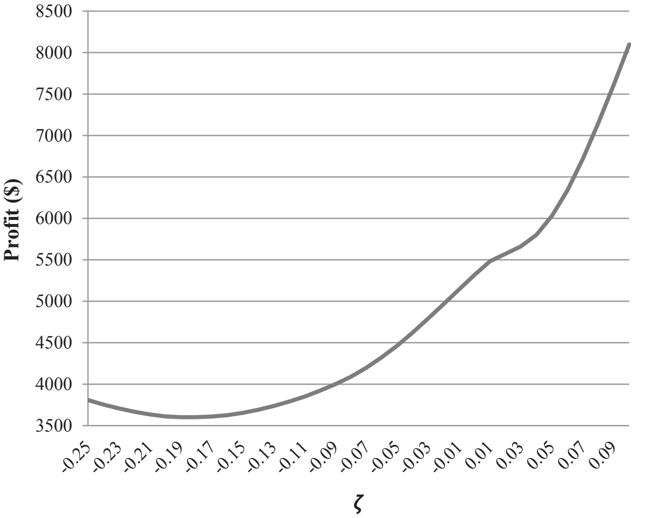

Fig. 11. Retailer's profit for different wholesale prices ($).

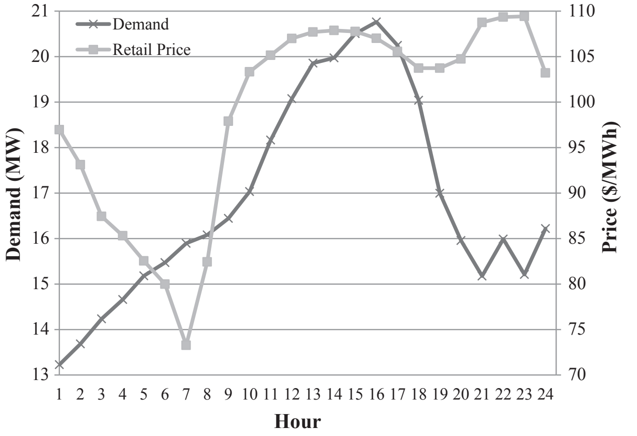

Fig. 12. Demand and retail-price for a risk-averse retailer based on $\vartheta = 0.1$ ($).

Table 7
Energy providing strategy of risk-averse retailer for based on $\vartheta = 0.1$ (MW).

t	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	$P_{t,1}^{FC}$	$P_{t,2}^{FC}$	P_t^{DAB}	P_t^{DAS}
1	3.12	2.00	2.82	2.99	3.00	4.50	0.00	5.19
2	2.79	2.49	2.53	2.69	3.00	4.50	0.00	4.32
3	2.35	2.11	2.14	2.28	3.00	4.50	0.00	2.15
4	2.04	1.86	1.87	1.99	3.00	0.00	3.90	0.00
5	1.84	1.69	1.70	1.81	3.00	0.00	5.14	0.00
6	1.54	1.44	1.44	1.54	0.00	0.00	9.50	0.00
7	0.98	0.97	0.95	1.02	0.00	0.00	11.98	0.00
8	1.89	1.73	1.74	1.85	3.00	0.00	5.87	0.00
9	3.26	2.88	2.94	3.12	3.00	4.50	0.00	3.26
10	3.57	3.14	3.22	3.41	3.00	4.50	0.00	3.81
11	3.78	3.32	3.40	3.60	0.00	3.00	1.06	0.00
12	3.93	3.44	3.50	3.74	0.00	3.00	1.47	0.00
13	3.97	3.47	3.50	3.77	0.00	3.00	2.14	0.00
14	3.98	3.48	3.50	3.78	0.00	3.00	2.23	0.00
15	3.98	3.48	3.50	3.78	0.00	3.00	2.76	0.00
16	3.91	3.43	3.50	3.72	0.00	3.00	3.20	0.00
17	3.77	3.31	3.39	3.59	0.00	3.00	3.18	0.00
18	3.6	3.17	3.24	3.43	0.00	3.00	2.59	0.00
19	3.71	3.26	3.34	3.53	0.00	3.00	0.16	0.00
20	3.74	3.28	3.36	3.56	0.00	3.00	0.00	0.97
21	4.05	3.54	3.50	3.84	0.00	3.00	0.00	2.75
22	4.08	3.57	3.50	3.87	0.00	3.00	0.00	2.04
23	4.03	3.53	3.50	3.83	0.00	3.00	0.00	2.67
24	3.64	3.20	3.28	3.47	3.00	4.50	0.00	4.86

