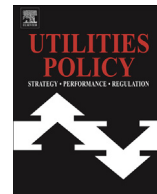




Contents lists available at ScienceDirect

Utilities Policy

journal homepage: www.elsevier.com/locate/jup

Decision-making framework for supplying electricity from distributed generation-owning retailers to price-sensitive customers

Meysam Khojasteh, Shahram Jadid*

Center of Excellence for Power Systems Automation and Operation, Department of Electrical Engineering, Iran University of Science and Technology (IUST), Tehran 1684613114, Iran

ARTICLE INFO

Article history:

Received 14 October 2014
Received in revised form
17 March 2015
Accepted 17 March 2015
Available online xxx

Keywords:

Distributed generation
Elasticity
Electricity retailer
Information gap decision theory
Strategic risk management
Optimization

ABSTRACT

In this paper, a robust bi-level decision-making framework is presented for distributed generation (DG) owning retailers to supply the electricity to price-sensitive customers. Uncertainties about client demand and wholesale prices are the main difficulties faced by the electricity retailer. Clients can adjust their consumption according to the retailer's selling price. A higher selling price increases retailers' profit but decreases client consumption. Hence, the retailer faces a tradeoff between the price and sales. In the proposed model, the optimal selling price and the retailer's energy-supply strategy are modeled in the lower sub-problem. According to the proposed selling price, the optimal energy consumption of price-sensitive clients is determined in the upper sub-problem. To evaluate the financial risk arising from uncertain prices, the Information Gap Decision Theory (IGDT) approach is addressed in the lower sub-problem. Additionally, the risk-based optimization problem is formulated for risk-averse and risk-taker retailers via the robustness and opportunity functions, respectively. The robustness of the optimal solution against price variations is evaluated such that the associated profit will be more than the electricity retailer's acceptable threshold. The efficiency and performance of the decision-making framework are analyzed via a case study, and the numerical results are discussed.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Energy trading in the wholesale market is only accessible by large generation companies (GENCOs) and customers who can connect to the transmission network. Additionally, distribution companies (DISCOs) are responsible for providing the electricity required by end-use consumers. The selling price is based on the consumption time and is stable and fixed for all customers within specific periods. Therefore, there is no competition in the distribution level, and end-use customers do not receive wholesale price signals. In other words, they have no motivation to reduce their consumption within critical periods, when system operators face capacity shortages.

Over the last decade and after restructuring of electricity distribution networks, the responsibility for meeting the energy requirements of end-use customers is given to new marketers, known as retailers. Electricity retailers act as an intermediary

between customers and generation companies (GENCOs). They meet clients' requirements via different sources of energy, such as participating in the wholesale market, self-generation facilities, and bilateral contracts with energy suppliers. The energy prices in the retail market are based on negotiations between buyers and sellers. Various retail pricing schemes are proposed in the technical literature, including fixed-tariff pricing (FTP), time-of-use (TOU) pricing, critical peak pricing (CPP), and real-time pricing (RTP) (Celebi and Fuller, 2007). The energy price in all schemes except RTP is fixed during agreed periods. A RTP scheme enables retailers to divert the risk of wholesale price uncertainty to end-use consumers. Electricity retailers are specifically exposed to the uncertainties of energy price (on the supply side) and load (on the demand side) due to the unpredictable fluctuations in wholesale market prices and client demand (Boroumand and Zachmann, 2012). Ignoring the risk of uncertain parameters may impose great financial losses to the retailer. For example, in the U.S. ERCOT market, one retailer (Texas Commercial Energy or TCE) procured the majority of its customers' required energy from the spot market. TCE used the FTP scheme in selling contracts. In February 2004, real-time energy prices reached the maximum

* Corresponding author.

E-mail addresses: Khojasteh@iust.ac.ir (M. Khojasteh), Jadid@iust.ac.ir (S. Jadid).

allowable threshold, which imposed substantial financial losses to TCE, and the retailer ultimately declared bankruptcy (Gabriel et al., 2006). In competitive electricity markets, the forward market is predicted to be an effective solution for managing the financial risk arising from uncertain parameters. However, according to the Australian experience, forward contracts cover less than 50% of the total requirements (Anderson et al., 2007). Therefore, electricity retailers cannot hedge the entire financial risk via forward contracts. Self-generation is another alternative that enables retailers to neutralize the financial risk of wholesale price and client requirement uncertainties. Hence, an optimal energy procurement framework evaluates profit and financial risk, simultaneously.

The electricity retailer's challenge of optimal energy supply is discussed to some extent in the technical literature and different methods are proposed, such as stochastic programming (Gabriel et al., 2006; Carrion et al., 2007), dynamic programming (Palamarchuk, 2010), game theory (Zugno et al., 2013), and the clustering technique (Mahmoudi-Kohan et al., 2010). As mentioned before, profit maximization and financial-risk minimization are two main objectives of the retailer. The bi-level optimization methodology is reported as an efficient framework to evaluate the optimal strategy of the retailer in the wholesale and forward markets (Gabriel et al., 2006; Carrion et al., 2007). In bi-level optimization, the optimal decision (such as the amount of purchased power from the wholesale market and bilateral contracts) is determined in the upper sub-problem and the relevant risk is evaluated in the lower sub-problem. To analyze the risk of price uncertainty and rival strategies, the stochastic programming is addressed (Gabriel et al., 2006; Hatami et al., 2011; Yusta et al., 2005). Moreover, the conditional value-at-risk methodology (CVaR) (Carrion et al., 2007; Palamarchuk, 2010; Yusta et al., 2005), risk-adjusted recovery on capital (RAROC), capital-asset pricing model (CAPM) (Karandikar et al., 2007, 2010), and expected downside risk (EDR) (Ahmadi et al., 2013) are suggested to quantify financial risk. It should be noted that the uncertain parameters can be modeled via the probabilistic and deterministic methods, such as variation interval (Gabriel et al., 2004) and probability distribution function (Gabriel et al., 2002). The planning horizon of the retailer can be divided into equal periods, and the optimal selling price within each period can be calculated via the quadratic non-linear optimization methodology (Yusta et al., 2005). In some retail markets, the retailer could provide the difference between the forecast and the actual demands from the balancing market. The optimal strategy of the retailer for supplying electricity to price-sensitive clients (that is, customers with price-elastic demand) can be presented in a way that the expected cost of purchasing energy from the day-ahead and the balancing markets is minimized (Erik and Pettersen, 2005).

In deregulated distribution networks, end-use customers can more readily adjust their electricity consumption according to real-time prices. Customers desire to optimize their electricity consumption patterns and costs relative to their operational constraints in order to maximize expected profits from their businesses. The selling price plays a crucial role in negotiating contracts between clients and retailers. Increasing the selling price decreases the consumption of price-sensitive clients. In other words, the retailer faces an optimization problem between the selling price and clients' consumption. It should be noted that the electricity retailer's business can be profitable only if revenues from sales are greater than the cost of supply operations. Therefore, retailers must design the optimal selling price in a way that covers costs and brings them an acceptable profit. Additionally, the offered price must convince clients to procure the electricity from the retailer.

2. Research approach

As mentioned before, electricity retailers must model and evaluate the impact of uncertain parameters in order to hedge relevant financial risk. A good representation of a random variable is very important for understanding the retailers' energy-supply problem. In the stochastic programming methodology, uncertain parameters are usually characterized by probability density functions. Nevertheless, this approach is not always applicable, because the future values of the uncertain parameters may be affected by many unknown factors. Additionally, for practical reasons, it may be impossible to model the uncertain parameters by the probability density function (e.g., due to the lack of historical data or incomplete technical understanding). The IGDT methodology is proposed as a risk-management approach for evaluating unknown random variables. In IGDT, the uncertain parameters are approximated via variation intervals. In addition, the optimal decision is specified based on the desired performance (or acceptable profit threshold), which is defined by the retailer. The IGDT-based models do not require any probabilistic estimation of the uncertain parameters. Hence, they are not sensitive to the random variable forecast. The IGDT method has already been applied to many risk-based optimization problems of power systems, including the optimal scheduling of demand (Zare et al., 2010a), energy procurement strategies of large customers (Zare et al., 2010b), and self-scheduling of GENCOs (Mohammadi-Ivatloo et al., 2013).

