TNE19 Agent - Predicting Energy Demand in PowerTAC Smart Grid *

Joao Dias Conde[1], Luis Martins[1], and Renato Campos[1]

University of Porto, Faculty of Engineering, Portugal

Abstract. Future sustainable energy systems will eventually have to employ a smart grid approach. In such scenario, consumers are able to choose one from many energy providers. The Power Trading Agent Competition (or PowerTAC for short) provides a smart grid simulation platform. This paper presents TNE19 agent,which design approach focuses on the prior research of successful agents and implementation of both common strategies as well as our own balancing and wholesale markets strategies. In fact, our agent predicts the wholesale needs in future timeslots using data from previous similar timeslots in order to be able to decide which asks/bids he should place in the wholesale market for each timeslot always aiming to make money in this market. These predictions are made using data from previous executions of PowerTAC competition. Our agent also intends to be a model for other agents since it uses a REST API for getting data from external sources allowing many different predicting models to be used in the same agent without compromising the agent performance. In order to show this functionality our agent uses a external python model in the wholesale market prediction.
Keywords: BROKER · WHOLESALE MARKET · RETAIL MARKET · POWERTAC · DISTRIBUTED AGENTS · SMART GRID SIMULATION

1 Introduction

Environmental challenges like pollution and CO2 emissions have become one of the main drivers of the energy industry innovation. The electricity market is a relevant field of study as it directly deals with the social, environmental and financial aspect of the energy industry.

The Smart Grid is a complex composition of different layers, from the energy layer, where there are increasing efforts to include renewable energy sources like wind turbines and solar systems, to the ICT layer, which provides real time data about energy consumption and production, and the market layer, which consists of energy brokers that create tariffs and trade energy on the wholesale market. The objective of the market layer is to provide a truly sustainable energy system of the future, in which end-consumers can receive and react to price signal from multiple suppliers. In such scenario, analysis can be performed in multiple contexts. Our research focuses the market layer of the grids: a compromise between

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getting clients that need energy and having enough energy to provide them is the big problem.

In order to evaluate the performance of different strategies, some simulation systems are already proposed, like IEEE SMART Competition and GECAD WWCI. However, PowerTAC is presented as the current state of the art platform for simulating smart grids markets. Power TAC is a competitive simulation that models a "liberalized" retail electrical energy market, where competing business entities or "brokers" offer energy services to customers through tariff contracts, and must then serve those customers by trading in a wholesale market. Brokers are challenged to maximize their profits by buying and selling energy in the wholesale and retail markets, subject to fixed costs and constraints; the winner of an individual "game" is the broker with the highest bank balance at the end of a simulation run. Costs include fees for publication and withdrawal of tariffs, and distribution fees for transporting energy to their contracted customers. Costs are also incurred whenever there is an imbalance between a brokers total contracted energy supply and demand within a given time slot [4].

Fig. 1 shows the main components of the Power TAC simulation are the following:

- **Wholesale Market**: a periodic double auction where brokers can buy and sell energy contracts to be used on each one of the next 24 timeslots.

- **Tariff/Customer Market**: brokers buy and sell energy in the customer market by offering energy tariffs contracts;

- **Distribution Utility (DU)**: represents the regulated electric utility entity that owns and operates the distribution grid;

- **Balancing Market**: is responsible for real-time balance of supply and demand. The market creates an incentive for brokers to balance their own portfolios;

- **Weather Reports**: weather forecasts and current-hour weather conditions are sent to brokers in each time slot;

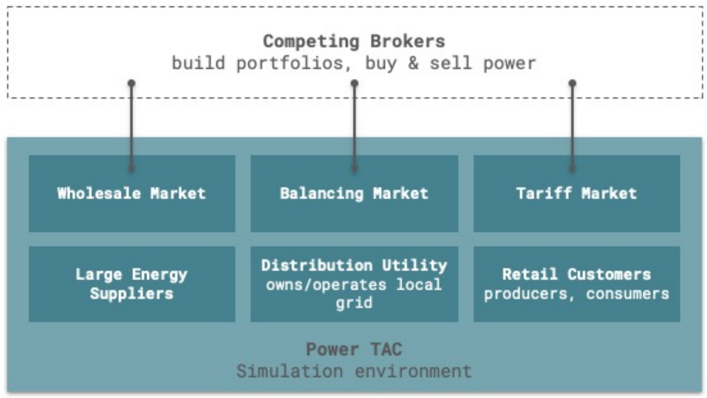

Fig. 1. powertac competition organization

In this paper, we focus on the hypothesis of having a self-sustained Wholesale Market strategy. Furthermore, we analyze different tariff contract strategies that help to reduce the costs of the Balancing Market. Additionally, we show that it is possible to use a RESTful prediction model service, without any downside, in an environment in which predictions need to be done in less than 1 second.