Table 8
Energy providing strategy of risk-taker retailer for based on ϑ0.1 (MW).

t	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	$P_{t,1}^{FC}$	$P_{t,2}^{FC}$	P_t^{DAB}	P_t^{DAS}
1	3.71	2.00	3.34	3.54	3.00	4.50	0.00	16.29
2	3.37	2.97	3.04	3.22	3.00	4.50	0.00	17.56
3	2.89	2.57	2.62	2.77	3.00	4.50	0.00	13.92
4	2.55	2.29	2.33	2.47	3.00	4.50	0.00	6.71
5	2.34	2.11	2.14	2.27	3.00	4.50	0.00	7.02
6	2.02	1.84	1.86	1.98	3.00	0.00	2.51	0.00
7	1.42	1.34	1.33	1.42	0.00	0.00	7.97	0.00
8	2.39	2.15	2.18	2.32	3.00	4.50	0.00	11.54
9	3.87	3.39	3.48	3.68	3.00	4.50	0.00	17.97
10	4.21	3.67	3.50	3.99	3.00	4.50	0.00	11.12
11	4.43	3.86	3.50	4.20	4.50	3.00	0.00	17.43
12	4.59	3.99	3.50	4.34	4.50	3.00	0.00	15.28
13	4.63	4.00	3.50	4.38	4.50	3.00	0.00	15.62
14	4.64	4.00	3.50	4.39	4.50	3.00	0.00	15.70
15	4.64	4.00	3.50	4.39	4.50	3.00	0.00	14.19
16	4.57	3.98	3.50	4.32	4.50	3.00	0.00	14.85
17	4.42	3.85	3.50	4.19	4.50	3.00	0.00	15.65
18	4.24	3.70	3.50	4.02	4.50	3.00	0.00	13.40
19	4.35	3.80	3.50	4.12	4.50	3.00	0.00	19.97
20	4.38	3.82	3.50	4.15	4.50	3.00	0.00	18.57
21	4.71	4.00	3.50	4.45	4.50	3.00	0.00	15.54
22	4.75	4.00	3.50	4.49	4.50	3.00	0.00	14.32
23	4.70	4.00	3.50	4.44	4.50	3.00	0.00	12.50
24	4.28	3.73	3.50	4.05	3.00	4.50	0.00	18.14

imposes the repair cost to the retailer.

It should be noted that in Table 1 *FC*, *RC*, *RGC*, *SDC*, and *SUC* represent fuel, repair, regulation, startup, and shutdown costs. In order to perform repair action, generating units should be cooled. Cooling costs in various operating modes are different. In Table 1, CC^k depicts cooling cost of self-generating facilities in operating mode k (U = Up, D = Down, SU = Startup, and SD = Shutdown).

As mentioned before, the retailer could compensate the capacity shortage from the regulation market, when self-generating units are unavailable. The regulation cost is calculated as follows:

$$RGC_{i,t} = \pi_t^{RG} \times P_{i,t}\,; \quad \forall\, t \in T, \quad i = 1,\ldots,N_{SG} \tag{12}$$

where π^{RG} is cost of energy in the regulation market.

According to Table 1, the operation cost of generating unit i within operation period t could be calculated as follows:

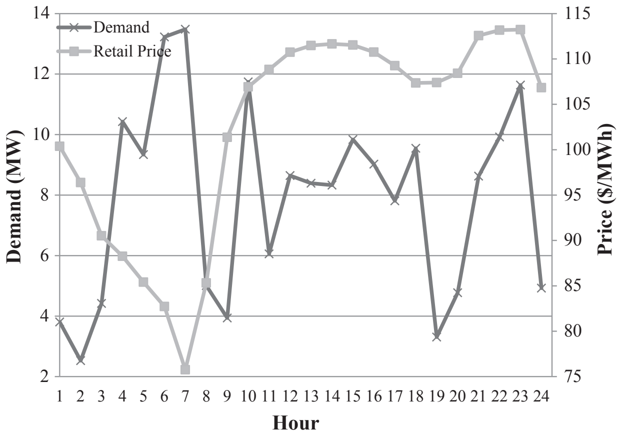

Fig. 13. Demand and retail-price for a risk-taker retailer based on $\vartheta = 0.1$ ($).

