Decision-Making for Electricity Retailers: A Brief Survey

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***Abstract*—With the continuous development of smart grid and further restructuring of power industry, modern power systems have been transformed to complex cyber-physical systems characterized with high renewable energy penetrations, distributed facilities, advanced metering, and communication technologies, as well as ever-increasing customer awareness. These new development trends pose significant challenges for electricity retailers and call for innovative decision-making methods. To help researchers and engineers have a better overview of the state-of-the-art on electricity retail decision-making schemes, this paper aims to survey the latest progress on this subject. Some critical and open issues in this field are also discussed.**

***Index Terms*—Electricity retail, retail pricing, retail energy forecasting, demand side management, decision-making.**

I. Introduction

SINCE early 1990s, both the generation and retail sectors of the power industry have been progressively experiencing the restructuring processes around the world. As a result of market deregulation, the fixed pricing scheme under regulation has been considered to be a limitation for optimizing the grid operation. A considerable amount of research work therefore has been conducted to develop more flexible pricing schemes for electricity retailing in the context of liberalized electricity markets.

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Depending on the involved market entities, electricity pricing can be categorized into two types: wholesale pricing and retail pricing. In this paper, the focus is on the available publications of retail pricing. Currently, the retail pricing schemes can be broadly classified into two categories: static and dynamic pricing schemes. It is widely accepted that the elasticity of the demand side can be well utilized under real-time pricing (RTP) which follows the price variations in the wholesale market. The major disadvantage of RTP is the exposure of end-users to the risks resulted from price fluctuations. On the other hand, the static pricing scheme, known as time-of-use (TOU) pricing, can achieve a better balance between protecting end-users from price risks and utilizing demand elasticity. Due to the advantages of TOU pricing over RTP at the demand side, it has been widely adopted in practice and also has attracted more attentions from researchers.

In the TOU pricing scheme, since the retail tariffs in the same time interval are fixed to customers, the price risks from the spot market are undertaken by electricity retailers. Therefore, it is important for electricity retailers to manage the risks by simultaneously trading in wholesale markets (such as the spot market and futures market), and then design proper retail pricing schemes which match the trading strategies in wholesale markets. In more details, electricity retailers firstly need to perform long-term demand forecasting for end-users; secondly, they need to assess potential risks caused by the volatilities of customer demand and spot market prices. Moreover, innovative pricing schemes are also necessary by taking into account the emerging factors such as the increasing penetration of renewable energy, widely deployment of distributed generation and storage devices, adoption of advanced information and communication technologies and rising customer awareness of switching among electricity suppliers.

To help researchers and engineers understand the state-of-the-art of electricity retailer pricing, this paper presents a comprehensive survey of recent works in subject. The rest of this paper is organized as follows. Section II presents the decision framework for electricity retail. Sections III–V review the long-term demand forecasting, energy procurement and retail pricing strategies, respectively; in Section VI, the risk management strategies for electricity retailers are summarized; Section VII discusses some potential future research directions in electricity retailing; finally, the paper is concluded in Section VIII.

II. DECISION FRAMEWORK

An electricity retailer is an intermediary between electricity producers and consumers. Currently, the electricity retail company is usually operated as an entity that is independent of any generation or distribution company. The retailer purchases energy from the wholesale and futures markets and resells it to customers through various retail contracts. In order to gain profits, electricity retailers face the problem of making optimal decisions on electricity markets in both the supply and retail sides. Obviously, the electricity consumption of customers is the basis for electricity retailers running their business. Therefore, estimation of load demand should be the first thing in the decision-making process of retailers.

Many decision-making problems with the presence of uncertainty in energy markets are discussed in the well-known book [1]. In [1], firstly, a detailed introduction to the structure of the electricity market and the stochastic programming based decision-making methodology are presented. Then, the decision-making process of electricity producers and retailers is further studied, respectively. In addition, the book also provides backgrounds and models of the electricity market clearing process. In this paper, the main procedures in electricity retailers' decision-making are considered, including the retail energy forecasting, portfolio evaluation, and risk management.

A. Retail Energy Forecasting

The retailer runs its business by purchasing energy from the wholesale electricity market and then reselling it to end-users through retail contracts. In electricity retail markets, the retail contracts usually span from several months to several years. In order to gain profits and ensure the business going well, retail energy forecasting is of great importance in following aspects:

(1) Load forecasting is necessary for the retailer to reliably supply electricity to customers. Retailers need to forecast the energy demand of their customers so as to make electricity purchase decisions in the electricity market.

(2) Load forecasting is the prerequisite for making optimal purchasing portfolio. Accurate understanding of customers' load can help retailers avoid making too loose portfolio decisions, which will result in unnecessary costs. On the contrary, if the decisions are too tight, it will also cause high risks on electricity supply and cost.

(3) Load forecasting is crucial to electricity retailers in the course of managing their risks. The retailer mainly faces two kinds of uncertainties: wholesale electricity price and client demand. Through improved understanding of customer loads, the retailer will be able to uncover and mitigate excess exposure to load and price volatility risks.

(4) Load forecasting is essential for developing competitive retail pricing schemes. When serving customers, the volume, shape and variability of load demand determine the final cost. Accurate load forecasting can help provide a beforehand understanding of the true cost and risk, which would result in pricing systems that improve retailers' competitiveness and profitability.

Considering the significance of retail energy forecasting on electricity retailers' decision-making, the long-term load forecasting techniques are firstly analyzed in Section III.

B. Portfolio Evaluation

A significant challenge for an electricity retailer is to accurately determine the value of its portfolios. The retailer is a middle person between generation companies and customers, and its core business is to purchase electricity from various sources and resell it to customers. An optimal energy procurement portfolio could thus help the retailer not only ensure a stable and reliable supply source, but also control the cost. On the retailing side, portfolio valuation of electricity retail contracts is necessary when developing retail plans. Competitive retail plans should provide stable revenue by attracting more customers. Moreover, because of uncertain spot market prices and random end-user demands, the retailer is exposed to significant risks. Therefore, risk management is a critical element for electricity retailers when making optimal portfolio.

As the main components of portfolio evaluation for electricity retailers, the existing researches on retailer's energy procurement and retail pricing strategies are reviewed in Sections IV and V, respectively.

C. Risk Management for Electricity Retailer

Due to the volatility of spot prices and the stochastic nature of customer demands, the retailer faces profit risks when making retail decisions. Even though the retail profit is usually characterized by its expected value, the retailer needs proper risk measures to control the volatility of profit in case of suffering from extreme loss. Various risk measures and risk management strategies have been proposed and incorporated into the decision-making process of electricity retailers. In Section VI, the risk management in electricity retail market is discussed in detail.

III. LONG-TERM LOAD FORECASTING FOR ELECTRICITY RETAILERS

Load forecasting is a field in which extensive researches have been reported. Based on the forecast lead times, load forecasting problems can be generally categorized into two categories, namely short-term load forecasting (STLF) and long-term load forecasting (LTLF). STLF refers to the load forecasting with lead times of up to several weeks, which is mainly conducted for short-term power system operations. LTLF aims to forecast the future load with a longer lead-time up to a few years. LTLF is mainly used for long term system planning.

Most of the existing load forecasting methods focus on STLF, and much less researches are reported on LTLF. Various techniques for STLF have been proposed, such as artificial neural networks (ANNs) including the extreme learning machine (ELM) in [2] and [3] and the SVM in [4], the linear regression in [5], the semi-parametric additive model in [6], and the statistical method in [7]. STLF in the smart grid context is studied in [8] where the smart data collected by advanced metering infrastructure are used to improve the forecasting accuracy.

In particular, in [9] a comprehensive review of the evolution of energy forecasting practices is presented, starting from the time when Edison founded his steam-powered station. Load forecasting approaches that are proposed from the pre-PC era to current smart grid ear are summarized.

In this section, the discussion will focus on LTLF. This is due to the fact that the retailer's decision is usually made for a long period of time.

In traditional load forecasting, the aim is usually to forecast the total consumption of the whole power system or a specific node. After the market deregulation, the load forecasting of electricity retailers is becoming an emerging research topic. Comparing with the system/node level load forecasting which is less affected by the customer behaviors of changing their electricity retailers, retailer load forecasting is amore challenging problem due to the short history of electricity retail markets and the changing behaviors of customers.