2 Related Work

2.1 Agent UDE

Agent UDE [6], designed by University of Duisburg-Essen and Poznan University of Economics, placed first in 2018, 2017 and 2014 competitions. The authors claim to use a genetic algorithm to optimize a wide set of tariff contract parameters. Agent UDE reduces peak demand charges by using Time-of-Use tariffs. Time-of-Use means that rates are higher when peak-demands are expected. The TOU schemes are created based on the Wholesale Market data. Due to tariffs having publication fees, the gap between tariff publications is proportional to the publication fee.

On the Wholesale Market it predicts the volatility of each of the following timeslots and the balancing costs to create buy and sell limit prices. As the gap between the order and delivery hour closes, the limit-price is increased to the balancing price [7].

2.2 VidyutVanika

VidyutVanika [1], placed second in 2018 competition. In fact, this was one of the few agents using two different strategies for each Retail and Wholesale markets.

In order to accomplish this, VidyutVanika relies on reinforcement learning in the Retail market and dynamic programming in the Wholesale market to solve modified versions of known Markov Decision Process formulations. The authors claim that through some different heuristics this agent can convert near-optimal fixed tariffs to time-of-use tariffs aimed at mitigating transmission capacity fees. It can also spread out its orders in the wholesale market across several auctions to procure energy at a lower price.

2.3 TugaTAC

Agent TugaTAC creates market tariffs using fuzzy models [5] that represent the agents interest on selling or buying energy. The fuzzy models return an interest between [0,1] to buy and sell energy. That interest is then used to make its tariffs more competitive. Uses a Tit-For-Tat approach in the beginning when a tariff for the same power type does not exist in its portfolio. If there is some similar tariff in TugaTACs portofolio, it triggers the fuzzy model to improve the tariff.

2.4 CrocodileAgent2018

CrocodileAgent2018 placed third in the 2018 competition with the highest profitability rate of 91%. The agent is based on the Efficient Market Hypothesis that assumes that every other agent has perfect information and therefore the market value of energy actually reflects the true value of said energy. Balancing market fees are also taken into account, as the agent attempts to minimize these. This results in a more defensive agent design. On the retail market, CrocodileAgent places 3 types of tariffs: a general purpose one, an interruptible one that can curtail the electric load and one to enable the purchase of energy from prosumers such as solar homes. All of these are subject to a Time-of-Use parameter. On the wholesale market, the agent estimates the subscription count and energy demand for the future. This is achieved using the Erev-Roth reinforced learning method.[2]

2.5 Mapping - Table

We compiled ten relevant parameters to take into account whilst analyzing each literature.

- **f0** – uses weather data
- **f1** – imbalance optimization
- **f2** – time-of-use tariffs
- **f3** – wholesale volatility prediction
- **f4** – evolutionary tariffs
- **f5** – reinforcement learned tariffs
- **f6** – energy demand prediction
- **f7** – predict prices through dummy orders
- **f8** – estimate agent interest on buying and selling energy

Paper Index	**Features**								
	f0	***f1***	***f2***	***f3***	***f4***	***f5***	***f6***	***f7***	***f8***
AgentUDE17		X	X	X	X		X		
VidyutVanika	X		X	X	X		X	X	
TugaTac									X
CrocodileAgent2018			X				X		X

Table 1. Mapping table

2.6 Gap analysis

While analyzing the existent work one can verify that, although almost every existing broker tries to predict the demand that his customers will need and that therefore the broker will need to buy through auctions in the Wholesale Market, there were not much research on exploring Wholesale Market in a way of predicting total quantity and price cleared in each timeslot of this market regarding the whole system needs instead of just his customers' needs.