$$\begin{aligned}Cost_{i,t}^{DG} &= ((1-FOR_i) \times FC_{i,t})\\ &+ (FOR_i \times (RC_i \times (U_{i,t}-\mu_{i,t}) + CC_i^{U} \times (U_{i,t}-\mu_{i,t}) + RGC_{i,t} \times (U_{i,t}-\mu_{i,t})))\\ &+ ((1-FOR_i) \times SDC_i \times \nu_{i,t})\\ &+ (FOR_i \times (RC_i \times \nu_{i,t} + CC_i^{SD} \times \nu_{i,t}))\\ &+ ((1-FOR_i) \times SUC_i \times \mu_{i,t})\\ &+ (FOR_i \times (RC_i \times \mu_{i,t} + CC_i^{SU} \times \mu_{i,t} + RGC_{i,t} \times \mu_{i,t}))\\ &+ (FOR_i \times (RC_i \times (1-U_{i,t}-\nu_{i,t}) + CC_i^{D} \times (1-U_{i,t}-\nu_{i,t})))\\ &+ \left(FOR_i \times \sum_{k=t}^{t+RT_i} RGC_{i,k}\right) =\\ &((1-FOR_i) \times (FC_{i,t} + SDC_i \times \nu_{i,t} + SUC_i \times \mu_{i,t})) +\\ &\left(FOR_i \times \left(\sum_{k=t}^{t+RT_i} RGC_{i,k} + RC_i + CC_i^{U} \times (U_{i,t}-\mu_{i,t}) + CC_i^{SD} \times \nu_{i,t}\right.\right.\\ &\left.\left.+ CC_i^{SU} \times \mu_{i,t} + CC_i^{D} \times (1-U_{i,t}-\nu_{i,t})\right)\right); \quad \forall\, t \in T, \quad i = 1,\dots,N_{SG}\end{aligned} \tag{13}$$

Fuel cost is calculated as follows:

$$FC_{i,t} = a_i P_{i,t}^2 + b_i P_{i,t} + c_i \times U_{i,t}\,; \quad \forall\, t \in T, \quad i = 1,\dots,N_{SG} \tag{14}$$

where a_i, b_i, c_i are cost function coefficients, P_i is the generating power of unit i, and U_i is the status binary variable of unit i ($U_i = 1$ when unit i th is on, and $U_i = 0$, otherwise).

It should be noted that in this work, the fixed repair, startup and shutdown costs are considered for generating units. The startup and shutdown decision variables are represented by μ and ν, respectively. The relationship between μ, ν, and U are as follows:

$$\mu_{i,t} + \nu_{i,t} \leqslant 1\,; \quad \forall\, t \in T, \quad i = 1,\dots,N_{SG} \tag{15a}$$

$$\mu_{i,t} - \nu_{i,t} = U_{i,t} - U_{i,t-1}\,; \quad \forall\, t \in T, \quad i = 1,\dots,N_{SG} \tag{15b}$$

2.3. Demand

As mentioned before, the competitive market in distribution level gives the opportunity to end-users to choose other retailers, when selling prices of their energy providers are not low enough. In this work, clients' demand (P^L) is considered as a function of difference between the selling prices of retailer (π_t^{RET}) and rivals (π_t^k). Therefore, clients' demand is affected by rival-retailers' strategy, which is modeled by fuzzy numbers. During the operation period t, the difference between selling prices of the retailer and rival k th (Δ_t^k) is represented as follows:

$$\Delta_t^k = \pi_t^k - \pi_t^{RET}\,; \quad \forall\, t \in T, \quad k = 1,\dots,N_{riv} \tag{16}$$

The relation between Δ_t^k and clients' consumption is modeled by the membership function $\tau_{A_t^k}(\Delta_t^k)$. The membership function is a curve that specifies how each point in the input space (difference between selling prices) is mapped to a membership value. In this paper, the right shoulder membership function is used that is shown in Fig. 2. The fuzzy number A_t^k that demonstrates the impact of rivals' offers on demand is represented as follows:

$$A_t^k = \begin{cases} 0; & \Delta_t^k < \Delta_t^{k,\min} \\ \frac{\Delta_t^{k,\min} - \Delta_t^k}{\Delta_t^{k,\min}}; & \Delta_t^{k,\min} \leqslant \Delta_t^k \leqslant 0\,; \quad \forall\, t \in T, \quad k = 1,\dots,N_{riv} \\ 1; & 0 < \Delta_t^k \end{cases} \tag{17}$$

The expected consumption of clients is presented in Fig. 3. According to the proposed procedure, retail-selling prices are compared with rivals one by one.

where

N_{ϕ}^k is set of selling-prices of rival k th,
N_{riv} is the number of rival retailers
Pr_r^k is the probability of selling price r th of rival k th.

In this work, realizations of rivals' selling prices are modeled by PEM that is introduced in next subsection.