In this work, the optimal energy-supply framework of the retailer is divided into two sub-problems. In the upper sub-problem, a profit-based model is designated to estimate the energy consumption of end-use customers, based on the real-time pricing scheme. The optimal selling price and the energy-supply strategy of the retailer are formulated in the lower sub-problem. Finally, the optimal decision (selling price and supply strategy) is determined in a way that maximizes profits of both retailers and clients, simultaneously. The optimal decision is specified according to the retailers' risk preferences. Here, risk-averse retailers choose the lower risk-level to hedge financial losses arising from uncertain parameters, while risk-taker retailers prefer the higher risk-level in the hope of obtaining higher profits. Therefore, two performance functions are defined for the risk-averse and risk-taker retailers: the robustness and the opportunity functions, respectively. In the proposed robustness function, the optimal solution and the maximum variation interval of the wholesale price are determined in a manner that guarantees the minimum profit threshold. Additionally, according to the suggested opportunity function, the optimal strategy ensures that the desired maximum profit is achievable within the minimum variation interval of the wholesale price.

The main contributions of the presented model are as follows:

- The optimal strategy of the retailer is determined based on the price sensitivity of clients to selling prices. Selling prices are calculated in a manner that maximize the profits of clients and retailers, simultaneously.
- The proposed method allows the retailer to specify the energy-supply strategy according to desired performance.
- The model is formulated for risk-averse and risk-taker retailers via the robustness and opportunity functions, respectively.

The rest of the paper is organized as follows: the proposed strategy for the retailer is introduced in Section 3. Section 4 depicts the formulation of the risk-management framework based on the IGDT methodology. In Section 5, a case study is presented and simulation results are discussed. Finally, concluding remarks are provided in Section 6.

3. Proposed energy-supply strategy

As mentioned before, in this work the optimal energy-supply framework of the retailer is formulated as a bi-level optimization problem. The energy consumption of final clients and the optimal strategy of the retailer are determined in the upper and lower sub-problems, respectively.

3.1. Upper sub-problem: Optimal consumption of final clients

End-use customers desire to determine their energy procurement strategies in a way that maximizes net profits. Therefore, the profit function of end-use customers can be represented as follows:

$$Profit^{cl} = \sum_{t=1}^T Inc_t^{cl} - Cost_t^{cl} \quad (1)$$

Where:

- $Profit^{cl}$ is the total profit of clients (\$),
- Inc_t^{cl} is clients' income within the operation period t (\$),
- $Cost_t^{cl}$ is clients' energy procurement cost within the operation period t (\$),
- T is the set of operation periods.

End-use customers can respond to selling price variations by changing their consumption. The elasticity coefficient represents the sensitivity of demand to price variations and expressed as follows:

$$\epsilon_t = \frac{\pi_t^*}{d_t^*} \frac{\Delta d_t}{\Delta \pi_t^{ret}} = k \frac{\pi_t^*}{d_t^*}, \quad \forall t \in T \quad (2)$$

Where:

- ϵ_t is the price elasticity of demand,
- d_t^* is the initial demand (MW),
- d_t is clients' consumption (MW),
- π_t^* is the initial retail selling price (\$/MWh),
- π_t^{ret} is retail selling price (\$/MWh).

The elasticity coefficient is negative since increasing the energy price is associated with a reduction in consumption, and vice versa. To determine the income of electricity consumption, we rely on prior research (Schweppe et al., 1985) to suppose that:

$$\frac{\partial Inc_t^{cl}(d_t)}{\partial d_t} = \pi_t^{ret}, \quad \forall t \in T \quad (3)$$

The Taylor series of $Inc_t^{cl}(d_t)$ can be represented as follows:

$$\begin{aligned} Inc_t^{cl}(d_t) &= Inc_t^{cl} + \left. \frac{\partial Inc_t^{cl}(d_t)}{\partial d_t} \right|_{d_t^0} \times (d_t - d_t^0) + \frac{1}{2} \times \left. \frac{\partial^2 Inc_t^{cl}(d_t)}{\partial d_t^2} \right|_{d_t^0} \times (d_t - d_t^0)^2 + \dots \\ &= Inc_t^{cl} + \pi_t^0 \times (d_t - d_t^0) + \frac{1}{2} \times \left. \frac{\partial}{\partial \pi_t^{ret}} \left(\frac{\partial Inc_t^{cl}(d_t)}{\partial d_t} \right) \right|_{d_t^0} \times \left. \frac{\partial \pi_t^{ret}}{\partial d_t} \right|_{\pi_t^0} \times (d_t - d_t^0)^2 \\ &= Inc_t^{cl} + \pi_t^0 \times (d_t - d_t^0) + \frac{1}{2} \times \frac{\pi_t^0}{\epsilon_t d_t^0} \times (d_t - d_t^0)^2 \end{aligned} \quad (4)$$

The procurement cost of clients to purchase power from the retailer is calculated as follows:

$$Cost_t^{cl} = d_t \times \pi_t^{ret}; \quad \forall t \in T \quad (5)$$

By substituting (4) and (5) in (1), the clients' profit function can be formulated as follows:

$$Profit^{cl} = \sum_{t=1}^T Inc_t^{cl} + \pi_t^0 \times (d_t - d_t^0) + \frac{1}{2} \times \frac{\pi_t^0}{\epsilon_t d_t^0} \times (d_t - d_t^0)^2 - d_t \times \pi_t^{ret} \quad (6)$$

Customers desire to determine the optimal hourly load in a manner that maximizes their net profits. Therefore, by differentiating equation (6), we will have:

$$\frac{\partial Profit^{cl}}{\partial d_t} = \frac{\partial}{\partial d_t} \left(\sum_{t=1}^T Inc_t^{cl} + \pi_t^0 \times (d_t - d_t^0) + \frac{1}{2} \times \frac{\pi_t^0}{\epsilon_t d_t^0} \times (d_t - d_t^0)^2 - (d_t \times \pi_t^{ret}) \right) = 0 \quad (7a)$$

$$\pi_t^0 + \frac{\pi_t^0}{\epsilon_t d_t^0} (d_t - d_t^0) - \pi_t^{ret} = 0; \quad \forall t \in T \quad (7b)$$

$$d_t = (\pi_t^{ret} - \pi_t^0) \times \frac{\epsilon_t d_t^0}{\pi_t^0} + d_t^0; \quad \forall t \in T \quad (7c)$$

$$d_t^{\min} \leq d_t \leq d_t^{\max}; \quad \forall t \in T \quad (7d)$$

As seen in (7c), by increasing the retail-selling price, client electricity consumption is decreased, and vice versa. Due to the physical constraints, the electricity consumption of final clients must be in the specific interval, which is demonstrated by (7d).

3.2. Lower sub-problem: Optimal energy-supply strategy of the retailer

In the proposed framework, the retailer's optimal strategy is determined in the lower sub-problem. The retailer can supply the required energy via the wholesale market, forward contracts, and self-generation facilities. Moreover, the retailer can resell the provided energy in the retail and wholesale markets. The retailer's supply cost and income functions are formulated in this subsection.

3.2.1. Retailers' Procurement Cost

The cost of providing the required energy of final clients ($Cost^{ret}$) is represented as follows:

$$Cost^{ret} = \sum_{t \in T} Cost_t^{WS} + Cost_t^{FC} + Cost_t^{DG} \quad (8)$$

Where:

$Cost_t^{WS}$ is the procurement cost of the wholesale market within the operation period t (\$),
 $Cost_t^{FC}$ is the procurement cost of the forward market within the operation period t (\$),
 $Cost_t^{DG}$ is the operational cost of DG units within operation period t (\$).

The wholesale procurement cost within the operation period t is formulated as follows ($P_t^{WS_B} \geq 0; \forall t \in T$):

$$Cost_t^{WS} = P_t^{WS_B} \times \pi_t^{WS}; \quad \forall t \in T \quad (9)$$

Where:

π_t^{WS} is the energy price of the wholesale market within the operation period t (\$/MWh),
 P_t^{WS} is the amount of the purchased power from the wholesale market within the operation period t (MW)

The forward market is another source of providing energy that enables the retailer to hedge the financial risk of uncertain wholesale prices. The energy price in the forward market is determined based on negotiations. A forward contract has the advantage of being transparent and constant during the agreed period. Sellers usually encourage buyers to have more participation in the forward market by decreasing the selling price as the amount of the procured power increases. The selling offers in this market are usually represented as the stepwise format. The characteristics of a typical forward contract are represented in Fig. 1.