3 TNE19 Agent

3.1 General Approach

The main purpose of this agent is to have a good influence in the wholesale market while also participating in the retail market using a Tit-for-Tat strategy in order to be able to explore both of the main markets of the competition

3.2 Participation in the Wholesale Market

As being the main source for brokers to get energy to their costumers, the Wholesale Market is a day-ahead market where each broker can place asks and bids for a specific future timeslot at most 24 timeslots ahead. Since the Wholesale Market is a double auction system each ask/bid can be cleared or not depending on the other existent bids/asks. Therefore, for each timeslot t the system runs auctions for timeslots *t+1* until *t+24* and for each auction all brokers are informed of the cleared total quantity in that auction as well as the cleared price.

3.2.1 Important data Having this information for each timeslot t a broker can calculate which is the exact quantity available to be used in the timeslot *t+1* as well as the average price of the auction in which that energy was trade. This kind of information is important to be able to predict the total cleared quantity and cleared average price for future timeslots.

$$CQ_t = \sum_{i=0}^{24} PCQ_{t-24+i}$$

For each timeslot t the total available quantity that was cleared in the wholesale market CQ_t is given by the sum of all the cleared quantities of each partial that were cleared for timeslot t through the previous 24 timeslots PCQ_{t-24+i}

$$CP_t = \frac{\sum_{i=0}^{24} PCP_{t-24+i}}{24}$$

For each timeslot t the average price of the cleared trades in the wholesale market CP_t is given by the sum all the prices of the cleared trades for timeslot t through the previous 24 timeslots PCP_{t-24+i} divided by 24 since these trades happened through 24 timeslots

3.2.2 Agent Design and Strategy

- **Prediction**
  As presented in *Fig. 2*, to predict prices and quantities for each timeslot, our agent starts by collecting, for each timeslot, the total cleared amounts, average cleared prices and weather reports of each of the previous 24 timeslots. Furthermore, for each timeslot, we collect the current weather report, the weather forecasts, the already cleared energy amount and the already cleared energy average price for each of the following 24 timeslots. In each timeslot t, we use all the data that we collected from t-24 to t+24 to predict the wholesale average prices and quantities in the next 24 hours.

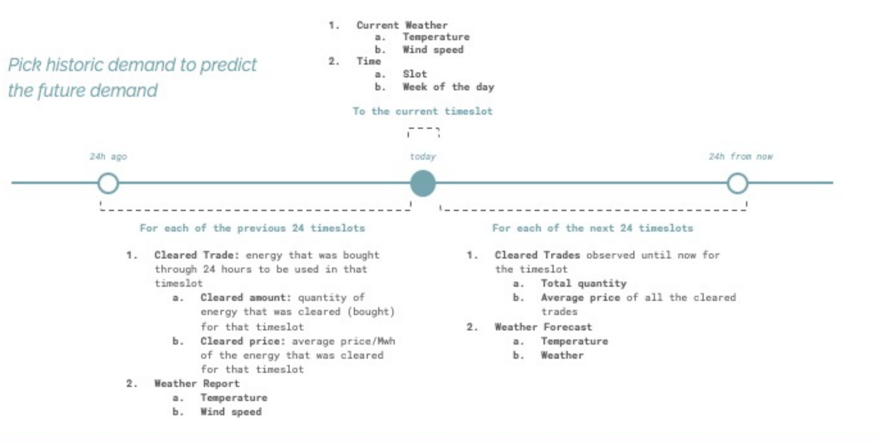

Fig. 2. wholesale auction prediction data

We do this by training a python RESTful prediction model, which can be running anywhere on the network. Having prediction models that implement a REST interface, like the one shown in *Fig. 3* is very interesting as it allows one to quickly swap and test different models without having to modify the agent code.