Most of the existing load forecasting methods focus on STLF, and much less research reported on LTLF. To forecast the long-term consumption of a retailer, the existing LTLF approaches can also be applied after modified by adding a module of forecasting the number of consumers with electricity provided by the concerned detailer. Therefore, the long-term retailer load forecasting mainly consists of several sub-tasks: model establishment, variable selection, scenario simulation, and forecasting of the number of consumers supplied by the retailer.

A. *Forecasting Model Establishment*

Many STLF approaches are employed to solve LTLF problems with minor modifications. Multiple linear regression analysis and semi-parametric additive models are used for LTLF in [7] and [10], respectively. In [7], STLF models are modified for LTLF by adding a macroeconomic indicator. While in [10], to perform LTLF, the model is split into sub-models which represent annual effects (economic and demographic variables) and half-hourly effects (temperature and calendar variables) respectively; each sub-model is then estimated separately. In [11], a forecasting model library is established, including a logistic model, a time series approach based model, a straight model, a gompertz model, an exponential model, and a polynomial model. The model library is then combined with an expert system to accept user inputs and predefined production rules to choose the most suitable model for LTLF.

Some researchers directly apply STLF models to LTLF. This is based on the assumption that there is no significant change in the electricity consumption patterns of an ordinary residential customer over a few years. Xie *et al.* [12] used STLF techniques to do LTLF for residential customers. The only difference between their work and the traditional STLF methods is that they model the number of future customers as a factor which influences the long-term load of customers.

B. *Variable Selection*

Weather, economic, demographic, and calendar variables are the most important factors in LTLF models. Weather variables [10] could include the average temperature in last 7 days, maximum/minimum temperature in last 24 hours, temperature deviations of the same time period of previous days, temperatures of the same time period for last two days, and so forth. Economic variables [7] include macroeconomic indicators such as GSP (gross state product), GDP (gross domestic product), and GMP (gross metropolitan product). The values of these variables should be determined based on the territory covered by the LTLF. Other economic variables namely CPI (consumer price index), household sector per capita disposable income, average electricity price, and the proportion of households with an air-conditioning unit also have been used in LTLF [10]. Demographic variables could include the residential population, persons per household, and number of households [10]. Several calendar variables are usually considered, including the day of a week, holiday effect, and day of summer effect [10], [12].

In addition to the variables discussed above, other variables deriving from the interdependences among these factors could also be incorporated into LTLF models. Nevertheless, more variables do not necessarily lead to more accurate forecasting results. For a specific application, the most suitable variables are usually selected through repetitive trials.

C. *Scenario Simulation*

For LTLF, probabilistic forecasting techniques are more preferred over point forecast techniques that are often used in STLF. In probabilistic forecasting techniques, various forward scenarios of weather, economic, and demographic need to be created. Usually, the long-term economic and demographic information could be obtained from the supervisory authorities or purchased from third parties. Therefore, existing publications often focus on the simulation of forward weather scenarios.

For scenario based probabilistic LTLF, temperature data ranging from 20 to 50 years are usually used to generate weather scenarios. In [7], temperature data of the past 30 years are used to generate scenarios by combining with base, aggressive, and conservative macroeconomic scenarios, respectively. While for the density forecasting of LTLF, a large number of possible simulated series are necessary to generate accurate estimations. However, there are no enough historical data available due to the short history of the electricity retail market. To tackle this problem, a double seasonal block bootstrap method is proposed in [10]. In the method, the annual temperature data are firstly segmented into multiple blocks and each block consists of an integer indicating the number of days. Then, the simulated annual bootstrap series are generated in which each block is from the same time period of a randomly selected year. Therefore, both daily and annual seasonality of historical temperature data are preserved when generating weather scenarios. Fig. 1 [10] gives an example of the simulated yearly bootstrap series.

B1:2007	B2:2005	B3:2002	B4:2001	⋯	B17:1999
B1:1999	B2:2007	B3:2002	B4:1999	⋯	B17:1998
B1:2002	B2:1997	B3:2003	B4:2001	⋯	B17:2004
⋮					
B1:2003	B2:2003	B3:2004	B4:2006	⋯	B17:1997

Fig. 1. Schematic diagram of a demonstrated bootstrap series.

D. Consumer Count Forecasting

A fundamental element of consumer count forecasting is to model the switching activities of consumers between electricity retailers and forecast the tenured customers. Survival analysis (also known as time-to-event analysis) was introduced to analyze the customer behavior [12].

By analyzing the data of the lifetime of each customer account, the LIFETEST procedure of SAS [12] was used to derive the hazard function represented by Eq. (1), which is the probability of having the disconnection at time t given no prior occurrence of the event. After estimating the parameters in the hazard function using the life table method, the conditional probability of a customer i stay with the retailer within T_i days to stay connected for additional k days can be expressed by Eq. (2).

$$H_T = P(T = t | T \geq t) \tag{1}$$

$$S_{T_i+k|T_i} = \prod_{j=0}^{k-1} \left(1 - H_{T_i+j}\right) \tag{2}$$

Finally, the expected number of existing event-free customers that will stay connected for additional k days can be obtained by Eq. (3),

$$N^{\text{Tenured}} = \sum_{i=1}^{n} \prod_{j=0}^{k-1} \left(1 - H_{T_i+j}\right) \tag{3}$$

where N^{Tenured} is the number of loyal customers for the retailer; n is the total number of event-free customers at the beginning of the forecast.

Different from the methods discussed above, a method is presented in [13] to estimate the future load of a retailer. By using the Monte Carlo simulation technique, multiple scenarios with different load levels (low, medium, and high) are generated. Then, various portfolios of strategies for estimating loads of retailers, including overestimating, underestimating, always using a median estimated value and always using the maximum estimated possible, are evaluated while taking into account the cumulative track record of the profit from previous hours. By assessing the profit distributions of the estimation strategies, the best strategies can be finally selected.

IV. Energy Procurement Strategy for Electricity Retailers

When determining the optimal procurement strategy, the retailer first needs to identify available energy sources, which mainly include the electricity spot market and futures market. Various internal and external factors are incorporated into the decision process of retailers, such as price trend, risk management strategies, end-user demand, and market competition. Then the retailer establishes its optimal energy procurement portfolio after the calculation using preferred procurement optimization approaches. In particular, the energy procurement process consists of following parts.

A. Sources of Electricity Supply and Involved Markets

As a middleman between the generation company and customer, the electricity retailer purchases electricity from various sources and then sells it to customers. In [14]–[18], the retailer supplies consumer demands by purchasing from the spot market, forward contracts, call options, and self-production facilities. Interruptible load contracts that allow the retailer to interrupt part or all of the electricity supply to customers over some periods of time can also be introduced. In [19], the electricity procurement of a retailer is modeled as an investment problem where the retailer invests in both the whole sale electricity market and financial market. In most of the existing publications, energy storage units are rarely considered in the energy procurement decision-making process. In [20], energy storage units owned by the retailer are considered and scheduled in the procurement strategy optimization in the energy market.

Retailers can acquire the consumer demand from various sources, but they need to participate in the bidding process of the spot market through submitting their bidding curves. In [21], retailers submit hourly price-quantity bidding pairs to the spot market for purchasing and conduct real time balancing either through trading in the regulation spot market or using the self-production facility. Aiming at maximizing the profit, when offering retail plans for customers, spot market indexed contract and TOU price based contract are considered, respectively. In [22], it is supposed that the retailer also submits hourly price-quantity bids to both the day-ahead and intraday markets. Given the forecast of consumer loads, the bidding model is built by minimizing the purchasing cost at the sequential trading opportunities in the joint market.

B. Factors Influencing Energy Procurement

The energy procurement strategy of a retailer is influenced by several uncertain factors in electricity markets, such as spot prices, demand elasticity of customers, and the competition among retailers. These risks need to be properly measured to quantify their impacts. As the demand elasticity and competitions in the retailing market will determine the total load served by the retailer, a few approaches have been proposed to model their impacts on the procurement strategies.

1) Uncertain Factors: In the retail market, uncertainties are mainly from the prices in the spot market and customer demand. Various methods have been proposed to model the dynamics of electricity prices in the spot market by considering the price characteristics such as seasonality, time-varying volatility, mean-reversion, and jumps and spikes [14].

The probabilistic processes of the electricity price and customer demand are considered to be independent [14], [19] and correlated [16]–[18], respectively. Normal distribution is the most common one for modeling the electricity price and customer load due to its simplicity [17], [23]. Other models have also been used, including the GARCH-jump model [14], GARCH model [14], mean-reverting Ornstein-Uhlenbeck stochastic process [16], and envelope bound model [18].