2.3.1. Point estimate method

To evaluate the performance of PEM, suppose that X and S are input uncertain parameters and objective function vectors, respectively.

$$S = f(X) \tag{18}$$

PEM is an useful technique that enables decision-makers to estimate the expected value and standard deviation of output vector (S), according to expected value and standard deviation of X. PEM technique performs $2n + 1$ calculations to determine the expected value ($E(S)$) and variance ($E(S^2)$) of S, which n is the number of random variables. Let x_l ($l = 1, 2, \dots, n$) be random input variables with expected value μ_{x_l} and standard deviation σ_{x_l}. In PEM, each random variable is estimated by three location points ($x_{l,j}$; $j = 1, 2, 3$), as follows:

$$x_{l,j} = \mu_{x_l} + \sigma_{x_l} \times \eta_{x_{l,j}}; \quad j = 1,2,3 \tag{19}$$

where $\eta_{x_{l,j}}$ is standard location and calculated as follows:

$$\eta_{x_{l,j}} = \frac{\theta_{x_l,3}}{2} + (-1)^{3-j}\sqrt{\left(\theta_{x_l,4} - \frac{3}{4}\theta_{x_l,3}^2\right)}; \quad j = 1,2 \tag{20}$$

$$\eta_{x_{l,3}} = 0 \tag{21}$$

where $\theta_{x_l,3}$ and $\theta_{x_l,4}$ are the third and fourth central moments of x_l, and calculated as follows:

$$\theta_{x_l,3} = \frac{E\left[(x_l - \mu_{x_l})^3\right]}{(\sigma_{x_l})^3} \tag{22}$$

$$\theta_{x_l,4} = \frac{E\left[(x_l - \mu_{x_l})^4\right]}{(\sigma_{x_l})^4} \tag{23}$$

In Eqs. (22) and (23), E is expectation operator. Another important parameter in PEM is weighting factor ($w_{l,k}$), which can be represented as follows:

$$w_{l,j} = \frac{(-1)^{3-j}}{\eta_{x_{l,j}} \times (\eta_{x_{l,1}} - \eta_{x_{l,2}})}; \quad j = 1,2 \tag{24}$$

$$w_{l,3} = \frac{1}{m} - \frac{1}{\theta_{x_l,4} - \theta_{x_l,3}^2} \tag{25}$$

For each uncertain parameter, the objective function is calculated for two location points while other uncertain parameters are equal to their expected values:

$$S(x_l,1) = f(\mu_{x_1}, \mu_{x_2}, \dots, x_{l,1}, \dots, \mu_{x_n}) \tag{26}$$

$$S(x_l,2) = f(\mu_{x_1},\mu_{x_2},...,x_{l,2},...,\mu_{x_n}) \tag{27}$$

Hence, for *n* uncertain input variable, the objective function should be calculated 2*n* times. The last calculation depicts the value of objective function for μ_{x_l}; $l = 1, …, n$.

$$S(x_l,3) = S_\mu = f(\mu_{x_1},\mu_{x_2},...,\mu_{x_n}) \tag{28}$$

The expected value (μ_S) and standard deviation (σ_S) of objective function are calculated as follows:

$$\mu_S = E(S) = \sum_{l=1}^{n}\sum_{j=1}^{3} w_{l,j} \times S(x_l,j) \tag{29}$$

$$E(S^2) = \sum_{l=1}^{n}\sum_{j=1}^{3} w_{l,j} \times (S(x_l,j))^2 \tag{30}$$

$$\sigma_S = \sqrt{(E(S^2) - E^2(S))} \tag{31}$$

In this work, vector *S* represents selling prices of rival-retailers, and its expected values and standard deviation?? are available based on historical data.

2.4. Operational constraints

The operational constraints of generating units can be summarized as follows [10]:

2.4.1. Minimum On-time

$$[T^{On}_{C_i,t-1} - T^{On}_{i,\min}] \times [U_{i,t-1} - U_{i,t}] \geqslant 0\ ;\quad \forall\ t \in T, i = 1,...,N_{SG} \tag{32}$$

where

- $T^{On}_{C_i,t}$ is the number of continuous on-time hours of unit *i* up to hour *t* (h),
- $T^{On}_{i,\min}$ is the minimum on-time of unit *i* (h).

2.4.2. Minimum Off-time

$$[T^{Off}_{C_i,t-1} - T^{Off}_{i,\min}] \times [U_{i,t} - U_{i,t-1}] \geqslant 0\ ;\quad \forall\ t \in T, i = 1,...,N_{SG} \tag{33}$$

where

- $T^{Off}_{C_i,t}$ is the number of continuous off-time hours of unit *i* up to hour *t* (h),
- $T^{Off}_{i,\min}$ is the minimum off-time of unit *i* (h).

