Initial Exploration of Machine Learning to Predict Customer Demand in an Energy Market Simulation

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Abstract

The PowerTAC competition focuses on trading activities in energy markets. One of the important subtasks of designing an effective agent for this scenario is to predict the energy use and generation of the customer agents in the marketplace. These predictions can inform pricing and tariff design questions, as well as decisions to balance power use and generation over time. Similar prediction problems are also important in real world energy markets. Here we present some initial experiments applying machine learning to predict future customer energy usage patterns in the PowerTAC simulation.

1. Introduction

Energy markets play a key role in modern energy infrastructure. We anticipate that this role will only increase as energy production becomes more decentralized, and there is a greater application of smart grid technologies throughout the energy system. With the increasing role of intelligent systems throughout the grid, these markets are also likely to become increasingly reliant on automated trading strategies. The design of these next-generation energy markets and the intelligent, automated trading strategies needed to participate in the markets pose a large number of research challenges. Many of these challenges take the form of prediction problems, where an agent needs to predict features of the environment or the behaviors of other agents to improve decisions.

We focus on a specific prediction problem motivated by the PowerTAC competition (Ketter et al. 2012). In particular, we consider how the agent can learn to predict the future energy use and generation patterns of the customer agents in the market. Many of the decisions an agent needs to make in the game to create a profitable and balanced energy portfolio rely on predictions about energy use, so this problem is a natural one to focus on early in the agent design process. Prediction of market behaviors has also been the subject of substantial research in other Trading Agent Competition games (Hogenboom et al. 2009) (Ketter et al. 2009) (Kiekintveld et al. 2008) (Pardoe and Stone 2007).

We present our initial experiments in applying machine learning techniques to this prediction problem. We conduct our study using the PowerTAC game as a simulation environment to generate data and evaluate the learned models. The PowerTAC game is a complex simulation environment of an energy market with smart grid features that was designed to support research on trading agents as part of the annual Trading Agent Competition (http://tradingagents.org).

1.1. PowerTAC

PowerTAC (Ketter et al. 2012) is the newest scenario in the Trading Agent Competition, which has been run annually since 2002. PowerTAC was introduced as a demonstration event in 2012, and will be played for the first time in 2013. The goal of the competition is to facilitate and promote research on trading agent strategies for energy markets. Participants in the competition design fully automated trading agents that compete to maximize their profits in a simulated market. The PowerTAC environment includes many realistic features, including interactions between customers, energy producers, and broker agents in an environment with significant uncertainty about weather, demand, energy production, the behaviors of other agents, etc. A game server that implements the PowerTAC environment is used to facilitate the competition, and is available for download to support experimentation.

Participants in the competition design a broker agent that must design tariff contracts to build a portfolio of long-term customers and energy production, and manage buying and selling operations on a short-term wholesale market to balance their energy portfolio. The broker acts as an intermediary to purchase energy from utilities and customers, and to sell the energy to customers. These decisions are subject to substantial uncertainties in the environment (e.g., changes in weather resulting in changes in solar and wind power generation), customer behavior (e.g., changing patterns of daily use), and the strategic decisions of other brokers. Designing a successful agent poses a large number of interesting research challenges, but we chose to focus on the problem of predicting the energy consumption and production patterns of customer agents in the simulation.

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2. Machine Learning Approach

Machine learning methods have been successfully used in several successful agent designs for other TAC competitions (Hogenboom et al. 2009) (Ketter et al. 2009) (Kiekintveld et al. 2008) (Pardoe and Stone 2007). Here, the prediction problem we address is to predict how much energy a specific customer will use and/or generate in a future time slot. As in the real world, customer usage is affected by many different variables such as the weather, time of the day, and etc. In addition, the PowerTAC simulation implements a variety of different customer models with different characteristics, ranging from small-scale models representing residential customers, to office complexes and villages that aggregate large numbers of customers in a single entity.

We attempt to learn predictive models of energy use for each of the customer models in the game, using observable features including historical usage patterns, the time of the day and week, the price of energy, and weather predictions. We make use of the Weka (Hall et al. 2009) toolkit in our study to learn these models. Weka is a standard open source data mining toolkit that includes implementations of standard machine learning algorithms and other tools aid in the initial data analysis.

We began by running approximately 30 simulations of the game to generate a data set using default agents provided with the game server implementation. Each game generates a detailed log file that can be parsed to extract information about the environment and the customer usage patterns. We wrote code to extract all data pertaining to the time of day (24 hours), time of the week (24 hours * 7 days = 168 hours), temperature, wind direction, wind speed, cloud cover, a customer’s energy usage, and price the customer was billed per energy unit. This data was then compiled into data files for Weka to read.

We experimented with several machine learning techniques to learn models of customer usage patterns. The first is a baseline that simply averages the previous usage in specific time slots. We create 168 records for a single customer covering each hour-long period for an entire week from Sunday to Saturday. For each of these records, we store the average usage, updating the average each time data corresponding to a specific time slot is observed during the game.

We also tested variations of two basic learning algorithms from Weka: linear regression and M5P decision trees. M5P decision trees were shown to have effective

Figure 1 is a Weka plot that shows the energy usage of one sample customer model (BrooksideHomes) on the y-axis and the time of the week across the x-axis. One week of data is shown in the figure. A positive energy usage value indicates the customer’s produced energy, zero is for no activity, and a negative value is a customer’s energy consumption. In the figure the main trend that can be observed is that a customer’s usage is closely tied with the time of the day, and that there seems to be regular cyclical patterns that can be exploited by the learning algorithms. The fourteen dips in the graph represent the periods with the highest energy usage. When split up into pairs it is easy to see that the first sink in the pair indicates the morning when customers get ready for the day. While the second sink occurs in the evening when there is less light.