However, the electricity price and customer demand are not always assumed to follow a particular probabilistic distribution. For example, when applying the robust optimization approach to develop optimal energy procurement strategy, it would be only necessary to know the estimated boundaries of the random variables.

2) Risk Measurement: The problem of developing an optimal electricity retailing strategy can usually be formulated as a multistage stochastic optimization problem, which could be nonlinear, non-convex, and the stochastic variables are not always assumed to follow the normal distribution. This would lead to the failure of risk measures such as variance in measuring the risks faced by retailers. In contrast, as a coherent risk measures, CVaR (conditional value-at-risk) is an alternative to VaR (value-at-risk), which overcomes the disadvantages of VaR and has been widely used in risk management for electricity retailers [14], [16].

Other risk measures have also been used, including the risk adjusted recovery on capital (RAROC) and expected downside risk (EDR). In [15], a risk measures called RAROC which indicates the ratio between the expected investment return and economic capital is introduced to quantify the risk of signing different bilateral contracts for a retailer. When the loss function is convex, EDR is convex. Due to this merit, EDR is employed in [17] and [18] to measure the risk associated with a decision by its failure to meet the predefined targeted profit.

3) Demand Elasticity of Customers: Several functions have been used to represent the price elasticity of demand, such as the linear function [24], [25], power function [21], [26], [27], and stepwise function [28]. Among these methods, the stepwise function namely a stepwise price-quota curve is the most commonly one.

In [17], [18], and [23], demand elasticity is modeled through a stepwise price-quota curve, which describes the amount of electricity that a customer is willing to buy at a certain price. Meanwhile, this stepwise price-quota curve also describes the switching activity of customers among retailers when facing different retail pricing schemes.

In the above mentioned publications, demand elasticity is modeled as a function of the electricity price only. By taking into account external variables (e.g., outdoor temperature), the demand price elasticity is modeled by finite impulse response (FIR) models in [29] and [30]. In [30], both linear and nonlinear FIR models are derived to capture the demand price elasticity. In order to estimate the coefficients in the FIR models, recursive and adaptive estimation is employed.

In modelling the demand elasticity, there are difficulties related to collect information about the load schedule and utility function of an individual. It is even harder when end users have privacy concerns. To overcome this problem, in [31] the utility function of a responsive load is modelled by a parametric stochastic process and the parameters are estimated through statistical analysis of load variances under different RTP scenarios. However, the proposed statistical demand elasticity model is only useful for aggregated loads.

Unlike other studies in which an assumption about the demand elasticity function is often a prerequisite, data-driven methods that do not require such an assumption are proposed in [32] and [33].

As is well known, a typical optimization problem is a forward problem because it identifies the values of observable parameters (optimal decision variables), given the values of the model parameters (cost coefficients, right-hand side vector, and the constraint matrix). On the contrary, an inverse optimization problem is to infer the values of the model parameters (cost coefficients, right-hand side vector, and the constraint matrix), given the values of observable parameters (optimal decision variables) [34].

In [32], the inverse optimization is the first time adopted to infer the feasible region of price-responsive demand in aggregator's optimal consumption decision model. The main merit is that it does not require any assumption about the expression of the price-responsive load. The deferrable demand is described by a series of quadruples, namely the lower and upper limits of consumption power and cumulative energy for each load. Using above mentioned deferrable demand model, a cost minimization model is built for aggregators to make optimal consumption decision. Through generating simulated price-consumption data, the inverse optimization method is used to solve the aggregator's decision model to reveal the feasible region of price-responsive load demand. Besides, a data-driven pricing model for the utility is formulated based on the estimated price-responsive demand.

Similarly, the parameters of price responsive demand are also estimated through inverse optimization in [33]. However, some external variables that can potentially affect the electricity consumption are considered, such as temperature, solar radiation, and wind speed. These external variables are incorporated into the model by using the affine functions.

4) Competition Among Electricity Retailers: Except for the stepwise price-quota curve, the market share function introduced from the econometrics is another way to model the competition of retailers. In [14], the market share function indicating the percentage of the overall load that can be served by the retailer at different prices is adopted.

Instead of using the stepwise price-quota curve and market share function, Karandikar *et al.* [15] consider the situation that a part of total load is switchable. The retailer who has lower bids will win the switching load.

C. Procurement Optimization Approaches

Up to now, a variety of models and approaches on energy procurement optimization have been proposed, which can be categorized as follows.

1) Stochastic Optimization Models: A mixed-integer stochastic programming model is proposed in [14] to determine both the optimal retail pricing and procurement strategy for a given retailer by considering the risk and competitions among retailers. In [23], an optimal strategy composed of a medium term planning model and a short term planning model is presented. The medium term planning is modeled as a stochastic optimization problem where the energy purchased from forward contracts and electricity retail price are determined. Given decisions determined in the medium term model, in the short-term model, the interruptible load contract and the amount of energy procured in the spot market are optimized.

Scenario based stochastic optimization models are proposed in [16], [17], and [35] to generate the random scenarios of electricity price and customer demand. Various scenario generation techniques, i.e., scenario tree [16], Roulette wheel mechanism and lattice Monte Carlo simulation (LMCS) [17], are employed to generate scenarios over the planning horizon, respectively.

In [35], stochastic programming is used to model the medium-term decision making problem faced by a distribution company (DisCo). The DisCo is equivalent to an electricity retailer, but it also takes in charge of the operation of distribution networks. Therefore, the studied DisCo not only deals with the portfolio evaluation and retail pricing, but also considers the economic operation of distribution networks. Scenario generation and reduction techniques are used to transform the stochastic model into a deterministic problem. The nonlinear terms are linearized through the piecewise linear approximation. Finally, the proposed model is formulated and solved as a mixed integer linear programming (MILP) problem.

In [36], the impacts of various retail prices on DisCo's forward contract scheduling are studied. The stochastic decision making framework is established to simulate DisCo's decision making processes. Different retail pricing schemes including flat, TOU, and RTP prices are considered, respectively. The results show that RTP rates provide the most benefits to DisCos, since RTP can directly pass DisCo's risk to customers. TOU rates can also bring high profits but it has no significant impact on risk exposure. Besides, amounts of forward purchases required for risk management are almost identical when adopting flat and TOU schemes.

2) Bi-Level Optimization Models: Unlike the research work reported in [14]–[18], [23] which study the medium-term or long-term procurement strategies for electricity retailers, the decision-making problem of the retailer is represented by a two-stage model in [20]. The decision variables in [20] include the day-ahead retail prices, operational strategies of energy storage units, and energy contracts. In the first stage, a Stackelberg game is established and a bi-level programming problem is formulated, where the retail price determination problem and customers' energy consuming pattern identification problem are modeled in the upper and lower levels, respectively. In the second stage, another bi-level model is formulated. The operations of energy storage unit are optimized in the upper level model and the lower level model is the same with that in the first stage.

3) Models Based on Other Theories: In [18] and [37], the information gap decision theory (IGDT) based electricity procurement models are proposed. The envelope bound model and info-gap model are used to model the uncertainties of parameters, respectively. These models can produce both a robust strategy and an opportunity strategy depending on the risk-averse degree of retailers. The robust strategy is immune against losses or low profit due to unfavorable deviations of spot prices from the forecasted values. While the opportunity strategy enables a risk-seeker retailer to benefit from these favorable variations.

A mean-variance investment model is developed in [19] to seek optimal decisions for a retailer. The retailer is modeled to allocate a part of the associate wealth to purchase electricity from the utility company concerned for reselling and to allocate the remaining wealth in the financial market.

V. Retail Pricing Strategy for Electricity Retailers

Widly adopted retail pricing schemes in real world are investigated and summarized in [38]. Retail pricing schemes are categorized by their rate structures in which prices vary on an hourly, daily, or longer time-period basis, respectively. Specifically, hourly pricing includes basic hourly pricing which is directly indexed to hourly wholesale energy prices, block and index pricing, two-part RTP, and unbundled RTP with self-selected baseline load. Daily pricing includes the day-type TOU rate, variable peak rate, critical peak pricing (CPP), variable CPP, CPP linked to a standard tariff, and peak-day rebate. Other pricing schemes are also included, such as the fixed TOU pricing and seasonal flat pricing. For each category of retail prices, price description, principles for setting the prices, and examples of implemented versions are elaborated. Besides, the advantages and drawbacks of above mentioned time-based price structures are discussed in detail. Readers interested are advised to refer to [38] for further information.