2.4.3. Ramp rate

$$P_{i,t} - P_{i,t-1} \leqslant R_i^{Up} \times U_{i,t-1} + R_i^{SU} \times \mu_{i,t}\ ;\quad \forall\ t \in T,\quad i = 1,...,N_{SG} \tag{34}$$

$$P_{i,t-1} - P_{i,t} \leqslant R_i^{Down} \times U_{i,t} + R_i^{SD} \times \nu_{i,t}\ ;\quad \forall\ t \in T,\quad i = 1,...,N_{SG} \tag{35}$$

where

- R_i^{Up} is the ramp-up rate of unit *i* (MW/h),
- R_i^{Down} is the ramp-down rate of unit *i* (MW/h),
- R_i^{SU} is the startup ramp-rate of unit *i* (MW/h),
- R_i^{SD} is the shutdown ramp-rate of unit *i* (MW/h).

2.4.4. Capacity

$$P_i^{\min} \times U_{i,t} \leqslant P_{i,t} \leqslant P_i^{\max} \times U_{i,t}\ ;\quad \forall\ t \in T,\quad i = 1,...,N_{SG} \tag{36}$$

$P_i^{\max}$ is the maximum allowed capacity of unit *i* (MW),
$P_i^{\min}$ is the minimum allowed capacity of unit *i* (MW).

2.4.5. Energy balance

$$P_t^{DA_B} + \sum_{i=1}^{N_{SG}} P_{i,t} + P_t^{FC} = P_t^L + P_t^{DA_S}\ ;\quad \forall\ t \in T \tag{37}$$

2.5. Profit function

According to presented income and cost functions, the profit function of retailer without considering the uncertainty of wholesale price can be formulated as follows:

$$Profit = \sum_{t\in T}\left(\begin{array}{l} P_t^L \times \pi_t^{RET} + P_t^{DA_S} \times \pi_t^{DA} - P_t^{DA_B} \times \pi_t^{DA} - \sum\limits_{f\in\Xi}\sum\limits_{b=1}^{N_t^f} (\overline{P}^{FC}_{t,f,b} \times \pi^{FC}_{t,f,b} \times \delta_{t,f,b}) \\ - \sum\limits_{i=1}^{N_{SG}}\left(\begin{array}{l} ((1-FOR_i) \times ((a_iP_{i,t}^2 + b_iP_{i,t} + c_i \times U_{i,t}) + SDC_i \times \nu_{i,t} + SUC_i \times \mu_{i,t})) \\ + \left(FOR_i \times \left(\begin{array}{l} \sum\limits_{k=t}^{t+RT_i} \pi_k^{RG} \times P_{i,k} + RC_i + CC_i^U \times (U_{i,t} - \mu_{i,t}) \\ + CC_i^{SD} \times \nu_{i,t} + CC_i^{SU} \times \mu_{i,t} + CC_i^D \times (1 - U_{i,t} - \nu_{i,t}) \end{array}\right)\right) \end{array}\right) \end{array}\right) \tag{38}$$

Subject to: Eqs. (4b), (6b), (8), (9), (15a), (15b), (32)–(37).

To evaluate impacts of uncertain wholesale price, IGDT based formulations are presented in next subsection.

2.6. IGDT-based framework

It is necessary to develop the retailer's strategy coping with the uncertain nature of wholesale price, and immunize it against various price realizations. The main advantage of IGDT methodology is that it does not require any mathematical or probabilistic estimation of uncertain variables, while some risk control approaches such as mean-variance and scenario-based models need many assumptions of the nature of uncertainty and require a procedure to generate scenarios in order to characterize behavior of random variables. IGDT methodology has already been applied in many risk-management problems of power systems such as generation and transmission expansion planning [26,27], bidding strategy [28], and energy procurement problem [29,30].

IGDT is an attractive deterministic method and it quantifies the uncertainty as the size of gap between what is known and what could be happen [31]. Moreover, the robustness of optimal decision is demonstrated effectively by determining the variation bound or the robustness region of uncertain parameter in a way that within the interval, the optimal decision ensures a predefined performance constraint, which is specified by decision-makers.