The energy procurement cost of the forward market is given as follows:

$$\delta_{t,f,b} \in \{0, 1\}; \quad \forall t \in T, \forall f \in \Xi, b = 1, \dots, N_t^f \quad (10a)$$

$$0 \leq \sum_{b=1}^{N_t^f} \delta_{t,f,b} \leq 1; \quad \forall t \in T, \forall f \in \Xi \quad (10b)$$

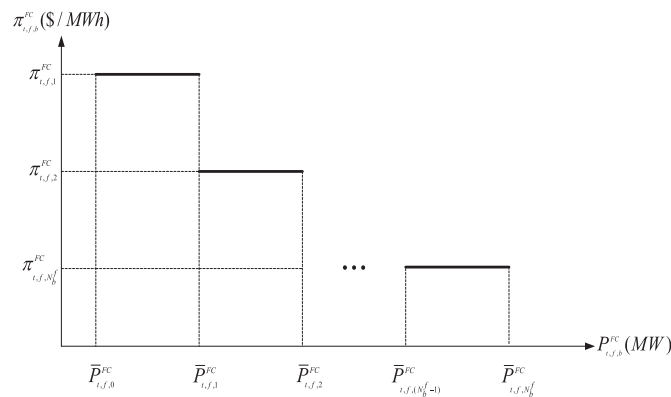


Fig. 1. Price-quota curve of a typical forward contract.

$$\bar{P}_{t,f,b-1}^{FC} \times \delta_{t,f,b} \leq P_{t,f,b}^{FC} \times \delta_{t,f,b} \leq \bar{P}_{t,f,b}^{FC} \times \delta_{t,f,b}; \quad \forall t \in T, \forall f \in \Xi, b = 1, \dots, N_t^f \quad (10c)$$

$$P_{t,f}^{FC} = \sum_{b=1}^{N_t^f} P_{t,f,b}^{FC} \times \delta_{t,f,b}; \quad \forall t \in T, \forall f \in \Xi \quad (10d)$$

$$P_t^{FC} = \sum_{f \in \Xi} P_{t,f}^{FC}; \quad \forall t \in T \quad (10e)$$

$$Cost_t^{FC} = \sum_{f \in \Xi} \sum_{b=1}^{N_t^f} P_{t,f,b}^{FC} \times \pi_{t,f,b}^{FC} \times \delta_{t,f,b}; \quad \forall t \in T \quad (10f)$$

$P_{b,f,t}^{FC}$ is the amount of 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),
 $\bar{P}_{b,f,t}^{FC}$ is the upper limit of b -block of forward contract f (MW),
 $\pi_{b,f,t}^{FC}$ is the selling price of b -block of forward contract f (\$/MWh),
 N_t^f is the number of power blocks of forward contract f ,
 $\delta_{b,f,t}$ is the status 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.

The operational cost of DG units consists of fuel, startup, and shutdown costs. Hence, $Cost_t^{DG}$ is formulated as follows:

$$Cost_t^{DG} = \sum_{i=1}^{N_{DG}} Cost_{i,t}^{Fuel} + SUC_{i,t} + SDC_{i,t}; \quad \forall t \in T \quad (11)$$

Where:

$Cost_{i,t}^{Fuel}$ is the fuel cost of DG unit i (\$),
 $SUC_{i,t}$ is the startup cost of DG unit i (\$),
 $SDC_{i,t}$ is the shutdown cost of DG unit i (\$).

The fuel cost of thermal DG units is usually modeled by a quadratic function. Therefore, the operational cost of DG units is given as follows:

$$Cost_t^{DG} = (a_i P_{i,t}^2 + b_i P_{i,t} + c_i) \times U_{i,t} + \overline{SUC}_i \times \mu_{i,t} + \overline{SDC}_i \times \nu_{i,t}; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (12)$$

Where:

a_i, b_i, c_i are cost function coefficients of DG unit i ,
 \overline{SUC}_i is the constant startup cost of DG unit i (\$),
 \overline{SDC}_i is the constant shutdown cost of DG unit i (\$),
 $\mu_{i,t}$ is the startup decision binary variable of DG unit i ,
 $\nu_{i,t}$ is the shutdown decision binary variable of DG unit i ,
 $U_{i,t}$ is status binary variable of DG unit i within the operation period t ($U_{i,t} = 1$ when the DG unit is on, and $U_{i,t} = 0$ otherwise).

Additionally, the relationship between three binary variables $\mu_{i,t}, \nu_{i,t}$ and $U_{i,t}$ are as follows:

$$\mu_{i,t} + \nu_{i,t} \leq 1; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (13)$$

$$\mu_{i,t} - \nu_{i,t} = U_{i,t} - U_{i,t-1}; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (14)$$

3.2.2. Retailer's Income

Retailers must supply the required energy of final clients at the agreed price. Moreover, they can auction off any surplus energy in the wholesale market. Hence, the retailers' income can be formulated as follows (It should be noted $\forall t \in T; P_t^{WSs} \geq 0$):

$$Inc_t^{ret} = d_t \times \pi_t^{ret} + P_t^{WSs} \times \pi_t^{WS}; \quad \forall t \in T \quad (15)$$

By substituting (7c) in (15), we have:

$$\begin{aligned} Inc_t^{ret} &= \left((\pi_t^{ret} - \pi_t^0) \times \frac{\epsilon_t d_t^0}{\pi_t^0} + d_t^0 \right) \times \pi_t^{ret} + P_t^{WSs} \times \pi_t^{WS} \\ &= \frac{\epsilon_t d_t^0}{\pi_t^0} (\pi_t^{ret})^2 + (d_t^0 - \epsilon_t d_t^0) \pi_t^{ret} + P_t^{WSs} \pi_t^{WS} \end{aligned} \quad (16)$$

The operational constraints of DG units are modeled as follows.

3.3. Operational Constraints of DG units

3.3.1. Minimum On-time Constraint

To reduce the thermal stress on the equipment of generation units, these units should be turned on for a specific minimum period. The minimum on-time constraint is modeled as follows:

$$[T_{C_i,t-1}^{On} - T_{i,\min}^{On}] \times [U_{i,t-1} - U_{i,t}] \geq 0; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (17)$$

Where:

$T_{C_i,t}^{On}$ is the number of continuous on-time hours of DG unit i up to the operation period t ,

$T_{i,\min}^{On}$ is the minimum on-time of DG unit i .

3.3.2. Minimum Off-time Constraint

During a shutdown, mandatory maintenance is performed on generation units. The minimum required time for mandatory maintenance is formulated as follows:

$$[T_{C_i,t-1}^{Off} - T_{i,\min}^{Off}] \times [U_{i,t} - U_{i,t-1}] \geq 0; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (18)$$

$T_{C_i,t}^{Off}$ is the number of continuous off-time hours of DG unit i up to the operation period t ,

$T_{i,\min}^{Off}$ is the minimum off-time of DG unit i .

3.3.3. Ramp-rate Limits

Due to operational constraints, the variation rate of output power of a generation unit should be in the safe bound, as follows:

$$P_{i,t} - P_{i,t-1} \leq R_i^{Up} \times U_{i,t} + R_i^{SU} \times \mu_{i,t}; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (19)$$

$$P_{i,t-1} - P_{i,t} \leq R_i^{Down} \times U_{i,t-1} + R_i^{SD} \times \nu_{i,t}; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (20)$$

Where:

R_i^{Up} is ramp-up rate limit of DG unit i (MW/h),

R_i^{SU} is startup ramp-rate limit of DG unit i (MW/h),

R_i^{Down} is ramp-down rate limit of DG unit i (MW/h),

R_i^{SD} is shutdown ramp-rate limit of DG unit i (MW/h).

3.3.4. Generation Capacity Limit

The generating power of DG unit i in operation period t must be between the upper (P_i^{\max}) and lower (P_i^{\min}) limits, as given below:

$$P_i^{\min} \times U_{i,t} \leq P_{i,t} \leq P_i^{\max} \times U_{i,t}; \quad \forall t \in T, i = 1, \dots, N_{DG} \quad (21)$$

3.3.5. Energy Balance Constraint

The total purchased power from the wholesale and forward markets and the generated power of the DG units should be equal to the sum of the amount of power sold in the wholesale market and the clients' demand, as follows:

$$P_t^{WSB} + \sum_{i=1}^{N_{DG}} P_{i,t} + P_t^{FC} = P_t^{WSs} + d_t; \quad \forall t \in T \quad (22)$$

3.4. Retailer's Profit Function

According to the presented cost and income functions, the profit function of the DG-owning retailer can be rewritten as follows:

$$Profit = \sum_{t=1}^T \left(\sum_{i=1}^{N_{DG}} \left((a_i P_{i,t}^2 + b_i P_{i,t} + c) \times U_{i,t} + \overline{SUC}_i \times \mu_{i,t} + \overline{SDC}_i \times \nu_{i,t} \right) + P_t^{WSB} \pi_t^{WS} + \sum_{f \in \Xi} \sum_{b=1}^{N_f^f} P_{t,f,b}^{FC} \times \pi_{t,f,b}^{FC} \times \delta_{t,f,b} \right) \quad (23)$$

Subject to (7d), (10a) – (10c), (13) – (14), (17) – (22).

