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Predicting Prices in the Power TAC Wholesale Energy Market

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Abstract

The Power TAC simulation emphasizes the strategic problems that broker agents face in managing the economics of a smart grid. The brokers must make trades in multiple markets and to be successful, brokers must make many good predictions about future supply, demand, and prices. Clearing price prediction is an important part of the broker's wholesale market strategy because it helps the broker to make intelligent decisions when purchasing energy at low cost in a day-ahead market. I describe my work on using machine learning methods to predict prices in the Power TAC wholesale market, which will be used in future bidding strategies.

Introduction

The traditional energy grid lacks several important features such as effective use of pricing and demand response of energy, customer participation, and proper distribution management for variable-output renewable energy sources etc (Ketter, Peters, and Collins 2013). The smart grid has the potential to address many of these issues by providing a more intelligent energy infrastructure (Ketter, Collins, and Reddy 2013). Researchers rely on rich simulations such as Power TAC to explore the characteristics of future smart grids. In the Power TAC smart grid simulation, brokers participate in several markets including the wholesale market, the tariff market, and the load balancing market to purchase energy and sell it to customers. This game was designed as a scenario for the annual Trading Agent Competition, a research competition with over a decade of history. The wholesale market attempts to simulate existing energy markets such as the European or North American wholesale energy markets. The wholesale market is a “day ahead market” where the energy is a perishable good and it allows brokers to buy and sell quantities of energy for future delivery. Market structures like this exist across many different types of perishable goods, so finding effective, robust, automated bidding strategies for these markets is an important research challenge. I present my initial work on the price prediction part of this problem.

Power TAC Wholesale Market Prediction

In the Power TAC simulation, a timeslot refers to a simulated hour and a typical simulation has 1440 timeslots. The wholesale market is modeled by a periodic double auction market that allows brokers to trade energy between 1 and 24 timeslots into the future. Our baseline agent SPOT (which had no machine learning technique to predict prices) uses a moving average price prediction based on the price history of the agent. I have been experimenting with three machine learning algorithms to predict prices: 1) REPTree (Decision tree) 2) Linear Regression and 3) Multilayer Perceptron (Neural network). I chose some potential features that are available in the simulation at runtime to train a price predictor. I included 8 price features into my feature set because recent trading histories reflect the present wholesale market economy. These include the clearing prices for the previous hour, as well as the same time slot in the previous day and week. I also included the weather forecast data and time related data because the energy production of the producers (e.g. renewable energy sources as energy producers in the system) are related with this. I selected the number of participants in the game as a feature because the amount of competition affects the market clearing price. I also included the moving average prices predicted by the baseline SPOT agent as a feature so that I could get a better predictor model than the baseline.

Methodology

In the Power TAC competition automated broker agents play many games against different numbers of opponents. In this work, I experiment with games with three brokers, fixing two of them to be SPOT (baseline) and SPOTV2 (which is used to introduce several learned predictors and gather training data). The remaining variable broker is selected from a pool of five agents : TacTex14, CwiBroker15, Maxon15, Maxon14 and AgentUDE14. I use the available agent binaries from the previous Power TAC tournaments. I ran one simulation for each of the five variable agent from the agent pool using four different initializations of the simulation. As a result, each initialization has five training datasets and in total I generated twenty training datasets. I used Weka (Hall et al. 2009 2015) and 5, 10, 15 and 20 games training datasets to generate the predictor models. Each of the Linear regression, 3 layer Multilayer Perceptron (25,40,35 nodes respectively on each layer) and REPTree (Decision tree) predictor models has four different versions according to the number of games.

Results [1]

I used mean absolute error as an evaluation metric for the performance of different versions of the prediction module. Many auctions in the game do not clear due to a spread between the ask prices and bid prices. In this scenario, I get null clearing prices for those specific auctions. Since I have 8 price features in our training dataset and I found that these null clearing prices significantly affect the performance of the predictor models. To improve this I have used an estimated clearing prices for null auctions by taking the average of lowest ask price and highest bid price. Figure 1 shows the prediction errors during the course of a single simulation for two different REPTree models trained on 20 games, one with estimated clearing prices and the other without. We also include the errors for a simple moving average price predictor as a baseline for comparison. Each data point shows the average error for all auctions in a window of five timeslots. The data show that both REPTree models outperform the moving average predictor, but the version with estimated clearing prices is dramatically better, and produces much more consistent predictions throughout the entire game. I have

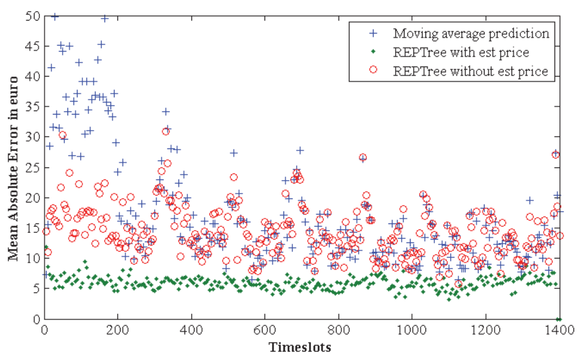

Figure 1: Comparison of 3 prediction models

conducted experiments using AgentUDE15 (AgentUDE15 2015) as a variable agent and generated four test datasets using four different initializations. The experimental results shows that a decision tree model makes good predictions compared to other models. The decision tree model slowly improves according to the number of games where other models do not show this trend. I also tested these models for cwiBroker15 and TacTex14 agent using the same procedure. Figure 2 shows that the models do best against AgentUDE (which was in the training set), and there is a significant decrease in accuracy when playing either cwiBroker (cwi 2015) or TacTex (TacTex14 2015). While our current results show substantial improvements over the simple moving average methods, I plan to continue to explore additional features and training with larger datasets to further improve prediction accuracy.

[1]http://www.cs.utep.edu/kiekintveld/students/porag/index.html

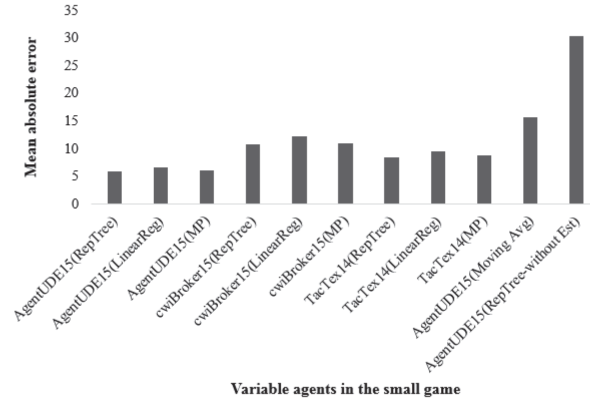

Figure 2: Comparison of several prediction models

Conclusion

It will be a great advance if intelligent bidding agents can replace humans in wholesale energy markets. I have shown as a first step that I can successfully use machine learning to predict market prices in these auctions in a realistic smart grid simulation. These predictions are much more accurate than baselines that use moving averages to predict prices, and the amount of error is small enough that these should be useful in more sophisticated bidding strategies. My current work focuses on designing and evaluating new bidding strategies for these auctions the make use of the price prediction methods described here.

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