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A hybrid-learning based broker model for strategic power trading in smart grid markets

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ABSTRACT

Smart Grid markets are dynamic and complex, and brokers are widely introduced to better manage the markets. However, brokers face great challenges, including the varying energy demands of consumers, the changing prices in the markets, and the competitions between each other. This paper proposes an intelligent broker model based on hybrid learning (including unsupervised, supervised and reinforcement learning), which generates smart trading strategies to adapt to the dynamics and complexity of Smart Grid markets. The proposed broker model comprises three interconnected modules. Customer demand prediction module predicts short-term demands of various consumers with a data-driven method. Wholesale market module employs a Markov Decision Process for the one-day-ahead power auction based on the predicted demand. Retail market module introduces independent reinforcement learning processes to optimize prices for different types of consumers to compete with other brokers in the retail market. We evaluate the proposed broker model on Power TAC platform. The experimental results show that our broker is not only is competitive in making profit, but also maintains a good supply-demand balance. In addition, we also discover two empirical laws in the competitive power market environment, which are: 1. profit margin shrinks when there are fierce competitions in markets; 2. the imbalance rate of supply demand increases when the market environment is more competitive.

1. Introduction

Smart Grid markets are complex and dynamic. The complexity is ascribed to the various participators and interactions between multiple stakeholders. There are various participants, including large energy generators, general consumers, interruptible consumers and storage consumers, and even renewable energy producers, such as solar power systems and wind turbines. In such a two-way power flow system, there are multiple interactions between consumers, prosumers[1] and energy suppliers. The dynamics are caused by the varying energy demands, changing prices and customer migrations. The energy demands can vary from time to time because of the fluctuations of energy needs by time and the mutable weather conditions. Prices may also change according to the designed pricing mechanisms [11], or the energy supply and demand status. The autonomous end users may switch tariffs based on their own utilities. Due to the complexity and dynamics, it is of great challenge to manage Smart Grid markets.

To ameliorate the management of such complex markets, brokers are widely employed. Brokers, who buy energy from the wholesale market and sell it to the retail market, form a decentralized mode to enhance the efficacy of Smart Grid markets. In the power trading, brokers simultaneously interact with the wholesale and retail markets. In the wholesale market, brokers buy energy 24 h ahead through auctions. There are different energy suppliers, such as thermal power generators, hydropower generators and wind power generators. The various energy suppliers exhibit different prices, quantities and stabilities. In the retail market, brokers try to attract more customers and sell out their energy to make more profit. Different consumers have different requirements on the price, quantity, quality and time of energy usage. A successful broker should not only maximize his own profit, but also keep a good supply-demand balance in the two markets to improve the energy efficiency. However, the excellent broker has to cope with the omnifarious challenges. For the wholesale market, there are dynamics in energy price, quantity and stability because of the various energy suppliers. To purchase a proper amount of energy for the each of coming 24 h, a customer demand prediction is needed, but is a very challenging issue in Smart Grid due to

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[1] Prosumer refers to the market participant as both a producer and a consumer, first used by Alvin Toffler in 1970.

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the various behaviors of different customers and customers' migrations between brokers. Moreover, a bidding strategy is required to optimize the bidding prices in auctions, with the considerations of competitions among other brokers. For the retail market, there are variety of consumers with various behaviors. An excellent broker should consider the different types of consumers and their different power usages. Besides, the broker should also deliberate on the dynamics and uncertainty of customers' behaviors in power usage. Moreover, the broker also needs an efficient strategy to compete with other brokers to attract customers in the retail market.

To construct a systematic broker model and to efficiently surmount the challenges in Smart Grid markets, three goals are established in our designation of a good broker model: **Goal 1** is to efficiently predict the energy demand of customers, so as to keep a good balance of supply and demand; **Goal 2** is to obtain energy as the required demand in the wholesale market with a lower price; and **Goal 3** is to sell energy to customers with a proper price, which can ensure a good profit and attract customers. This paper proposes a broker model with effective methods to achieve the above three goals. For Goal 1, a data-driven method is proposed to first cluster various customers according to their energy consumption patterns, and then predict the one-day-ahead hourly demand of subscribed customers. For Goal 2, the Markov Decision Process (MDP) is employed for energy auctions in the wholesale market. For Goal 3, independent reinforcement learning processes are introduced to optimize prices for different types of customers. The proposed broker model is evaluated on the platform of Power Trading Agent Competition [8] (Power TAC), which supplies a practical simulation of the complex Smart Grid markets based on real data.