In this work, the variation interval measures the distance between the possibility of wholesale price (π_t^{DA}) and its estimation ($\overline{\pi}_t^{DA}$), as follows:

$$\left|\frac{\pi_t^{DA} - \overline{\pi}_t^{DA}}{\overline{\pi}_t^{DA}}\right| \leqslant \lambda_t;\quad \lambda_t \geqslant 0\ ,\quad \forall\ t \in T \tag{39}$$

In IGDT, the optimal decision is determined based on the decision-makers' risk preferences. In this regard, two types of the performance function are defined for risk-averse and risk-taker retailers, which are known as robustness and opportunity functions [28]. The robustness function (*RF*) represents the greatest uncertainty level of wholesale price (or the maximum λ_t) such that the defined minimum profit is always achieved for all $\pi_t^{DA} \in [(1-\lambda_t)\overline{\pi}_t^{DA},(1+\lambda_t)\overline{\pi}_t^{DA}]$. The opportunity function (*OF*) addresses the appropriate face of uncertainty, and the possibility of reaching a desired performance resulting from the random parameter variations. In *RF*, the minimum variation interval of wholesale price is calculated in a way that ensures the desired maximum profit is achievable for at least one $\pi_t^{DA} \in [(1-\lambda_t)\overline{\pi}_t^{DA},(1+\lambda_t)\overline{\pi}_t^{DA}]$.

The risk-averse retailer chooses the lower risk level to hedge the financial risk arising from uncertain price variations. Hence, this type of retailer chooses *RF* and determines optimal energy providing strategy based on the worst condition up to the horizon of uncertainty. The risk-taker retailer selects a higher risk level in the hope that obtains the desired performance. Therefore, risk-taker retailer chooses *OF* and specifies the optimal strategy based on the best condition up to the horizon of uncertainty [28].

According to Eq. (38), *RF* can be written as follows:

$$RF = \max \lambda_t \quad \forall\, t \in T, \quad s.\ t.$$

$$\min_{\substack{\pi_t^{RET}, P_t^{DA_S}, P_t^{DA_B} \\ \delta_{t,f,b}, P_{i,t}, \nu_{i,t}, \mu_{i,t} \\ U_{i,t};\forall\, t \in T, \forall\, f \in \Xi, \\ i = 1,\ldots,N_{SG}, \\ b = 1,\ldots,N_t^f}} \quad Profit = \sum_{t \in T} \begin{array}{l} P_t^L \times \pi_t^{RET} + P_t^{DA_S} \times \pi_t^{DA} - P_t^{DA_B} \times \pi_t^{DA} - \displaystyle\sum_{f \in \Xi} \sum_{b=1}^{N_t^f} (\overline{P}_{t,f,b}^{FC} \times \pi_{t,f,b}^{FC} \times \delta_{t,f,b}) \\ - \displaystyle\sum_{i=1}^{N_{SG}} \begin{pmatrix} ((1-FOR_i) \times ((a_i P_{i,t}^2 + b_i P_{i,t} + c_i \times U_{i,t}) + SDC_i \times \nu_{i,t} + SUC_i \times \mu_{i,t})) \\ + \left(FOR_i \times \begin{pmatrix} \displaystyle\sum_{k=t}^{t+RT_i} \pi_k^{RG} \times P_{i,k} + RC_i + CC_i^U \times (U_{i,t} - \mu_{i,t}) \\ + CC_i^{SD} \times \nu_{i,t} + CC_i^{SU} \times \mu_{i,t} + CC_i^D \times (1 - U_{i,t} - \nu_{i,t}) \end{pmatrix} \right) \end{pmatrix} \end{array} \geqslant Profit_{cr}^{RA};$$

$$\pi_t^{DA} \in [(1-\lambda_t)\overline{\pi}_t^{DA}, (1+\lambda_t)\overline{\pi}_t^{DA}] \quad \& \quad Profit_{cr}^{RA} = (1-\vartheta) \times E[Profit] \tag{40}$$

Similarly, *OF* can be formulated as follows:

$$OF = \min \lambda_t \quad \forall\, t \in T, \quad s.\ t.$$

$$\min_{\substack{\pi_t^{RET}, P_t^{DA_S}, P_t^{DA_B} \\ \delta_{t,f,b}, P_{i,t}, \nu_{i,t}, \mu_{i,t} \\ U_{i,t};\forall\, t \in T, \forall\, f \in \Xi, \\ i = 1,\ldots,N_{SG}, \\ b = 1,\ldots,N_t^f}} \quad Profit = \sum_{t \in T} \begin{array}{l} P_t^L \times \pi_t^{RET} + P_t^{DA_S} \times \pi_t^{DA} - P_t^{DA_B} \times \pi_t^{DA} - \displaystyle\sum_{f \in \Xi} \sum_{b=1}^{N_t^f} (\overline{P}_{t,f,b}^{FC} \times \pi_{t,f,b}^{FC} \times \delta_{t,f,b}) \\ - \displaystyle\sum_{i=1}^{N_{SG}} \begin{pmatrix} ((1-FOR_i) \times ((a_i P_{i,t}^2 + b_i P_{i,t} + c_i \times U_{i,t}) + SDC_i \times \nu_{i,t} + SUC_i \times \mu_{i,t})) \\ + \left(FOR_i \times \begin{pmatrix} \displaystyle\sum_{k=t}^{t+RT_i} \pi_k^{RG} \times P_{i,k} + RC_i + CC_i^U \times (U_{i,t} - \mu_{i,t}) \\ + CC_i^{SD} \times \nu_{i,t} + CC_i^{SU} \times \mu_{i,t} + CC_i^D \times (1 - U_{i,t} - \nu_{i,t}) \end{pmatrix} \right) \end{pmatrix} \end{array} \geqslant Profit_{cr}^{RA};$$

