Utilities Policy 37 (2015) 1–12

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

A R T I C L E I N F O

Article history:
Received 14 October 2014
Received in revised form
17 March 2015
Accepted 17 March 2015
Available online 31 March 2015

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

A B S T R A C T

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.

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).

http://dx.doi.org/10.1016/j.jup.2015.03.002
0957-1787/

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 nonlinear 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 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.