With the fast development of smart grid technologies in recent years, some trial real-time retail pricing programs have been reported and viewed as a future trend [19]. One demerit of RTP is that it directly exposes end-users to the price fluctuation risks. Therefore, it is difficult for small electricity customers to accept the RTP scheme. As a pricing scheme falling in between flat pricing and RTP, time-of-use (TOU) pricing is widely adopted in practice [39]. There are also other pricing schemes developed by combing RTP and TOU pricing schemes. For convenience, here the term 'dynamic pricing' is used to denote the pricing schemes which are time-varying, and the term 'static pricing' refers to the pricing schemes which are pre-determined. The state-of-the-art of researches on these two classes of pricing schemes is summarized as below.

A. Dynamic Pricing Schemes

Various dynamic pricing schemes with different update cycles, such as 5 minute, 15minute and hourly, have been explored in existing publications. The market structure, volatility and trading mechanisms are the issues that need to be considered in designing new pricing schemes.

1) Architecture Design of Real-Time Pricing Market: With the advent of smart grids, real-time customer participation and electricity pricing are proposed. In actual operating electricity markets, these changes can be incorporated if the pre-requirements can be met.

In [40], a new bid-free real-time electricity market structure is proposed. Consumers and producers respond to the real-time signals by properly adjusting their consumption and production comparing with the day-ahead schedule. Then the transmission system operator (TSO) dispatches the real-time adjustment as balancing power in the regulating power market. Different from the centralized optimization method used in [40], in [41] a decentralized mechanism is proposed. In a multiple micro-grid system, the pricing problem is initially modeled as a centralized social welfare maximization problem. Through dual decomposition, the initial model is transformed into a non-cooperative game. Players in the game make decisions to maximize their own profits after receiving real-time prices from the ISO. It is proved that an elaborately designed subsidy function can ensure the existence of the Nash equilibrium of the non-cooperative game, and the Nash equilibrium coincides with the solution of the original problem.

Similarly, a distributed dynamic pricing scheme is presented in [42] based on a bidirectional communication network in the smart grid. Smart end users timely communicate with the regional control center through the community gateway installed within each community network and used for electricity usage collection and price indication. All the exchanged data are encrypted to protect the privacy of end users. Community gateways receive pre-defined parameters from the regional control center to dynamically differentiate peak and off peak periods, calculate real-time prices, and send the price signals to end users. Through enhanced encryption, the proposed scheme can protect the privacy of customers at a relatively high level.

2) Market Volatility Analysis Under Dynamic Pricing: Exposing retail consumers to the real-time electricity pricing mechanism will create a closed-loop feedback system and may also increase the market volatility. The influence of real-time pricing on market volatility is studied in [43]. Based on several assumptions, a theoretical framework for modelling and analyzing the dynamics of suppliers, consumers and the ISO is proposed. Several stability criteria are selected based on the Lyapunov theory and contraction analysis to conduct stability, invariance and volatility analysis. The theoretical analysis suggests that market volatility is linked to the ratio between the price elasticity of consumers and that of producers. The electricity market will become more volatile as the ratio increases.

3) Bi-level Real-Time Retail Pricing Models: Optimization problems constrained by complementarity and other optimization problem are appropriate for describing the interactions among market participants. Therefore, they are widely used to model the functioning of energy markets. Generally, if the lower-level optimization problems constraining the upper level problem are convex, they can be replaced by their corresponding Karush-Kuhn-Tucker (KKT) optimality conditions. All the mathematical models with complementary constraints are called complementarity problems. In [44], the applications of complementarity models in the energy market are comprehensively elaborated.

The problem of setting the day-ahead hourly retail price is studied in [20] and [45]. They both use the Stackelberg game to model the interaction between the retailer and its customers, and two- and single- stage games are established in [20] and [45], respectively. Different solving methods are adopted. In [20], the two-stage model is transformed into a mixed integer linear program, while in [45] the Pareto front of the consumer surplus vs. retail profit tradeoffs is generated.

When using the bi-level optimization to set retail prices, the pricing model often focuses on the interaction between the retailer and customers, and the merits are also manifold. Firstly, bi-level optimization can properly model the hierarchical decision process faced by the retailer in the hierarchical electricity market, i.e., wholesale and retail electricity markets. Secondly, customer load demand is determined through solving the lower level model instead of adopting an aggregated random variable (such as the approach in stochastic optimization model). Therefore, components of residential load can be more accurate.

However, there are also drawbacks. In the bi-level optimization, since load demand is determined through optimization, it fails to reflect the risk of uncertain electricity consumption in the final retail price. What's more, the lower level of the bi-level optimization needs to be properly modelled to be convex. If not, analytical tools for solving the complete hierarchical problem usually do not exist. If the lower-level problem is convex, it can be replaced by their corresponding KKT conditions. Then the bi-level optimization problem is transformed into a complementarity model.

Diverse linearization techniques are available to further transform the complementarity model into a mixed-integer linear programming problem (MILP), such as the Fortuny-Amat McCarl linearization [46], SOS1 and Penalty Function Linearization (Special Ordered Sets of Type 1 variables, SOS1 variables) [47], and other linearization methods based on exact algebraic transformations [44]. Only in a few literatures, the lower level is directly modelled as a linear and convex programming model like in [48]. In [20], the duality theory is used to linearize the lower level max-min problem. Non-linear complementarity constraints, which are derived from KKT reformulation, are linearized into linear disjunctive constraints through Fortuny-Amat McCarl linearization.

Besides, due to the flexible charging strategy and energy storage, an electric vehicle (EV) is viewed as a special load in the power system. Retail pricing for EV charging is studied in [48] and [49], the bi-level programming and stochastic optimization are used respectively to establish the retail pricing models. In [48], bilinear terms in the lower level model is linearized by discretizing the variable with reasonable granularity. After recasting the bi-level optimization into MILP, the problem can be easily solved using various off-the-shelf commercial solvers. In [50], the effect of CO_2 emission on retail pricing is addressed. The CO_2 emission tax is incorporated into wholesale market clearing models. As dynamic retail prices are linked to the wholesale market clearing price, two dynamic pricing strategies, i.e., critical peak pricing and RTP, are used to test the proposed method.

B. Static Pricing Schemes

There are various static pricing schemes, e.g., stepwise pricing, critical peak pricing, demand reduction programs and TOU. In [51], a stepwise power tariff (SPT) model for residential customers is proposed. However, the existing related publications are mainly devoted to the TOU pricing. The state-of-the-art on TOU pricing can be categorized as below.

1) Stochastic Programming Models: By modeling the uncertain factors with ARMA (autoregressive moving average model) [24], ARIMA (autoregressive integrated moving average model) [28], or scenario based method [26], [52], [53], stochastic programming models can then be built to maximize the profit of the retailer while minimizing the risk, or to maximize the total social welfare. The risk and expected profit are usually merged into one objective by adding a weighting factor. Moreover, constraints associated with forward contracts, elasticity of demand, and energy balance are also considered.

2) Equilibrium Models: The pricing problem in the retail market is modelled as an equilibrium problem of supply and demand in [27] and [39]. In their works, the objective of the supply side is modelled to minimize the total operating costs of generation facilities or to maximize the retailer's profit. And on the demand side, the customer demand is represented by demand equations that use the electricity price and lagged demand as independent variables. The objective of equilibrium model in [54] is to maximize the electricity supplier's profit.

3) Game-Theoretic Models: Unlike other publications where end-users have slow response, in [55] a game-theoretic model is proposed to optimize the TOU pricing strategies, where end-users are supposed to response immediately. In the model, the objective of the utility is to maximize its profit by taking into account the cost from the end user demand fluctuations. By using the backward induction, Nash equilibrium of the model is obtained.

VI. Risk Management in Retail Markets

It is generally agreed that the volatility of spot price and the stochastic nature of customer demand are two main risk sources for the electricity retailer. In addition, the risks arising from the sale contract maturity are considered in [56]. In most of the existing publications, after identifying the risk sources, CVaR is used to model the risk in the retail price determination process. The wide applications of CVaR are due to its satisfaction of properties of monotonicity, sub-additivity, homogeneity, and translational invariance [14]. Moreover, CVaR exhibits good mathematical properties and can be easily handled by using scenario based simulations [52].