$$\pi_t^{DA} \in [(1-\lambda_t)\overline{\pi}_t^{DA}, (1+\lambda_t)\overline{\pi}_t^{DA}] \quad \& \quad Profit_{cr}^{RA} = (1-\vartheta) \times E[Profit] \tag{41}$$

where ϑ is the profit deviation factor, $Profit_{cr}^{RA}$ and $Profit_{cr}^{RT}$ are critical profits of risk-averse and risk-taker retailers, respectively. It should be noted that $E[Profit]$ is the expected profit of the retailer and it is calculated based on the expected values of wholesale prices ($\pi_t^{DA} = \overline{\pi}_t^{DA}, \quad \forall\, t \in T$). To evaluate the performance of the proposed model, numerical simulations are provided in next section.

3. Numerical simulations

The case study includes a typical electricity retailer who has four thermal generating units [10]. Characteristics of self-generating units are provided in Table 2. As mentioned before, in this work the retailer can provide the required energy through wholesale and regulation markets, forward contracts, and self-generation units. Expected values of day-ahead price ($\overline{\pi}_t^{DA}$), and characteristics of forward contracts are provided in Fig. 4 and Table 3, respectively. It should be noted that the ratio of regulation and day-ahead prices is represented by ρ as follows:

$$\rho_t = \frac{\pi_t^{RG}}{\pi_t^{DA}}; \quad \forall\, t \in T \tag{42}$$

Fig. 5 presents characteristics of rival retailers' selling-prices. The initial hourly load without considering the risk of rivals' strategy (or $\overline{P}_t^{L,0}$) is shown in Fig. 6. Moreover, $\Delta_t^{k,\min}$ in Eq. (17) for $\forall\, t \in T$ and $k = 1,\ldots,N_{riv}$ is -5\$/MWh.

The optimal energy providing strategy for $\rho_t = 1.1; \quad \forall\, t \in T$ is presented in Table 4. It should be noted that the maximum profit in this case study is 5319$. Additionally, Fig. 7 shows clients' demand and retail-selling price in this case study. Evidently, increasing wholesale price leads to higher retail price and lower demand. Therefore, the retailer has more additional power that can be sold in wholesale market. Moreover, within low-price periods, the retailer prefers to supply clients' energy from the wholesale market.

To demonstrate effects of units' uncertainty, Table 5 presents the retailer's energy acquisition strategy for $FOR_1 = 5\%$, $FOR_2 = 10\%$, $FOR_3 = 15\%$, $FOR_4 = 5\%$. Comparing Tables 4 and 5 shows that increasing the uncertainty of units' availability reduces their generating power. In other words, the higher *FOR* imposes more regulation cost to the retailer. Therefore, the retailer prefers to purchase more power from the wholesale market. According to simulation results, increasing unavailability of self-generating units has negative impact on retailer's profit and the profit in this case study is 1317.2$.

Table 6 demonstrates effect of regulation price variations on retailer's strategy. As mentioned before, the unavailability of generating units within committed periods enforces the retailer to compensate energy shortage from the regulation market. According to Eqs. (12) and (13), the higher regulation price increases the cost of using self-generating facilities. Therefore, the generating power of these units is decreased. The retailer's profit in this case study is 5242.1$.

According to Eq. (17), decreasing of $|\Delta^{k,\min}|$, increases the probability of clients' switching to rivals, and vice versa. Clients' consumption and retailer selling prices for $\Delta^{\min} = -3$ and $\Delta^{\min} = -7$, are shown in Figs. 8 and 9, respectively. Comparing Figs. 8 and 9 shows that decreasing the risk of clients' switching to rivals (or higher $|\Delta^{k,\min}|$), gives the opportunity of proposing higher selling prices to the retailer. It should be noted that the sensitivity of demand to the selling price leads to reduction in clients' consumption by increasing $|\Delta^{k,\min}|$. The retailer's profits for $\Delta^{\min} = -3$ and $\Delta^{\min} = -7$ are 4978.4 and 5437.3$, respectively.