The next section provides the decision-making framework for determining the optimal strategy of the retailer based on wholesale price uncertainty.

4. Risk-management framework

The IGDT is a non-probabilistic risk-management methodology to determine the optimal decision based on the unknown uncertain parameter. As mentioned before, the unknown random variable is a kind of uncertainty that cannot be approximated via probabilistic methods. In IGDT-based models, the uncertainty of random variable is modeled as a variation interval between what is known and what could be known (Ben-Haim, 1999). The size of variation interval and the optimal decision are specified based on the desired performance of the decision-maker. The robustness of optimal decision against the uncertainty of random variable is demonstrated effectively within the variation interval such that the performance associated with this decision will be more than acceptable, as defined by the decision-maker. The variation interval is usually referred to as the robustness region. In this work, the wholesale energy price is considered as an unknown variable that cannot be approximated by the probability density functions. The robustness region of wholesale price can be represented as follows:

$$\left| \frac{\pi_t^{WS} - \bar{\pi}_t^{WS}}{\bar{\pi}_t^{WS}} \right| \leq \lambda, \lambda \geq 0 \tag{24}$$

$$\begin{aligned} \text{Robustness Function}^{\text{Risk-Averse}} = \max \lambda \quad & \text{s.t.} \\ \min \quad & \text{Profit}^{\text{ret}} \\ & \geq \text{Profit}_{cr}^{\text{RA}}; \pi_t^{WS} \in [(1-\lambda)\bar{\pi}_t^{WS}, (1+\lambda)\bar{\pi}_t^{WS}] \\ & \pi_t^{\text{ret}}, P_t^{WSs}, P_t^{WSb}, P_{t,f}^{\text{FC}}, P_{i,t} : \\ & \forall t \in T, i = 1, \dots, N_{DG} \\ & \text{Profit}_{cr}^{\text{RA}} = (1-\rho) \times \text{Profit}_{Exp} \end{aligned} \tag{25}$$

Where $\bar{\pi}_t^{WS}$ represents the expected value of the hourly price during operation period t . The gap between the expected and the uncertain hourly prices are modeled via λ . The optimal value of λ is calculated based on the decision-maker's acceptable performance. IGDT-based models define both the robustness and opportunity

functions. The robustness function represents the greatest uncertainty level (or the maximum λ) in a manner that the minimal critical performance is always achieved for all $\pi_t^{WS} \in [(1-\lambda)\bar{\pi}_t^{WS}, (1+\lambda)\bar{\pi}_t^{WS}]$. The opportunity function addresses the appropriate face of uncertainty and the possibility of reaching pre-determined performance (defined by the decision-maker) within the random parameter variation interval. Indeed, in the opportunity function the minimum deviation interval of the uncertain parameter is calculated to ensure that desired performance is achievable for at least one solution $\pi_t^{WS} \in [(1-\lambda)\bar{\pi}_t^{WS}, (1+\lambda)\bar{\pi}_t^{WS}]$.

Risk-averse decision-makers choose the lower risk-level to limit the financial risk arising from variation in the uncertain parameter. They prefer the robustness function and their optimal strategy is based on the worst condition up to the horizon of uncertainty. Risk-taker decision-makers select a higher risk-level in the hope of obtaining acceptable performance. They prefer the opportunity function and their optimal strategy is based on the best condition up to the horizon of uncertainty.

Risk-averse retailers would like to determine the optimal energy-supply strategy in a way that the desired profit is guaranteed against price variations. Therefore, the proposed robustness function represents the maximum variation interval of the wholesale price such that the minimum profit will be greater than the retailer's defined value. The robustness function can be expressed as follows:

Where, Profit_{Exp} is the expected profit (the expected profit is calculated based on $\bar{\pi}_t^{WS}$; $\forall t \in T$), and ρ is the profit deviation factor. By substituting (23) in (25), the robustness function can be rewritten as follows:

$$\begin{aligned} \text{Robustness Function}^{\text{Risk-Averse}} = \max \lambda \quad & \text{s.t.} \\ \min \quad & \sum_{t=1}^T \left[\left(\frac{\varepsilon_t d_t^0}{\pi_t^0} (\pi_t^{\text{ret}})^2 + (d_t^0 - \varepsilon_t d_t^0) \pi_t^{\text{ret}} + P_t^{WSs} \pi_t^{WS} \right) - \right. \\ & \left. \left(\sum_{i=1}^{N_{DG}} ((a_i P_{i,t}^2 + b_i P_{i,t} + c_i) \times U_{i,t} + \overline{SUC}_i \times \mu_{i,t} + \overline{SDC}_i \times v_{i,t}) \right) \right] \geq \text{Profit}_{cr}^{\text{RA}}; \\ & \pi_t^{\text{ret}}, P_t^{WSs}, P_t^{WSb}, P_{t,f}^{\text{FC}}, P_{i,t} : \\ & \forall t \in T, i = 1, \dots, N_{DG} \\ & \left. \left(+ \pi_t^{WS} \times P_t^{WSb} + \sum_{f \in \Xi} \sum_{b=1}^{N_f} P_{t,f,b}^{\text{FC}} \times \pi_{t,f,b}^{\text{FC}} \times \delta_{t,f,b} \right) \right] \end{aligned} \tag{26}$$

$$\pi_t^{WS} \in [(1-\lambda)\bar{\pi}_t^{WS}, (1+\lambda)\bar{\pi}_t^{WS}] \& \text{Profit}_{cr}^{\text{RA}} = (1-\rho) \times \text{Profit}_{Exp}$$

Constraints : (7d), (10a) – (10c), (13) – (14), (17) – (22).

In the case of risk-taker retailers, the minimum variation interval of the wholesale price is determined in a way that the maximum achievable profit will be greater than the pre-determined value. Therefore, the opportunity function of a risk-taker retailer is formulated as follows:

$$\begin{aligned}
 \text{Opportunity Function}^{\text{Risk-Taker}} &= \min \lambda \quad \text{s.t.} \\
 \max \quad & \text{Profit}^{\text{ret}} \geq \text{Profit}_{\text{cr}}^{\text{RT}}; \quad \pi_t^{\text{WS}} \in [(1 - \lambda)\bar{\pi}_t^{\text{WS}}, (1 + \lambda)\bar{\pi}_t^{\text{WS}}] \\
 & \pi_t^{\text{ret}}, P_t^{\text{WS}_s}, P_t^{\text{WS}_b}, P_{t,f}^{\text{FC}}, P_{i,t} : \\
 & \forall t \in T, \quad i = 1, \dots, N_{\text{DG}} \\
 & \text{Profit}_{\text{cr}}^{\text{RT}} = (1 + \rho) \times \text{Profit}_{\text{Exp}}
 \end{aligned} \tag{27}$$

By substituting (23) in (27), the opportunity function can be rewritten as follows:

$$\begin{aligned}
 \text{Opportunity Function}^{\text{Risk-Taker}} &= \min \lambda \quad \text{s.t.} \\
 \max \quad & \left[\left(\frac{\varepsilon_t d_t^0}{\pi_t^0} (\pi_t^{\text{ret}})^2 + (d_t^0 - \varepsilon_t d_t^0) \pi_t^{\text{ret}} + P_t^{\text{WS}_s} \pi_t^{\text{WS}} \right) - \right. \\
 & \sum_{t=1}^T \left(\sum_{i=1}^{N_{\text{DG}}} \left((a_i P_{i,t}^2 + b_i P_{i,t} + c_i) \times U_{i,t} + \overline{SUC}_i \times \mu_{i,t} + \overline{SDC}_i \times v_{i,t} \right) \right) \\
 & \left. + \pi_t^{\text{WS}} \times P_t^{\text{WS}_b} + \sum_{f \in \Xi} \sum_{b=1}^{N_f} P_{t,f,b}^{\text{FC}} \times \pi_{t,f,b}^{\text{FC}} \times \delta_{t,f,b} \right] \geq \text{Profit}_{\text{cr}}^{\text{RT}}; \\
 & \forall t \in T, \quad i = 1, \dots, N_{\text{DG}}
 \end{aligned} \tag{28}$$

$$\pi_t^{\text{WS}} \in [(1 - \lambda)\bar{\pi}_t^{\text{WS}}, (1 + \lambda)\bar{\pi}_t^{\text{WS}}] \& \text{Profit}_{\text{cr}}^{\text{RT}} = (1 + \rho) \times \text{Profit}_{\text{Exp}}$$

Constraints : (7d), (10a) – (10c), (13) – (14), (17) – (22).