The proposed broker model contributes to the research in Smart Grid markets in four aspects. 1) A systematic framework of broker model is designed to simultaneously balance supply and demand and optimize energy prices in both the wholesale and retail markets. This framework will enlighten the designations of future broker models in Smart Grid markets. 2) Hybrid learning is introduced as an effective way to adapt to the dynamics in markets. Unsupervised, supervised and reinforcement learning approaches are integrated to construct a systematic model, which can efficiently adapt to the dynamics in Smart Grid markets. The experiments have demonstrated that the proposed broker model works better than the previous models. 3) A new data-driven customer demand prediction method is proposed. This method deeply explores the energy consumption patterns of various customers, and then integrates supervised learning to predict the future energy demand. The proposed method provides an efficient way to predict the energy demand for a variety of customers, and can be extended to demand prediction in a market level. 4) Independent SARSA processes [2] are used for different consumers in the retail market, and the experimental results have demonstrated that it is an effective way to compete with other brokers.

2. Related work

Broker modeling in Smart Grid markets is an emerging research field and there have not been much literatures. In 2012, Power TAC started and supplied a simulated real-world Smart Grid market environment. Some broker models have been developed since then, but there have been not many available literatures. AstonTAC team [9] introduced MDP approach for auctions in the wholesale market, and employed different HMMs to predict the price of energy and the customer demand. The AstonTAC can keep a good supply-demand balance, but it does not take effective strategy to attract customers in the retail market. Urieli and Stone [22] developed a broker model called TacTex and won the Power TAC in 2013. They decomposed the global optimization into sub-optimizations in the wholesale and retail markets. Locally weighted linear regression was introduced to predict if the customers would subscribe his tariffs. The TacTex wins in profit making, but it does not make much effort on supply-demand balance. The CwiBroker team [10] used game theories in both wholesale and retail markets to maximize the profit. In contrast, our broker model takes both profit making and supply-demand balance into considerations, resulted in a more comprehensive method in coping with the complexity and dynamics in Smart Grid markets.

Demand prediction has been intensively studies in Smart Grid [19,23]. A variety of models have been proposed, including time series models[6], ARIMA [17], neural networks [4] and so on. Recently, some novel learning-based methods have been proposed. Srinivasan [18] introduces a group method of data handling (GMDH) neural network for mid-term energy demand prediction. In his method, six categories of consumers are predicted respectively, yet the customer groups are stipulated manually. Amjady et al. [3] uses a bilevel method, which is composed of a feature selection technique and a forecasting engine, to predict the demand of a single micro-grid. Their method has been tested on the demand prediction of a campus. However, a large scope of customers, especially for the market level, has not been demonstrated in their method. Motamedi et al. [12] combine a multi-input multi-output forecasting engine for joint price and demand prediction with data association mining algorithms, through which the relationship of demand and price is extracted. This method is applied to a macro scope, regardless the types of customers.

Generally, previous prediction methods either focus on all customers as a whole or a special customer. None of them explores the behaviors of different customers in a market level. The prediction method we proposed is a data driven method, based on the nature of customers. Customers are hierarchically clustered based on their historical usage data. Different usage prediction methods are tailored for customer clusters with different energy consumption patterns. Thus our method is applicable and effective for market level prediction.

Pricing mechanisms have been deeply explored in Smart Grid [5,11,15] with the objective of curtailing peak load, while literatures on pricing strategy on the stand of a broker are rare. Recent work in [13] by Peters et al. used reinforcement learning with function approximation to adapt to the economic signals from the retail market. In their work, a range of market features were studied and effective features are selected. Their work gives a good hint to this research. Different from their work, independent SARSA processes are introduced for different types of customers in our method. The independent SARSA processes can be easily implemented with parallel computing technology for efficiency.

3. Definitions and framework design

In this section, the terms that are used in the rest of the paper are defined, and the framework of the proposed broker model is described.

3.1. Definitions

Definition 1 (Bootstrap data)**.** Bootstrap data $\mathbf{B}_D$ are the historical data of customer usages in the retail market. It is represented as the following matrix,

$$\mathbf{B}_D = \begin{pmatrix} u_{11} & u_{12} & \cdots & u_{1T_b} \\ u_{21} & u_{22} & \cdots & u_{2T_b} \\ \vdots & \vdots & \vdots & \vdots \\ u_{N1} & u_{N1} & \cdots & u_{NT_b} \end{pmatrix}, \tag{1}$$