Retailer's participation levels in the wholesale market for $\Delta^{\min} = -3$ and $\Delta^{\min} = -7$ are shown in Fig. 10. As mentioned before, increasing $|\Delta^{k,\min}|$ reduces clients' consumption. Therefore, the retailer has more surplus energy that can be sold in wholesale market.

The impact of wholesale price variation on the on retailer's profit is shown in Fig. 12 ($\zeta = \frac{\pi^{DA} - \overline{\pi}^{DA}}{\overline{\pi}^{DA}}$). Evidently, increasing the wholesale price enforces retailer to offer higher selling price to cover supply cost. Additionally, according to Eq. (17) sensitivity of demand leads to clients reduce their consumption by increasing the selling price (The sensitivity of rival's price to wholesale price variation is neglected in this section). Hence, the retailer has more additional power that can be sold in wholesale market. It should be noted that offering higher selling price leads to increasing clients' switching probability that reduces retailer's profit. Therefore, within long-term period, offering higher selling price will reduce the retailer's profit.

According to Fig. 11, $E[Profit]$ is 5319$ ($\zeta = 0$). To evaluate the performance of the proposed IGDT-based model, the critical profits of risk-averse and risk-taker retailers are considered as 4787.1$ and 5850.9$, respectively ($\vartheta = 0.1$). Fig. 11 demonstrates that $\max\lambda$ (for risk-averse retailer) and $\min\lambda$ (for risk-taker retailer) to reach the defined performances are 0.0303 and 0.0424, respectively. Tables 7 and 8 represent the strategies of risk-averse and risk-taker retailer's, respectively. In other words, within the maximum variation interval $[0.9697\bar{\pi}_t^{DA}, 1.0303\bar{\pi}_t^{DA}]$, the presented strategy of Table 7 ensures that the risk-averse retailer's profit is higher than 4787.1$. Similarly, within the minimum variation interval $[0.9576\bar{\pi}_t^{DA}, 1.0424\bar{\pi}_t^{DA}]$, the proposed strategy of Table 8 guarantees the maximum profit 5850.9$ for the risk-taker retailer. Figs. 12 and 13 show demand and selling-prices of risk-averse and risk-taker retailers, respectively. Risk-averse retailers prefer to offer lower selling price to reduce the risk of clients switching. Hence, the risk-averse retailer's demand is higher than risk-taker's.

As mentioned before, risk-averse retailers specify their strategies based on the worst condition. Fig. 11 shows within the bound $[0.9697\bar{\pi}_t^{DA}, 1.0303\bar{\pi}_t^{DA}]$, the worst condition occurs for $\pi_t^{DA} = 0.9697\bar{\pi}_t^{DA}$. Similarly, within interval $[0.9576\bar{\pi}_t^{DA}, 1.0424\bar{\pi}_t^{DA}]$ the best condition occurs for $\pi_t^{DA} = 1.0424\bar{\pi}_t^{DA}$. In other words, risk-taker retailers determine their strategy based on maximum day-ahead prices. Hence, they prefer to increase the participation level of self-generating facilities in the hope that obtain higher profits. Self-generating units' output power in the risk-taker retailer's strategy is higher than risk-averse retailer's strategy. Comparing result of Tables 7 and 8 demonstrates this issue too.

4. Conclusions

This paper provides a reliability-constraint energy acquisition strategy for electricity retailers. Availability of self-generating units, variations of wholesale price, rival retailers' strategy, and clients' switching tendency are main sources of uncertainty that is modeled in proposed strategy. Moreover, Fuzzy-IGDT framework is used to specify the energy acquisition strategy of retailer based on the risk preferences. Simulation results show increasing the uncertainty of generating units and price of regulating market increase retail-selling price and reduce retailer's profit. Additionally, decreasing the risk of clients' switching to rivals enables retailers to propose higher selling prices that increase their profit. Increasing the wholesale price has increases and decreases retailer's profit within short-term and long-term periods, respectively. To evaluate the risk of wholesale price and specify the retailer's strategy based on the risk preference, the robustness and opportunity functions are proposed for the risk-averse and risk-taker retailers, respectively. Simulation results demonstrate that within the calculated interval of wholesale price, risk-averse retailers prefer to specify their strategy based on minimum prices. Similarly, the risk-taker retailers determine their strategy based on the maximum day-ahead prices in the hope that obtain higher profit. Therefore, the selling prices and the output power of self-generating units in the risk-taker retailer' strategy are higher than risk-averse retailers'.

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