The flowchart of the proposed bi-level optimization problem is demonstrated in Fig. 2. It should be noted that an adaptive recursive least-squares algorithms is used to determine the optimal energy-supply framework of the retailer (Liu and Ding, 2013).

In the next section, the performance of the proposed model is analyzed via a case study.

5. Numerical simulations

To evaluate the performance of the proposed framework, it is simulated for a price-taker retailer that has four thermal DG units. Table 1 tabulates the operational data of DG units. The quadratic cost function of DG units is approximated by a set of piecewise block (Carrion and Arroyo, 2006). In this work, we suppose that the forward prices are available and transparent at the time of decision-making. The characteristics of available stepwise forward contracts are represented in Table 2.

Initial retail selling prices (π_t^0), initial client's demand (d_t^0), and the expected values of wholesale price ($\bar{\pi}_t^{\text{WS}}$) are shown in Fig. 3.

Additionally, we suppose the maximum load variation in each operation period is equal to 20%, or $|d_t^0 - d_t| \leq 0.2d_t^0$. The optimal

consumption of end-use customers and the retail-selling price for different values of $k = \Delta d_t / \Delta \pi_t^{\text{ret}}$ are shown in Figs. 4 and 5, respectively. As seen in Fig. 5, by increasing the client's elasticity (or increasing k), the retail-selling price is decreased and vice versa. Therefore, according to (7c), the optimal consumption of clients is increased by increasing the clients' elasticity (as shown in Fig. 4).

For $k = -0.5$ and $k = -4$, the client's consumption reaches to the minimum ($d_t = 0.8d_t^0$) and maximum ($d_t = 1.2d_t^0$) thresholds, respectively.

The retailer's maximum profit for different values of k is shown

in Fig. 6. By decreasing the elasticity coefficient, the sensitivity of clients to the selling price is increased. A higher sensitivity, as seen in Fig. 5, the retailer has to offer the lower selling price, which reduces the retailer's maximum profit.

Fig. 7 demonstrates the impact of elasticity coefficient variation on the retailer's participation level in the wholesale market. It should be mentioned that in this Figure, $P_t^{\text{WS}_s}$ and $P_t^{\text{WS}_b}$ are represented by negative and positive values. According to Fig. 4, the more price-sensitive clients consume the higher electricity. Hence, the retailer has to purchase more energy from the wholesale market to compensate for the capacity shortage.

Optimal generation of the DG units as well as retailer's participation levels in the wholesale and forward markets for $k = -1$ and $\lambda=0$ (the uncertainty of wholesale price is ignored) are presented in Table 3. As seen in this table, during high-price and low-price periods, the retailer prefers to participate in the wholesale market as a seller or buyer, respectively. It should be noted that the maximum profit in this condition is equal to 9467 USD. The convergence speed of the proposed model is demonstrated in Fig. 8.

Fig. 9 shows the retailer's profit versus the wholesale price deviation factor (λ), for $(1 - \lambda)\bar{\pi}_t^{\text{WS}}$ and $(1 + \lambda)\bar{\pi}_t^{\text{WS}}$ ($k = -1$). The minimum profit is obtained at $0.95\bar{\pi}_t^{\text{WS}}$, which is equal to 9135.286

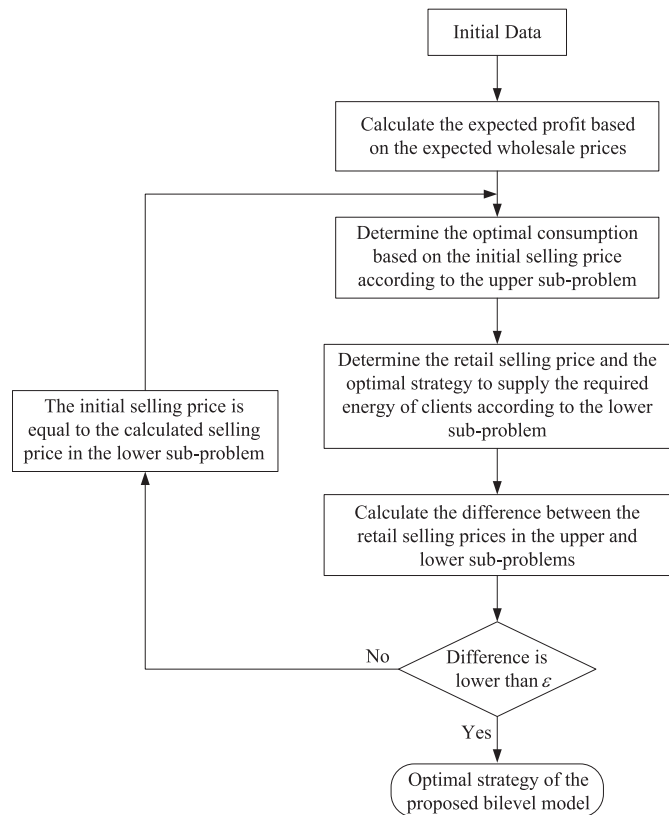


Fig. 2. The flowchart of the proposed bi-level optimization problem.

Table 1 Operational data of DG units.

DG unit	1	2	3	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)	55.30	53.2	54.0	53.8
c_i (\$)	34	33.5	34.5	32.8
$T_{i,\min}^{Up}$ (h)	1	0.5	1	0.5
$T_{i,\min}^{Down}$ (h)	1	0.5	1	0.5
\overline{SUC}_i (\$)	15	13	15	13
\overline{SDC}_i (\$)	10	9	10	9

Table 2 Characteristics of available stepwise 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

and the risk-taker ($Profit_{cr}^{RT}$) retailers are considered as 9200\$ and 11 000\$, respectively. Table 4 summarizes the optimal strategy of the risk-averse retailer based on the proposed performance. Simulation results show that for the risk-averse retailer (according to $Profit_{cr}^{RA} = 9200$ \$), the maximum variation interval of the wholesale price (λ) is equal to 0.02535.

The minimum variation interval of the wholesale price for $Profit_{cr}^{RT} = 11000$ \$ is equal to 0.05485. The optimal strategy of the risk-taker retailer is represented in Table 5.

The optimal strategy of the risk-taker retailer without considering the sensitivity of clients to the selling price is given in Table 6. The minimum price deviation in this condition ($Profit_{cr}^{RT} = 11 000$ \$) is equal to 0.167. Comparing the results of

USD. The increasing rate of profit for $(1 + \lambda)\overline{\pi}_t^{WS}$ is higher than $(1 - \lambda)\overline{\pi}_t^{WS}$. During peak-load (or high-price) periods, the retailer has to offer the higher selling price to cover the supply cost, leading to a decrease of clients' consumption. Therefore, the retailer has more surplus energy for selling into the wholesale market. In other words, client price sensitivity increases the surplus energy during peak-load periods, which in turn results in higher profits for the retailer.

To analyze the performance of the proposed robustness and opportunity functions, the critical profit of the risk-averse ($Profit_{cr}^{RA}$)

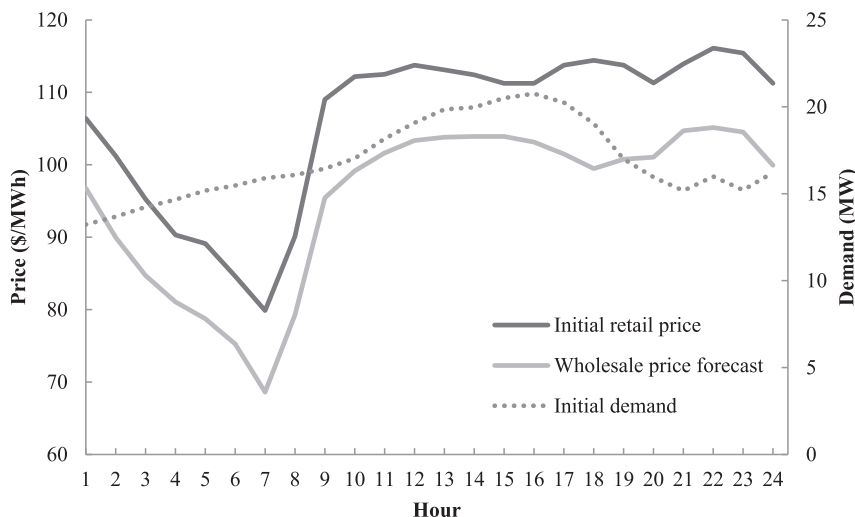


Fig. 3. Initial retail prices, client's demand, and the wholesale price forecast.