Using this visualization tool we also identified additional features that affected customers’ usage patterns. For example cloud coverage appears to be an important feature for customers that produced solar energy, while is has little impact on a normal household consumer. After the initial analysis, we decided to use the following features as inputs for the learning methods:

- Time of the week – This feature appears to be the most influential for all types of customers, based on the initial data analysis and the specification of the customer models. We divide each week into 168 hour-long time slots, and use both the day and the hour as features.
- Previous usage – We calculate the previous energy usage for the customer for the specific day and time of week, and use this as a feature.
- Cost of energy – This feature influences customer energy use by increasing usage when prices are low and decreasing usage when prices are higher. We take the most recent price paid by the customer as a feature.
- Temperature – The temperature predictions given in the weather reports.
- Wind direction – The wind direction is also given in the weather reports, and is most important for customers that use wind turbines.
- Wind speed – Wind speed is also given in the weather reports, and impacts wind turbines.
- Cloud cover – Also given in the weather reports, and has an impact on customers with solar energy production capabilities.
learning performance in previous studies on learning for the TAC Supply Chain Management game (Kiekintveld et al. 2008). We tested these algorithms both with and without 10-fold cross-validation during the modeling phase. We were also particularly interested in the impact of the weather features on the performance of the learning models. To test this, we created a basic model using only the following core features: time of the day/week, customer usage, and energy cost. Then, we created a separate set of models using an additional set of features related to weather predictions (temperature, wind speed, wind direction, amount of cloud cover). Finally, a version of k-Nearest Neighbors was tested using the full set of features. This model includes a basic method for updating the data online during the course of a game; our primary goal in examining this algorithm was to see whether online learning has the potential for significant improvements in performance, as seen in previous TAC competitions. The full set of algorithms included in our tests was:

- Historical timeslot average (Average)
- k-Nearest Neighbors with online updates (IBK Online)
- Linear regression using cross-validation (LR_CV10)
- Linear regression using cross-validation and weather (LR_CV10 w/ Weather)
- M5P decision trees (M5P)
- M5P decision trees using cross-validation (P5P_CV10)
- M5P decision trees using cross-validation and weather (M5P_CV10 w/ Weather)

3. Experimental Results

After learning each of the models described above using Weka based on the initial 30 games of sample data, we ran experiments to test the performance of the models in new games. During the simulation we made predictions using each of the models, and generated log files to document the performance of each model. The broker printed out the predicted values of each model and the actual usage for every turn. The results are shown in Figures 2 and 3. The graphs display the percentage error of seven predictor models (M5P, IBK Online, Average, LR_CV10, M5P_CV10, LR_CV10 w/ Weather, and M5P_CV10 w/ Weather) for all customers that had non-zero values. Each bar measures the mean error of the prediction model, normalizing by the actual usage over the entire game. Normalizing based on the mean over the entire game avoids some issues that can arise in using a daily percentage error metric when zero or very small values are encountered. The error is calculated according to the following formula:

$$\sum_{k=0}^{\text{all data points}} \frac{|\text{Actual Usage}_k - \text{Predicted Usage}_k|}{\text{Mean of actual usage for all data points} \times \text{number of data points}}$$

The data is presented in two separate figures because there are so many different customer models. Figure 2 contains the office and village type customer models, while Figure 3 has the seven remaining models. Some models that focus primarily on energy production are omitted because our current broker does not aggressively pursue these customers in the tariff market, so there is little or no data available to evaluate the predictions the agent makes about these models.
Overall, our results show that predicting the behavior of the customer usage is a difficult problem, particularly for the office and village customers. Even the best models still had significant error for many of the models, though some of the predictions for the customers in Figure 3 are quite good. In addition, the models appear to have varying characteristics, with some models producing more predictable behaviors than others, and certain algorithms performing better or worse depending on the models.

One feature of the data that is noticeable in Figure 2 is the difference in behavior between base and controllable versions of the village customers. The base customers have lower amounts of error per model. This stems from the behavior of controllable sources. The controllable sources tend to have more erratic behavior, which makes them more difficult to predict. However, this does not account for the ability of the agents to control aspects of the behavior for these models, which should make them more predictable in practice (our agents currently does not use this capability).

Another interesting result that is quite striking in Figure 2 is the strong performance of the IBK online method on the village models. This method shows much lower error than all of the others. IBK is the only model that updates the prediction model during a game instance, and this result provides some evidence that adaptive learning during a game is important to improving the performance of the predictions, especially for the village models. We plan to explore the results further in future work by testing more sophisticated methods for adaptive learning within a game instance.

Overall, the results show that there is promise in using machine learning methods to predict usage, but that there are significant challenges to doing this effectively. One of the main issues is the variability of the customer models; what works well for one type of customer may not work well for others. We are continuing our work to identify additional features that may be useful for improving the predictions on some of the specialized models where errors are currently high. The initial results from online learning are also promising, so we plan to try additional methods for online learning to improve predictions. Finally, we note that this is not the only interesting prediction problem in the PowerTAC game. Learning techniques could also be useful for predicting market prices, how likely customers are to adopt certain tariffs, and other features of the game.

4. References