To manage the risks faced by the retailer, several risk management strategies have been incorporated into the determination process of electricity retail prices.

A. Considering Risks in Retail Pricing Models

The objective of existing pricing models is often to maximize the sale profit of the retailer while minimize the risk. Therefore, the pricing model could be formulated as a multi-objective optimization problem. In [24], [28], and [57], multi-objectives are transformed into a single objective by incorporating the CVaR into the expected profit function of the retailer through a weighting factor, which reflects the risk aversion degree of retailers. By assigning different values to the weighting factor, the trade-off between the expected profit and the risk can be made in the final pricing scheme.

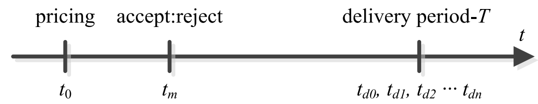

Fig. 2. Schedule from pricing time to the start of the delivery period [56].

B. Risk Premium Determination

Through incorporating CVaR into the expected profit function, the process of solving pricing models can be simplified. However, in many of existing works [24], [28], [57], the risk premium and retail price are coupled together. In [56], the risk premium from the contract-offer maturity is modelled, where the contract-offer maturity means the period from the time when the retailer sets the offer price for the consumer to the time when the consumer decides whether to accept or reject it, as shown in Fig. 2. Firstly, for the contract-offer with a maturity of t_m days, its difference with the zero-day maturity offer is calculated. Then, the risk premium $R_p(t_m)$ of the offered retail contract is derived by Eq. (4).

$$R_p(t_m) = \frac{R_{CVaR}(t_0) - R_{CVaR}(t_m)}{\sum_T E[D_d]_{t_0}} \tag{4}$$

where $R_{CVaR}(t_0)/R_{CVaR}(t_m)$ is the CVaR applied to the offer with a maturity of zero-day /t_m days; D_d is the expected electricity consumption in the delivery period forecasted at t_0; T is the length of the retail contract.

C. Establishment of a Derivatives Portfolio

In [58] and [59], the employment of derivatives to hedge the risk for generators and retailers is studied. To evaluate the appropriateness of different forward price forecasting methods in the marking-to-market process for determining the value of the derivative portfolio, two criteria are proposed. Based on the two criteria, a time series model and consensus forecast issued by the AFAM (Australian Financial Market Association) are evaluated and compared in details. In [59], different types of electricity financial and physical instruments are reviewed, including the electricity forwards, futures and swaps, electricity options, structured bilateral transactions, and financial derivatives on electricity transmission capacity. Followed by this, various risk management applications are discussed when utilizing such instruments to mitigate risks in electricity market.

VII. Evolution of Retail Strategy and Future Discussion

Due to the continuous restructuring and rising customer awareness, customers are able to switch among different retailers without any penalty. This allows customers to choose their most favoured retail contracts, which consequentially leads to a more competitive retail market. In the future electricity market, the retailer will see more opportunities, but also faces more technical and commercial challenges. Potential research directions related to electricity retailing are discussed in this section. Clearly, they are not restricted to the ones discussed hereafter.

A. Long-Term Retailer Load Forecasting

Up to now, only a few publications are aimed at studying the long-term retailer load forecasting problem. LTLF remains a challenging problem in power systems owing to various uncertain factors that drive electricity demand variations. Some researches have been carried out on commercial and industrial loads [7], [10], [11], [13]. However, in these publications STLF or modified STLF approaches are applied to solve LTLF. Long term load forecasting for residential users is studied in [12]. However, the research in [12] is based on the assumption that there is no significant change in electricity consumption patterns of residential customers. Therefore, in [12] the STLF techniques are directly used to forecast the long term demand of residential customers. The only difference between their works and the traditional STLF is that they model the forward customer count as a factor which influences the long-term customer load.

As a powerful method in the learning system, artificially neural network (ANN) based methods are widely used for STLF and electricity price forecasting in power systems. Especially, the extreme learning machine (ELM) is a new and popular one. Various modified versions of ELM algorithms have been developed and used. The ensemble ELMs are leveraged in [2] and [3] to conduct STLF, where individual ELMs are incorporated into one predicting model following specific ensemble schemes to improve the overall forecasting accuracy. The ELM, generalized extreme learning machine (G-ELM), and evolutionary extreme learning machine (E-ELM) are adopted respectively in [60]–[63] to construct accurate electricity prices forecasting methods. In [4], a review of some known ANN for load prediction in electric power systems is presented. The efficiency and performance of decay radial basis function neural network, support vector machine (SVM), and ELM in load forecasting are investigated.

Up to now, there is no novel forecasting method proposed for the long term residential load forecasting. With the emergence of smart grid technologies, there are increasing measurement data available from the low-voltage end-user side. These measurement data enable better understanding of the load composition and electricity consumption activities of end users. Since load profiles contain information about electricity consumption behaviour of end users, the development of behaviour analysis based methods will therefore be a promising research direction for long term residential load forecasting.

B. Structure Optimization of Electricity Retail Prices

In existing publications, the structure of TOU pricing is often assumed to be pre-determined in advance [24], [28], [55]. Without optimization of the retail pricing structure, these approaches cannot appropriately utilize the temporal difference between the system load and supplied load of a retailer. However, the temporal difference plays an essential role in developing flexible pricing schemes. The research work in this area is still preliminary, and how to appropriately model and customize electricity retail prices in the smart grid environment still remains an open question.

C. Customized Electricity Retail Plans

With the deployment of advanced metering and information techniques in power systems, more valuable information about end users could be collected. In the smart grid context, smart meter data would make it possible to model customer load at finer granular levels. Electric appliance identification is one of the applications to make use of smart meter data for big data analysis and enhance load modelling in future grid.

Different from load disaggregation which only classify load into different load categories (such as resistive loads and three-phase constant and quadratic torque induction motors) by their load characteristics [64], electric appliance identification aims to exactly recognize what exactly the power consumption equipment is. Depending on the methods of collecting load data, there are two kinds of appliance identification methods in existing research, namely intrusive load monitoring (ILM) [65] and non-intrusive load monitoring (NILM) [66]–[68]. In ILM, traces of appliances are firstly collected by the distributed measurement and actuation units (MAUs) and then stored in a database system. Secondly, the features of each appliance are extracted from the input traces, which include energy and power consumption levels, the shapes of the load profiles and so on. Finally, after choosing a proper classifier and training it with the features extracted above, namely through supervised learning, the appliances can be identified.

On the contrary, NILM only relies on a single measurement unit for a household's overall electricity consumption. Generally, NILM approaches include both supervised and unsupervised approaches. Supervised methods need the prior knowledge of electric devices to form the signatures for individual devices. Then optimization or pattern recognition based algorithms can be used for NILM. For unsupervised approaches, various methods based on particle filter (PF) and hidden Markov models (HMM) are proposed, such as the particle filter based load disaggregation (PALDi) in [69]. In [69], firstly, the probability density function (PDF) of appliance states, which may be on/off or multi-state, is estimated by PF according to previous observations. Then, each appliance is modelled by a hidden Markov model (HMM). Individual HMMs are combined together to form the factorial hidden Markov model (FHMM). The observation of the FHMM is namely the total household demand.

Through mining smart meter data, load modeling and forecasting can be more accurate. The retailer will also be able to capture detailed properties of customers such as their consumption characters, responsiveness to various retail strategies and even to conduct behavioral economic analysis of customers. Moreover, the interactions between the retailer and customers will be more frequent considering that the real time electricity price can be easily offered using the smart meters.

Offering a variety of pricing options to customers is an essential feature of competitive markets and a key method to attract end-users. Through utilizing the complementation between different customer types, customized retail plans can further motivate responsiveness of end-users. Up to now, less research has been reported on this topic, which could be thus considered as an open research direction in the next-generation energy market.

D. Management Strategy for Large-Scale Flexible Loads

The increasing penetration of intermittent renewable energy and installations of distributed generation and storage facilities are gradually changing the original single direction energy flow in the power system. Therefore, the retailer is experiencing a transition from an energy seller to an energy service provider. The retailer will get involved in business on both selling energy and offering services to local distributed facilities. In the retailing side of electricity market, operational frameworks are also needed to help customers locally balance their energy need and manage an optimal portfolio of their own distributed devices.