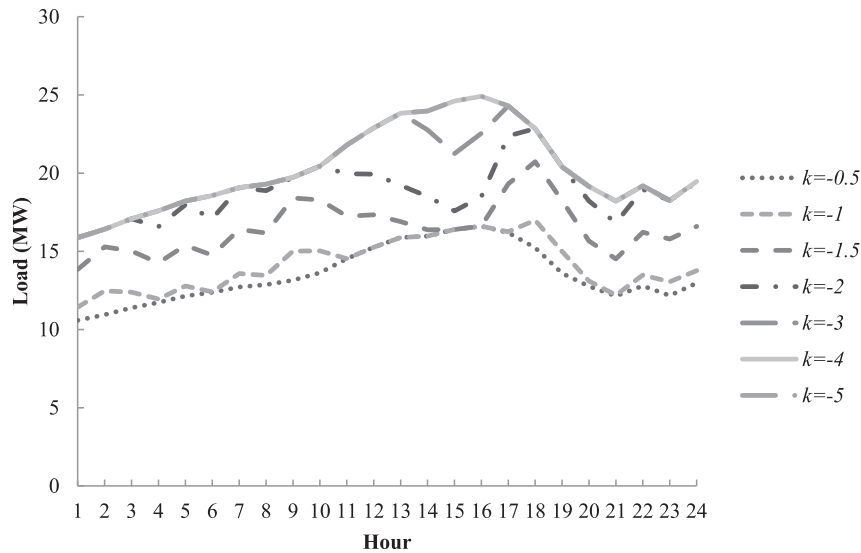


Fig. 4. Optimal consumption of price-sensitive customers.

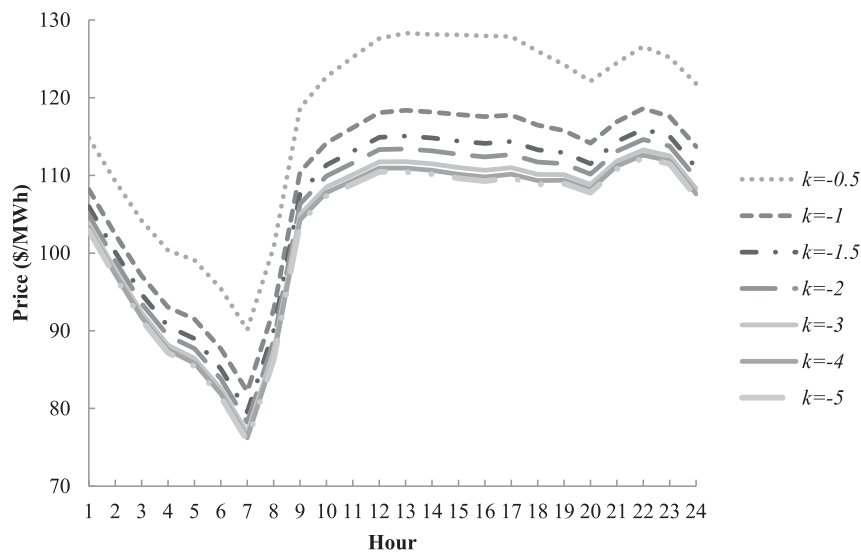


Fig. 5. Optimal retail selling price.

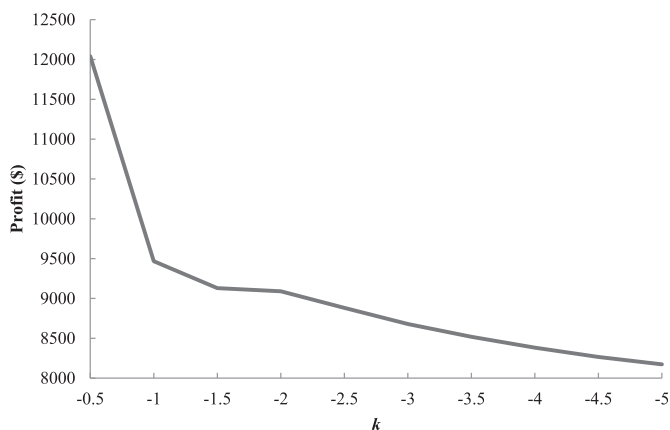


Fig. 6. Retailer's maximum profit versus k .

Tables 5 and 6 demonstrates that considering client price elasticity is associated with less DG production and more power sold into the wholesale market.

According to equations (27) and (29), the risk-averse and risk-taker retailers specify their optimal strategies based on minimum and maximum profits, respectively. As seen in Fig. 9, the minimum and maximum profits of the retailer are readily seen to occur for the minimum and maximum prices determined by the IGDT model on the horizon of uncertainty λ , which are equal to $(1 - \lambda)\bar{\pi}_t^{WS}$ and $(1 + \lambda)\bar{\pi}_t^{WS}$, respectively. Comparing Tables 4 and 5 shows that risk-taker retailers provide most of the required energy by final consumers via their generation facilities. As mentioned before, by increasing the wholesale price, the consumption of price-sensitive clients is decreased. Therefore, the risk-taker retailer has additional power and can participate in the wholesale market as a seller. The optimal selling prices for risk-averse and risk-taker retailers are shown in Fig. 10. Risk-averse retailers offer the lower selling price, because they specify their optimal strategy according to minimum wholesale prices.

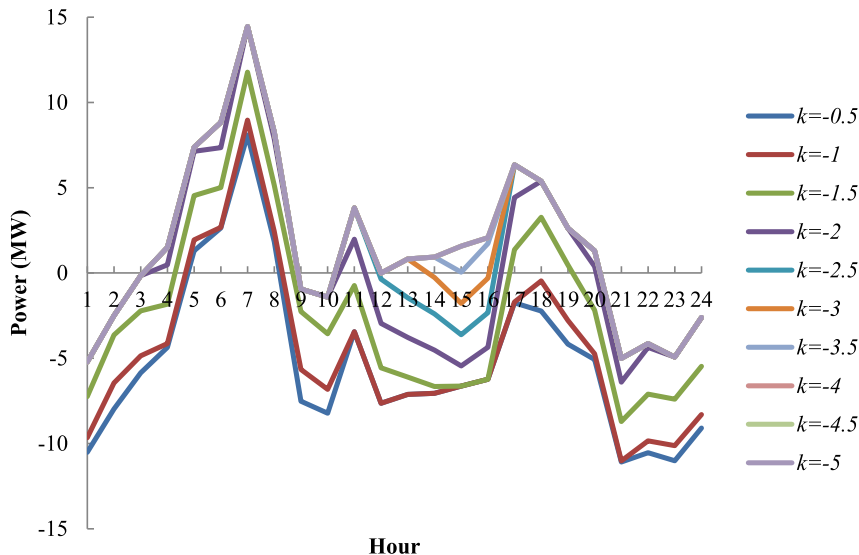


Fig. 7. Retailer's optimal participation level in the wholesale market for various elasticity coefficients.

Table 3
Retailer's optimal strategy for $k = -1$ and $\lambda = 0$.

Hour	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	p_t^{WS}	p_t^{WSb}	$p_{t,1}^{FC}$	$p_{t,2}^{FC}$
1	3.64	3.20	3.29	3.46	9.66	0.00	3.00	4.50
2	3.04	2.70	2.77	2.91	6.45	0.00	3.00	4.50
3	2.58	2.32	2.36	2.49	4.86	0.00	3.00	4.50
4	2.26	2.05	2.08	2.20	4.14	0.00	3.00	4.50
5	2.05	1.88	1.90	2.01	0.00	1.94	3.00	0.00
6	1.75	1.62	1.63	1.73	0.00	2.67	3.00	0.00
7	1.17	1.13	1.12	1.19	0.00	8.96	0.00	0.00
8	2.10	1.92	1.94	2.05	0.00	2.44	3.00	0.00
9	3.52	3.11	3.19	3.36	5.66	0.00	3.00	4.50
10	3.85	3.38	3.47	3.66	6.82	0.00	3.00	4.50
11	4.06	3.56	3.50	3.86	3.45	0.00	0.00	3.00
12	4.21	3.69	3.50	4.00	7.64	0.00	4.50	3.00
13	4.25	3.72	3.50	4.03	7.12	0.00	4.50	3.00
14	4.26	3.73	3.50	4.04	7.05	0.00	4.50	3.00
15	4.26	3.73	3.50	4.04	6.63	0.00	4.50	3.00
16	4.20	3.67	3.50	3.98	6.24	0.00	4.50	3.00
17	4.05	3.55	3.50	3.85	1.70	0.00	0.00	3.00
18	3.88	3.40	3.50	3.68	0.47	0.00	0.00	3.00
19	3.99	3.50	3.50	3.79	2.78	0.00	0.00	3.00
20	4.01	3.52	3.50	3.81	4.74	0.00	0.00	3.00
21	4.33	3.79	3.50	4.10	11.02	0.00	4.50	3.00
22	4.37	3.82	3.50	4.14	9.85	0.00	4.50	3.00
23	4.32	3.77	3.50	4.09	10.12	0.00	4.50	3.00
24	3.91	3.44	3.50	3.72	8.30	0.00	3.00	4.50