Due to customers' random consumption behaviours and the competition in electricity markets, uncertainties exist in the load demand and electricity price. If these uncertainties can be forecasted and managed well, it can help to reduce electricity cost and system peak demand. It's also beneficial to make better planning of power systems. In [70], smart meter data are used to forecast customers' consumption uncertainty. An additive quantile regression model for load forecasting is proposed and the model is estimated using the gradient boosting algorithm.

Flexible load is an ideal way to manage the uncertainties in power systems. In [71] and [72], flexible load and energy storage system are used to reduce electricity cost and balance power demand while considering the uncertainties of renewable energy. The electricity cost is reduced by shifting electricity consumption from high to low price periods when facing electricity uncertainties in [71]. In [72], the problem of power balancing in a renewable-integrated power grid with storage and flexible loads is studied. In order to improve computation efficiency and reduce communication overhead, a distributed power balancing solution is proposed.

With the increasing number of flexible loads in the smart grid, such as the electrical vehicles, thermostatically controlled loads, air conditioning loads, and water-heating systems, coordination strategies and pricing schemes are needed to optimally leverage their benefits to the power systems.

The mean field game theory studies the problem of strategic decision making in very large populations of small interacting individuals. In mean field games, the players are coupled through a mean field term which depends on the statistical information of all players' decisions. When the number of players is large, the coupled decision making can be captured by the interactions between an individual player and the mean field term instead of the detailed interactions among all the players.

In [73] and [74], this theory has been proven to be efficient to model the behaviour of large scale agents when constructing control framework and pricing schemes for flexible loads.

In [73], the scheduling of electrical vehicles' (EVs) charge is studied when the number of vehicles tends to infinity. It is presumed that all EVs are indistinguishable by having similar batteries and similar individual objectives. The objective of each EV is to determine its own consumption rates that minimize its total cost, given the consumption rates chosen by all the other EVs. The interaction among these infinite EVs is modelled as a mean field game. In the established model, all the EVs are coupled through the empirical distribution of battery state variables, which indicate the amount of energy stored in the battery of each EV. In order to get the mean field equilibrium, the fundamental differential equations describing the mean field equilibrium of the game, i.e., Hamilton-Jacobi-Bellman and Fokker-Planck-Kolmogorov equations, are derived.

In [74], the pricing problem for a large population of thermostatically controlled loads (TCL) is studied. The thermal dynamics of TCLs are modelled using the first-order continuous-time Equivalent Thermal Parameter (ETP) model. Each TCL load is optimized to maximize its individual utility. All the TCLs are coupled through a pricing function, namely the mean field term. The price is modelled as depending on the average value of all TCLs' decisions. Then the individual utility maximization problem forms a mean field game at the lower level. And also, a coordinator is modelled as a leader in the upper level with its objective to maximize the social welfare. The whole problem is formulated as a reverse Stackelberg game, and solved through connecting it to a team problem and the competitive equilibrium.

Besides, some other researchers study the operational planning strategies of customers in the presence of distributed energy resources. In [75], a retail electricity market framework with high penetration of distributed generation is proposed. In the proposed framework, residential customers locally operate and manage their distributed generators (DGs), distributed energy storage devices (DESDs), and dispatchable loads. The utility makes profits by selling electricity and providing ancillary services to residential customers. Even though some researchers have noticed this problem, there is still a significant room for studying the management strategy for distributed large-scale flexible loads.

E. Data-Driven Retail Pricing Algorithms

With the emergence of smart grid technologies, there are increasing measurement data available from the low-voltage end-user side. Therefore, big data analytics in smart gird is of great importance. Through data mining, the retailer can gain a better understanding of the load composition and electricity consumption activities of end users. Big data analytics can also help retailers to develop data-driven based pricing algorithms. In [76], the special section of big data analytics for grid modernization on IEEE transactions on Smart Grid is introduced in detail. Papers associated with big data analytics for modernizing the electric power grid are presented. The guest editor also pointed out that potential research opportunities lay in areas including data visualization, data-driven dynamic pricing, predictive asset management, and customer analytics. In [77], an overview discussion of the big data management and analysis in the smart grid is presented. The basic requirements of the big data analysis and the emerging bid data analysis technologies in the smart grid are introduced.

Based on big data analysis, more sophisticated energy retail policies can be made through analysing the energy usage data of the users. A variety of cloud computing platform and the data-centric data storage technology could be utilized to aggregate the energy usage data of the users, which could be generated by the advanced measurement infrastructure (AMI) in a smart grid or the load monitoring techniques. The data mining techniques could be then employed by the retailer to extract the energy usage characteristics and patterns of end-users. In data mining, the cloud plat-forms proposed in [78] and [79], and the MapReduce framework in [80] can be employed to improve the mining performance. Then the retailer can design highly customized incentive schemes that mostly fit the individual users.

A reinforcement learning based retail pricing algorithm is developed in [81]. The dynamic pricing problem for the electricity provider is firstly formulated as a Markov decision process (MDP). In order to solve the MDP, the well-known Q-learning algorithm is then chosen to search for the optimal action-selection policy both for the electricity provider and customers. In the MDP, the action of the electricity provider is to choose the optimal retail pricing policy aiming at minimizing its total cost. For the customers, their action is to decide electricity consumption based on observed retail price while aiming at minimizing the expected long-term electricity cost. The main merit is that the customer can determine its energy consumption in a distributed manner without a priori information exchange with the electricity provider and other customers.

Another research trend is to employ game-theoretic machine learning to develop retail pricing schemes. In [82], a game-theoretic machine learning approach is proposed for learning the best auction mechanism for sponsored searches. The proposed approach combines machine learning and game theory and its mathematical formulation is a bi-level optimization model. In the lower level, the Markov process is used to model advertisers' bidding behaviours. In the upper level, the objective is to maximize the revenue of the search engine. When learning the optimal auction mechanism for the search engine, advertiser's future bids are predicted using the learnt Markov model.

To some extent, the pricing problem for an electricity retailer is similar to that in [82], where the electricity consumer's consumption activity is the lower problem and the retailer's retail revenue is the upper problem. However, due to the bidding difference between the electricity market and that for search engine, special endeavours are needed to develop the corresponding machine learning approaches for electricity retailing.

TABLE I
THE NUMBER OF PUBLISHED PAPERS ON EACH DISCUSSED SUB-TOPIC FROM 2000 TO 2016

Sections in the paper	Discussed Sub-topics	Surveyed References	# of Published Journal Papers
Section III	Load forecasting	[2],[3],[4],[5],[6],[7],[8],[9],[10],[11],[12] ,[13]	887
	Long term load forecasting	[10],[11],[12] ,[13]	61
Section IV	Retail electricity procurement	[14],[15],[16],[17],[18],[19],[20],[21],[22],[23],[24],[25],[26],[27],[28],[29],[30],[31],[32],[33],[35],[36],[37]	53
Section V	Retail pricing	[38],[39],[40],[41],[42],[43],[45],[48],[49],[50],[51],[52],[53],[54], [55]	77
Section VI	Electricity risk management	[14],[24],[28],[52],[56],[57], [58],[59]	191
Section VII	Machine learning in forecasting	[60],[61],[62],[63]	93
	Load disaggregation	[64],[65],[66],[67],[68],[69]	25
	large-scale flexible load management	[70],[71],[72],[73],[74],[75]	17
	Big data in smart grid	[76],[77],[80]	47

VIII. CONCLUSION

To help researchers have an overall understanding of the existing research work on decision-making of electricity retailers, researches on electricity retailing in the last two decades are surveyed and discussed in this paper. The state-of-the-art of the long-term retailer load forecasting, energy procurement strategies, retail pricing schemes, and risk management in the retail market have been discussed respectively, which cover the entire decision-making process of the electricity retailer.

In Table I, the number of published papers in recent years on each sub-topic discussed in this survey is presented. During the period from 2000 to 2016, the topic of load forecasting has the highest number of publications, but only a small portion of these researches are devoted to LTLF. Therefore, novel LTLF techniques are still needed until now. Among all the sub-topics, retail pricing is of great importance and also attracts the high research interests, which can be verified by the number of published papers. From the literature survey, we found that the electricity procurement problem and the retail pricing for the retailer are always coupled together. Electricity retailers usually optimize their purchasing strategies and develop optimal retail contracts simultaneously.

Risk management has always been an important topic in competitive electricity markets. Risk measurement is considered in almost every decision-making process of the retailer. Various methods in the surveyed literatures have been proposed for the retailer to control their profit risks, such as the futures contract, flexible load, dynamic retail pricing, and the risk premium in retail prices.

In terms of future research trends, the sub-topics concerning the machine learning in forecasting, load disaggregation, large-scale flexible load management, and big data in smart grids are reviewed. The open issues that should be addressed in this field are critically discussed as well.

References

[1] A. J. Conejo, M. Carrión, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets* (International Series in Operations Research and Management Science). New York, NY, USA: Springer, 2010.

[2] S. Li, P. Wang, and L. Goel, "A novel wavelet-based ensemble method for short-term load forecasting with hybrid neural networks and feature selection," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 1788–1798, May 2016.

[3] R. Zhang, Z. Y. Dong, Y. Xu, K. Meng, and K. P. Wong, "Short-term load forecasting of Australian National Electricity Market by an ensemble model of extreme learning machine," *IET Gener. Transm. Distrib.*, vol. 7, no. 4, pp. 391–397, Apr. 2013.

[4] C. Cecati, J. Kolbusz, P. Różycki, P. Siano, and B. M. Wilamowski, "A novel RBF training algorithm for short-term electric load forecasting and comparative studies," *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6519–6529, Oct. 2015.

[5] T. Hong and P. Wang, "Fuzzy interaction regression for short term load forecasting," *Fuzzy Optim. Decis. Making*, vol. 13, no. 1, pp. 91–103, Mar. 2014.

[6] Y. Goude, R. Nedellec, and N. Kong, "Local short and middle term electricity load forecasting with semi-parametric additive models," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 440–446, Jan. 2014.

[7] T. Hong, J. Wilson, and J. Xie, "Long term probabilistic load forecasting and normalization with hourly information," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 456–462, Jan. 2014.

[8] F. L. Quilumba, W.-J. Lee, H. Huang, D. Y. Wang, and R. L. Szabados, "Using smart meter data to improve the accuracy of intraday load forecasting considering customer behavior similarities," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 911–918, Mar. 2015.

[9] T. Hong, "Energy forecasting: Past, present, and future," *Foresight Int. J. Appl. Forecast.*, no. 32, pp. 43–48, 2014.

[10] R. J. Hyndman and S. Fan, "Density forecasting for long-term peak electricity demand," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1142–1153, May 2010.

[11] M. S. Kandil, S. M. El-Debeiky, and N. E. Hasanien, "Long-term load forecasting for fast developing utility using a knowledge-based expert system," *IEEE Trans. Power Syst.*, vol. 17, no. 2, pp. 491–496, May 2002.

[12] J. Xie, T. Hong, and J. Stroud, "Long-term retail energy forecasting with consideration of residential customer attrition," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2245–2252, Sep. 2015.

[13] S. A. Gabriel, M. F. Genc, and S. Balakrishnan, "A simulation approach to balancing annual risk and reward in retail electrical power markets," *IEEE Trans. Power Syst.*, vol. 17, no. 4, pp. 1050–1057, Nov. 2002.

[14] A. R. Hatami, H. Seifi, and M. K. Sheikh-El-Eslami, "Optimal selling price and energy procurement strategies for a retailer in an electricity market," *Elect. Power Syst. Res.*, vol. 79, no. 1, pp. 246–254, Jan. 2009.

[15] R. G. Karandikar, S. A. Khaparde, and S. V. Kulkarni, "Strategic evaluation of bilateral contract for electricity retailer in restructured power market," *Int. J. Elect. Power Energy Syst.*, vol. 32, no. 5, pp. 457–463, Jun. 2010.

[16] J. Kettunen, A. Salo, and D. W. Bunn, "Optimization of electricity retailer's contract portfolio subject to risk preferences," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 117–128, Feb. 2010.

[17] A. Ahmadi, M. Charwand, and J. Aghaei, "Risk-constrained optimal strategy for retailer forward contract portfolio," *Int. J. Elect. Power Energy Syst.*, vol. 53, pp. 704–713, Dec. 2013.

[18] M. Charwand and Z. Moshavash, "Midterm decision-making framework for an electricity retailer based on information gap decision theory," *Int. J. Elect. Power Energy Syst.*, vol. 63, pp. 185–195, Dec. 2014.

[19] J. He, L. Cai, P. Cheng, and J. Fan, "Optimal investment for retail company in electricity market," *IEEE Trans. Ind. Informat.*, vol. 11, no. 5, pp. 1210–1219, Oct. 2015.

[20] W. Wei, F. Liu, and S. Mei, "Energy pricing and dispatch for smart grid retailers under demand response and market price uncertainty," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1364–1374, May 2015.

[21] M. Hajati, H. Seifi, and M. K. Sheikh-El-Eslami, "Optimal retailer bidding in a DA market—A new method considering risk and demand elasticity," *Energy*, vol. 36, no. 2, pp. 1332–1339, Feb. 2011.

[22] R. Herranz, A. M. S. Roque, J. Villar, and F. A. Campos, "Optimal demand-side bidding strategies in electricity spot markets," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1204–1213, Aug. 2012.

[23] M. Nazari and A. A. Foroud, "Optimal strategy planning for a retailer considering medium and short-term decisions," *Int. J. Elect. Power Energy Syst.*, vol. 45, no. 1, pp. 107–116, Feb. 2013.

[24] A. Hatami, H. Seifi, and M. K. Sheikh-El-Eslami, "A stochastic-based decision-making framework for an electricity retailer: Time-of-use pricing and electricity portfolio optimization," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 1808–1816, Nov. 2011.

[25] S. A. Gabriel, A. J. Conejo, M. A. Plazas, and S. Balakrishnan, "Optimal price and quantity determination for retail electric power contracts," *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 180–187, Feb. 2006.

[26] S.-E. Fleten and E. Pettersen, "Constructing bidding curves for a price-taking retailer in the Norwegian electricity market," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 701–708, May 2005.

[27] E. Celebi and J. D. Fuller, "A model for efficient consumer pricing schemes in electricity markets," *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 60–67, Feb. 2007.

[28] M. Carrión, A. J. Conejo, and J. M. Arroyo, "Forward contracting and selling price determination for a retailer," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 2105–2114, Nov. 2007.

[29] G. Dorini, P. Pinson, and H. Madsen, "Chance-constrained optimization of demand response to price signals," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2072–2080, Dec. 2013.

[30] O. Corradi, H. Ochsenfeld, H. Madsen, and P. Pinson, "Controlling electricity consumption by forecasting its response to varying prices," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 421–429, Feb. 2013.

[31] R. Yu, W. Yang, and S. Rahardja, "A statistical demand-price model with its application in optimal real-time price," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1734–1742, Dec. 2012.

[32] Z. Xu, T. Deng, Z. Hu, Y. Song, and J. Wang, "Data-driven pricing strategy for demand-side resource aggregators," *IEEE Trans. Smart Grid*, to be published.

[33] J. Saez-Gallego, J. M. Morales, M. Zugno, and H. Madsen, "A data-driven bidding model for a cluster of price-responsive consumers of electricity," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 5001–5011, Nov. 2016.

[34] R. K. Ahuja and J. B. Orlin, "Inverse optimization," *Oper. Res.*, vol. 49, no. 5, pp. 771–783, Jun. 2001.

[35] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "A medium-term decision model for DisCos: Forward contracting and TOU pricing," *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1143–1154, May 2015.

[36] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "Impacts of time-varying electricity rates on forward contract scheduling of DisCos," *IEEE Trans. Power Del.*, vol. 29, no. 2, pp. 733–741, Apr. 2014.

[37] A. Soroudi and M. Ehsan, "IGDT based robust decision making tool for DNOs in load procurement under severe uncertainty," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 886–895, Jun. 2013.

[38] S. Braithwait, D. Hansen, and M. O'Sheasy, *Retail Electricity Pricing and Rate Design in Evolving Markets*, Edison Elect. Inst., Washington, DC, USA, Jul. 2007, pp. 1–57.

[39] E. Celebi and J. D. Fuller, "Time-of-use pricing in electricity markets under different market structures," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1170–1181, Aug. 2012.

[40] Y. Ding *et al.*, "Real-time market concept architecture for EcoGrid EU—A prototype for European smart grids," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2006–2016, Dec. 2013.

[41] T. Namerikawa, N. Okubo, R. Sato, Y. Okawa, and M. Ono, "Real-time pricing mechanism for electricity market with built-in incentive for participation," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2714–2724, Nov. 2015.