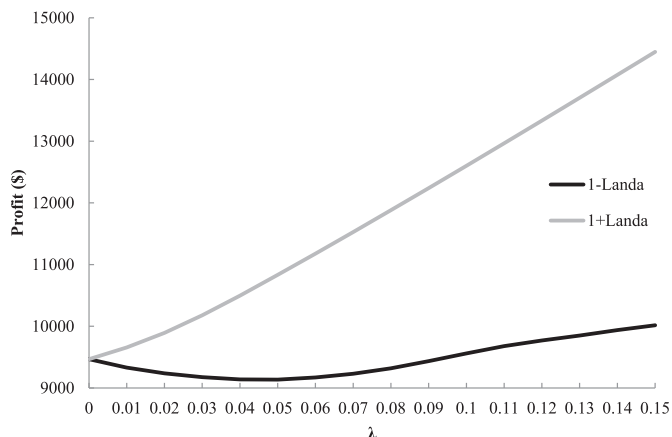


Fig. 9. Minimum and maximum profit for different values of λ .

Table 4
Risk-averse retailer's optimal strategy for $k = -1$ and $Profit_{cr}^{RA} = 9200\$$.

Hour	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	p_t^{WS}	p_t^{WSb}	$p_{t,1}^{FC}$	$p_{t,2}^{FC}$
1	3.42	3.02	3.10	3.27	7.65	0.00	3.00	4.50
2	2.84	2.53	2.59	2.73	4.58	0.00	3.00	4.50
3	2.39	2.16	2.20	2.32	3.10	0.00	3.00	4.50
4	2.08	1.90	1.92	2.03	0.00	2.04	3.00	0.00
5	1.88	1.73	1.75	1.85	0.00	3.58	3.00	0.00
6	1.58	1.48	1.49	1.58	0.00	7.23	0.00	0.00
7	1.01	1.00	0.99	1.05	0.00	10.39	0.00	0.00
8	1.93	1.77	1.79	1.89	0.00	4.09	3.00	0.00
9	3.31	2.93	3.00	3.16	3.68	0.00	3.00	4.50
10	3.63	3.19	3.28	3.45	4.77	0.00	3.00	4.50
11	3.84	3.37	3.46	3.65	1.51	0.00	4.50	3.00
12	3.98	3.49	3.50	3.78	1.72	0.00	0.00	3.00
13	4.02	3.53	3.50	3.82	1.98	0.00	0.00	3.00
14	4.033	3.53	3.50	3.83	1.92	0.00	0.00	3.00
15	4.03	3.54	3.50	3.83	1.49	0.00	0.00	3.00
16	3.97	3.48	3.50	3.77	1.10	0.00	0.00	3.00
17	3.83	3.36	3.46	3.64	0.00	0.25	0.00	3.00
18	3.65	3.22	3.30	3.48	0.00	1.60	0.00	3.00
19	3.76	3.31	3.40	3.58	0.78	0.00	0.00	3.00
20	3.79	3.33	3.42	3.60	2.76	0.00	0.00	3.00
21	4.10	3.59	3.50	3.89	4.55	0.00	0.00	3.00
22	4.14	3.62	3.50	3.92	3.37	0.00	0.00	3.00
23	4.08	3.58	3.50	3.88	3.66	0.00	0.00	3.00
24	3.69	3.25	3.34	3.52	6.26	0.00	3.00	4.50

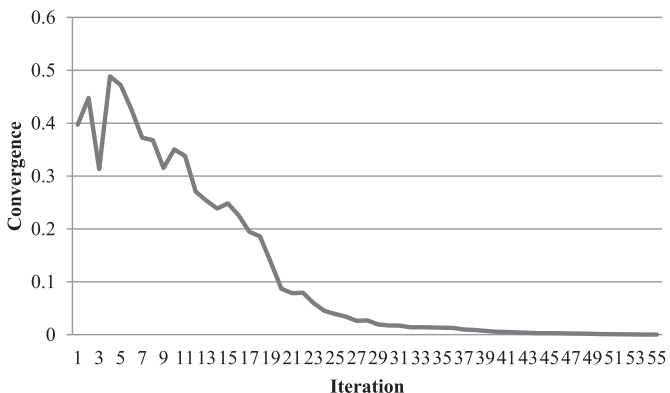


Fig. 8. Convergence speed of the proposed model.

Table 5
Risk-taker retailer's optimal strategy for $k = -1$ and $Profit_{cr}^{RT} = 11\ 000$ \$.

Hour	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	$P_t^{WS_s}$	$P_t^{WS_b}$	$P_{t,1}^{FC}$	$P_{t,2}^{FC}$
1	4.10	3.59	3.50	3.89	12.01	0.00	3.00	4.50
2	3.47	3.06	3.14	3.31	9.55	0.00	3.00	4.50
3	2.99	2.66	2.72	2.87	7.34	0.00	3.00	4.50
4	2.65	2.38	2.42	2.56	5.78	0.00	3.00	4.50
5	2.43	2.19	2.23	2.36	4.57	0.00	3.00	4.50
6	2.11	1.92	1.95	2.06	0.00	1.32	3.00	0.00
7	1.50	1.41	1.41	1.50	0.00	6.90	0.00	0.00
8	2.48	2.24	2.28	2.40	4.04	0.00	3.00	4.50
9	3.98	3.49	3.50	3.78	9.10	0.00	3.00	4.50
10	4.32	3.78	3.50	4.10	9.57	0.00	3.00	4.50
11	4.55	3.97	3.50	4.31	9.29	0.00	4.50	3.00
12	4.71	4.00	3.50	4.45	8.90	0.00	4.50	3.00
13	4.75	4.00	3.50	4.49	8.36	0.00	4.50	3.00
14	4.76	4.00	3.50	4.50	8.28	0.00	4.50	3.00
15	4.76	4.00	3.50	4.50	7.86	0.00	4.50	3.00
16	4.69	4.00	3.50	4.43	7.52	0.00	4.50	3.00
17	4.54	3.96	3.50	4.29	7.60	0.00	4.50	3.00
18	4.35	3.80	3.50	4.12	8.05	0.00	4.50	3.00
19	4.47	3.90	3.50	4.23	10.01	0.00	4.50	3.00
20	4.50	3.93	3.50	4.26	10.92	0.00	4.50	3.00
21	4.84	4.00	3.50	4.50	12.19	0.00	4.50	3.00
22	4.88	4.00	3.50	4.50	11.58	0.00	4.50	3.00
23	4.82	4.00	3.50	4.50	12.15	0.00	4.50	3.00
24	4.40	3.84	3.50	4.16	10.42	0.00	3.00	4.50

Table 6
Risk-taker retailer's optimal strategy without considering clients elasticity.

Hour	$P_{1,t}$	$P_{2,t}$	$P_{3,t}$	$P_{4,t}$	$P_t^{WS_s}$	$P_t^{WS_b}$	$P_{t,1}^{FC}$	$P_{t,2}^{FC}$
1	5.00	4.00	3.50	4.50	11.27	0.00	3.00	4.50
2	4.36	3.81	3.50	4.13	9.61	0.00	3.00	4.50
3	3.82	3.36	3.45	3.63	7.52	0.00	3.00	4.50
4	3.45	3.04	3.12	3.29	5.75	0.00	3.00	4.50
5	3.21	2.84	2.91	3.07	4.35	0.00	3.00	4.50
6	2.85	2.55	2.6	2.74	2.77	0.00	3.00	4.50
7	2.17	1.98	2.01	2.12	0.00	0.12	3.00	4.50
8	3.26	2.89	2.96	3.12	3.66	0.00	3.00	4.50
9	4.92	4.00	3.50	4.50	7.98	0.00	3.00	4.50
10	5.00	4.00	3.50	4.50	7.47	0.00	3.00	4.50
11	5.00	4.00	3.50	4.50	6.33	0.00	4.50	3.00
12	5.00	4.00	3.50	4.50	5.43	0.00	4.50	3.00
13	5.00	4.00	3.50	4.50	4.64	0.00	4.50	3.00
14	5.00	4.00	3.50	4.50	4.53	0.00	4.50	3.00
15	5.00	4.00	3.50	4.50	3.99	0.00	4.50	3.00
16	5.00	4.00	3.50	4.50	3.74	0.00	4.50	3.00
17	5.00	4.00	3.50	4.50	4.25	0.00	4.50	3.00
18	5.00	4.00	3.50	4.50	5.46	0.00	4.50	3.00
19	5.00	4.00	3.50	4.50	7.50	0.00	4.50	3.00
20	5.00	4.00	3.50	4.50	8.54	0.00	4.50	3.00
21	5.00	4.00	3.50	4.50	9.32	0.00	4.50	3.00
22	5.00	4.00	3.50	4.50	8.51	0.00	4.50	3.00
23	5.00	4.00	3.50	4.50	9.29	0.00	4.50	3.00
24	5.00	4.00	3.50	4.50	8.28	0.00	3.00	4.50

6. Conclusion

This paper presents a robust bi-level energy-supply model for DG-owning retailers to meet the energy requirements of price-sensitive clients based on the IGDT methodology. The optimal strategies for consumption by clients and supply by retailers are determined in the upper and lower sub-problems, respectively. Retailer strategies depend on their risk preferences. The proposed model is formulated for risk-averse retailers via the robustness and risk-taker retailers via the opportunity function. The proposed robustness function guarantees a specific profit within the robustness region of the wholesale price. The proposed opportunity function ensures that the desired profit of the retailer is achievable for at least one price within the robustness region. Simulation results show that by increasing the client's elasticity, the retail-selling price is decreased. Therefore, the clients' consumption

is increased. Moreover, during high-price periods, the retailer offers the higher selling price to cover the supply cost, which results in lower consumption. Thus, the retailer can sell the energy surplus into the wholesale market and obtain a higher profit. During low-price periods, the DG-owning retailer supplies most of their clients' demand through the wholesale market. According to the model results, DG units enable the retailer to obtain a higher profit under all conditions. The risk-averse and risk-taker retailers specify their optimal strategies based on minimum and maximum profits, which are obtained at the minimum and maximum prices determined by the IGDT model on the horizon of wholesale price uncertainty. Risk-taker retailers provide most of the required energy of clients via their generation facilities. Comparing the optimal strategies of risk-averse and risk-taker retailers shows that the risk-taker retailers participate more in the wholesale market as a seller, and they offer higher selling prices.

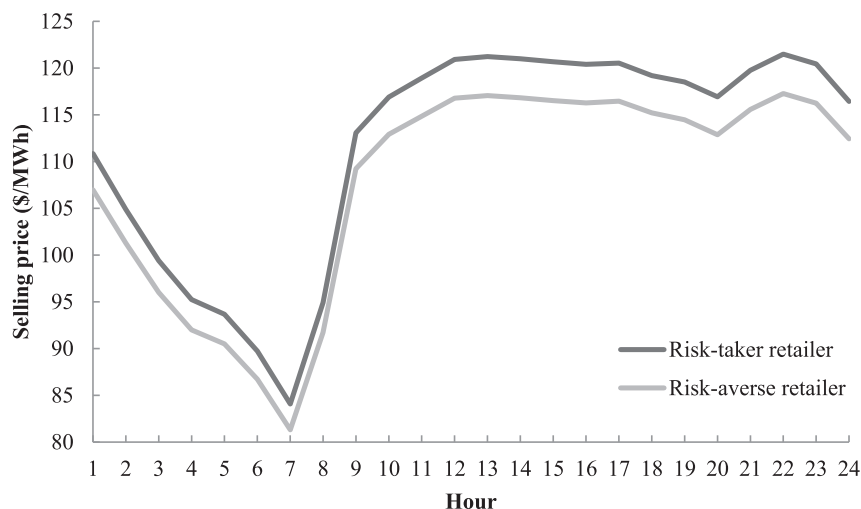


Fig. 10. Optimal selling price for risk-averse and risk-taker retailers.

References

- Ahmadi, A., Charwand, M., Aghaei, J., 2013. Risk-constrained optimal strategy for retailer forward contract portfolio. *Int. J. Electr. Power* 53, 704–713.
- Anderson, E.J., Hu, X., Winchester, D., 2007. Forward contracts in electricity markets: the Australian experience. *Energ. Policy* 35, 3089–3103.
- Ben-Haim, Y., 1999. Design certification with information-gap uncertainty. *Struct. Saf.* 21, 269–289.
- Boroumand, R.H., Zachmann, G., 2012. Retailers' risk management and vertical arrangements in electricity markets. *Energ. Policy* 40, 465–472.
- Carrion, M., Arroyo, J., 2006. A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem. *IEEE Trans. Power Syst.* 21, 1371–1378.
- Carrion, M., Conejo, A.J., Arroyo, J.M., 2007. Forward contracting and selling price determination for a retailer. *IEEE Trans. Power Syst.* 22 (4), 2105–2114.
- Celebi, E., Fuller, J.D., 2007. A model for efficient consumer pricing schemes in electricity markets. *IEEE Trans. Power Syst.* 22 (1), 60–67.
- Erik, S., Pettersen, E., 2005. Constructing bidding curves for a price-taking retailer in the Norwegian electricity market. *IEEE Trans. Power Syst.* 20, 701–708.
- Gabriel, S.A., Gence, M.F., Balakrishnan, S., 2002. A simulation approach to balancing annual risk and reward in retail electrical power markets. *IEEE Trans. Power Syst.* 17, 1050–1057.
- Gabriel, S.A., Kiet, S., Balakrishnan, S., 2004. A mixed integer stochastic optimization model for settlement risk in retail electric power markets. *Netw. Spat. Econ.* 4, 323–345.
- Gabriel, S.A., Conejo, A.J., Plazas, M.A., Balakrishnan, S., 2006. Optimal price and quantity determination for retail electric power contracts. *IEEE Trans. Power Syst.* 21, 180–187.
- Hatami, A., Seifi, H., Sheikh-El-Eslami, M.K., 2011. A stochastic-based decision-making framework for an electricity retailer: time-of-use pricing and electricity portfolio optimization. *IEEE Trans. Power Syst.* 26, 1808–1816.
- Karandikar, R.G., Khaparde, S.A., Kulkarni, S.V., 2007. Quantifying price risk of electricity retailer based on CAPM and RAROC methodology. *Int. J. Electr. Power* 29, 803–809.
- Karandikar, R.G., Khaparde, S.A., Kulkarni, S.V., 2010. Strategic evaluation of bilateral contract for electricity retailer in restructured power market. *Int. J. Electr. Power* 32, 457–463.
- Liu, Y., Ding, F., 2013. Convergence properties of the least squares estimation algorithm for multivariable systems. *Appl. Math. Model.* 37 (1), 476–483.
- Mahmoudi-Kohan, N., Parsa Moghadam, M., Sheikh-El-Eslami, M.K., 2010. An annual framework of clustering-based pricing for an electricity retailer. *Electr. Power Syst. Res.* 80 (9), 1042–1048.
- Mohammadi-Ivatloo, B., Zareipour, H., Amjady, N., Ehsan, M., 2013. Application of information-gap decision theory to risk-constrained self-scheduling of GenCos. *IEEE Trans. Power Syst.* 28, 1093–1102.
- Palamarchuk, S., 2010. Dynamic programming approach to the bilateral contract scheduling. *IET Gener. Transm. Distrib.* 4, 211–220.
- Schwepe, F.C., Caramanis, M.C., Tabor, R.D., 1985. Evaluation of spot price based electricity rates. *IEEE Trans. Power Appar.* 104, 1644–1655.
- Yusta, J.M., Rosado, I.J.R., Navarro, J.A.D., Vidal, J.M.P., 2005. Optimal electricity price calculation model for retailers in a deregulated market. *Int. J. Electr. Power* 27, 437–447.
- Zare, K., Parsa Moghadam, M., Sheikh-El-Eslami, M.K., 2010a. Electricity procurement for large consumers based on information gap decision theory. *Energ. Policy* 38, 234–242.
- Zare, K., Conejo, A.J., Carrion, M., Parsa Moghadam, M., 2010b. Multi-market energy procurement for a large consumer using a risk-aversion procedure. *Electr. Power Syst. Res.* 80, 63–70.
- Zugno, M., Morales, J.M., Pinson, P., Madsen, H., 2013. A bilevel model for electricity retailers' participation in a demand response market environment. *Energ. Econ.* 36, 182–197.