[42] X. Liang, X. Li, R. Lu, X. Lin, and X. Shen, "UDP: Usage-based dynamic pricing with privacy preservation for smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 141–150, Mar. 2013.

[43] M. Roozbehani, M. A. Dahleh, and S. K. Mitter, "Volatility of power grids under real-time pricing," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 1926–1940, Nov. 2012.

[44] S. A. Gabriel, A. J. Conejo, J. D. Fuller, B. F. Hobbs, and C. Ruiz, *Complementarity Modeling in Energy Market* (International Series in Operations Research and Management Science). New York, NY, USA: Springer, 2013.

[45] L. Jia and L. Tong, "Dynamic pricing and distributed energy management for demand response," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1128–1136, Mar. 2016.

[46] J. Fortuny-Amat and B. McCarl, "A representation and economic interpretation of a two-level programming problem," *J. Oper. Res. Soc.*, vol. 32, no. 9, pp. 783–792, Sep. 1981.

[47] S. Siddiqui and S. A. Gabriel, "An SOS1-based approach for solving MPECs with a natural gas market application," *Netw. Spat. Econ.*, vol. 13, no. 2, pp. 205–227, Jun. 2013.

[48] I. Momber, S. Wogrin, and T. G. S. Román, "Retail pricing: A bilevel program for PEV aggregator decisions using indirect load control," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 464–473, Jan. 2016.

[49] N. Y. Soltani, S.-J. Kim, and G. B. Giannakis, "Real-time load elasticity tracking and pricing for electric vehicle charging," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1303–1313, May 2015.

[50] T. Hahn, Z. Tan, and W. Ko, "Design of time-varying rate considering CO_2 emission," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 383–389, Mar. 2013.

[51] C. Li *et al.*, "A new stepwise power tariff model and its application for residential consumers in regulated electricity markets," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 300–308, Feb. 2013.

[52] R. García-Bertrand, "Sale prices setting tool for retailers," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2028–2035, Dec. 2013.

[53] R. de Sá Ferreira, L. A. Barroso, P. R. Lino, M. M. Carvalho, and P. Valenzuela, "Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2285–2295, Dec. 2013.

[54] B. F. Hobbs and U. Helman, "Complementarity based equilibrium modeling for electric power markets," in *Modeling Prices in Competitive Electricity Markets*. London, U.K.: Wiley, 2004, ch. 3.

[55] P. Yang, G. Tang, and A. Nehorai, "A game-theoretic approach for optimal time-of-use electricity pricing," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 884–892, May 2013.

[56] L. Bartelj, D. Paravan, A. F. Gubina, and R. Golob, "Valuating risk from sales contract offer maturity in electricity market," *Int. J. Elect. Power Energy Syst.*, vol. 32, no. 2, pp. 147–155, Feb. 2010.

[57] N. Mahmoudi-Kohan, M. P. Moghaddam, and M. K. Sheikh-El-Eslami, "An annual framework for clustering-based pricing for an electricity retailer," *Elect. Power Syst. Res.*, vol. 80, no. 9, pp. 1042–1048, Sep. 2010.

[58] M. J. Stevenson, L. F. M. do Amaral, and M. Peat, "Risk management and the role of spot price predictions in the Australian retail electricity market," *Stud. Nonlin. Dyn. Economet.*, vol. 10, no. 3, Sep. 2006, Art. no. 4.

[59] S. J. Deng and S. S. Oren, "Electricity derivatives and risk management," *Energy*, vol. 31, nos. 6–7, pp. 940–953, May/Jun. 2006.

[60] C. Wan, Z. Xu, Y. Wang, Z. Y. Dong, and K. P. Wong, "A hybrid approach for probabilistic forecasting of electricity price," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 463–470, Jan. 2014.

[61] X. Chen *et al.*, "Electricity price forecasting with extreme learning machine and bootstrapping," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 2055–2062, Nov. 2012.

[62] M. Rafiei, T. Niknam, and M. H. Khooban, "Probabilistic forecasting of hourly electricity price by generalization of ELM for usage in improved wavelet neural network," *IEEE Trans. Ind. Informat.*, to be published.

[63] C. Xiao *et al.*, "Rational and self-adaptive evolutionary extreme learning machine for electricity price forecast," *Memetic Comput.*, vol. 8, no. 3, pp. 223–233, Sep. 2016.

[64] Y. Xu and J. V. Milanović, "Artificial-intelligence-based methodology for load disaggregation at bulk supply point," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 795–803, Mar. 2015.

[65] A. Reinhardt *et al.*, "On the accuracy of appliance identification based on distributed load metering data," in *Proc. 2nd IFIP Conf. Sustain. Internet ICT Sustainabil.*, Pisa, Italy, Oct. 2012, pp. 1–9.

[66] Y. X. Yu, B. Liu, and W. P. Luan, "Nonintrusive residential load monitoring and decomposition technology," *Southern Power Syst. Technol.*, vol. 7, no. 4, pp. 1–5, Aug. 2013.

[67] M. Figueiredo, A. De Almeida, and B. Ribeiro, "Home electrical signal disaggregation for non-intrusive load monitoring (NILM) systems," *Neurocomputing*, vol. 96, pp. 66–73, Nov. 2012.

[68] M. Dong, P. C. M. Meira, W. Xu, and C. Y. Chung, "Non-intrusive signature extraction for major residential loads," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1421–1430, Sep. 2013.

[69] D. Egarter, V. P. Bhuvana, and W. Elmenreich, "PALDi: Online load disaggregation via particle filtering," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 2, pp. 467–477, Feb. 2015.

[70] S. B. Taieb, R. Huser, R. J. Hyndman, and M. G. Genton, "Forecasting uncertainty in electricity smart meter data by boosting additive quantile regression," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2448–2455, Sep. 2016.

[71] H. T. Nguyen, D. T. Nguyen, and L. B. Le, "Energy management for households with solar assisted thermal load considering renewable energy and price uncertainty," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 301–314, Jan. 2015.

[72] S. Sun, M. Dong, and B. Liang, "Distributed real-time power balancing in renewable-integrated power grids with storage and flexible loads," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2337–2349, Sep. 2016.

[73] R. Couillet, S. M. Perlaza, H. Tembine, and M. Debbah, "Electrical vehicles in the smart grid: A mean field game analysis," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 6, pp. 1086–1096, Jul. 2012.

[74] S. Li, W. Zhang, J. Lian, and K. Kalsi, "On reverse Stackelberg game and optimal mean field control for a large population of thermostatically controlled loads," in *Proc. Amer. Control Conf.*, Boston, MA, USA, Jul. 2016, pp. 3545–3550.

[75] W. Su and A. Q. Huang, "A game theoretic framework for a next-generation retail electricity market with high penetration of distributed residential electricity suppliers," *Appl. Energy*, vol. 119, pp. 341–350, Apr. 2014.

[76] T. Hong *et al.*, "Guest editorial big data analytics for grid modernization," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2395–2396, Sep. 2016.

[77] F. Luo *et al.*, "Enabling the big data analysis in the smart grid," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Denver, CO, USA, Jul. 2015, pp. 1–5.

[78] F. Luo *et al.*, "Hybrid cloud computing platform: The next generation it backbone for smart grid," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, San Diego, CA, USA, Jul. 2012, pp. 1–7.

[79] F. Luo *et al.*, "Cloud-based information infrastructure for next-generation power grid: Conception, architecture, and applications," *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 1896–1912, Jul. 2016.

[80] J. Dean and S. Ghemawat, "MapReduce: Simplified data processing on large clusters," in *Proc. 6th Conf. Symp. Opear. Syst. Design Implement.*, San Francisco, CA, USA, 2004, pp. 137–150.

[81] B.-G. Kim, Y. Zhang, M. van der Schaar, and J.-W. Lee, "Dynamic pricing and energy consumption scheduling with reinforcement learning," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2187–2198, Sep. 2016.

[82] D. He, W. Chen, L. Wang, and T. Y. Liu, "A game-theoretic machine learning approach for revenue maximization in sponsored search," in *Proc. 23rd Int. Joint Conf. Artif. Intell.*, Beijing, China, Aug. 2013, pp. 206–212.

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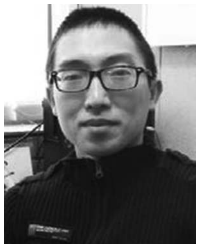

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