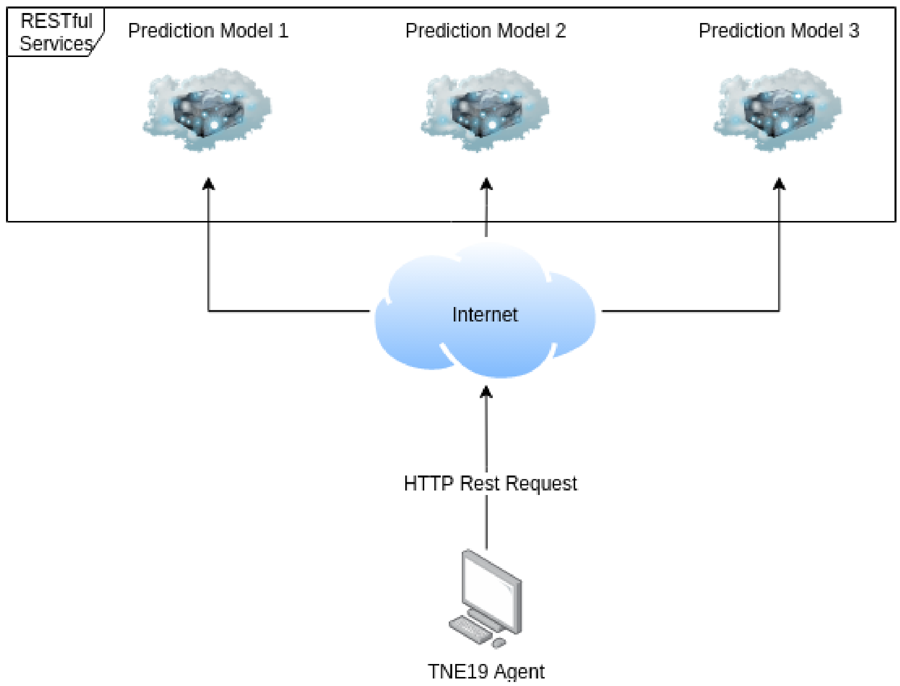

Fig. 3. RESTful prediciton models

- **Auction Price**
  Having predicted the average price for each of the following timeslots, and since the main goal is always to win money we follow a strategy of selling a bit above the average price and buying a bit under the average price. Therefore, we multiply those values by a constant greater than 1 to calculate the sell energy limit-price and by a constant lesser than 1 for the buy energy limit-price.

- **Auction Quantity**
  While negotiating in the Wholesale Market a broker must try to balance the remaining quantity he keeps at the end of each timeslot since it is important to be according to the system balance to avoid being punished by the balancing market fees. In fact, quantity prediction should be considered since a broker should only buy a quantity he knows (or at least predicts) he will be

able to sell in a near future, because otherwise he will be constantly punished by the Balancing Market in each timeslot that he keeps more energy than he should or he does not have enough energy to keep his energy promises (to his customers). Although being important having only a certain quantity of energy, a broker can also try to do some trading in this market trying to buy more energy when the price is lower to be able to sell it when it is higher. In order to do this kind of trading it is important to have a good prediction of the cleared energy quantity for each timeslot.

Having this in mind and since our agent has a predictable total amount of energy that will be cleared for each timeslot CQ_t as well as the energy that was already cleared for that timeslot QAC_t , we can estimate the amount of energy that the system has still to clear for that timeslot QNC_t and where we can try to make money.

$$QNC_t = CQ_t - QAC_t$$

Considering these predictions it is now possible to manage ours bids and asks in order to be able to buy at a lower price a certain quantity of energy that we predict we could be able to sell later at a higher price.

3.3 Participation in the Retail Market

In the begining, it was the intent of the group to only trade in the wholesale market. However, even though we managed to win in the wholesale market by using an wholesale strategy, we overall lost money. We concluded that the wholesale strategy by itself is not enough. This is a good indicator that PowerTAC is well designed and prevents agents from trying to cheat the system and make money without providing customers good services.

In order to win the competition or at least our simulation against the sample broker provided, we felt the need of a retail strategy. Our agent's retail strategy focuses on attracting a high number of customers and charge them above average. Of course, this may seem impossible. How do we gather enough customers by charging them above market average prices? The group found a strategy to overcome this difficulty.

Initially, the agent sets up tariffs at the mean market price. In this initial period of around 24 time slots (or a day), we gather data and take notes on competitors tariffs. After we identify several better tariffs from competitors, we choose the one to us that is the best and offer a similar one. Essentially, this is a Tit-For-Tat strategy, where we offer just a better enough tariff to steal the customers. We give a much bigger sign up payment bonus in order to attract the customers, but we charge more per energy consumption making it worth in the long run. We also place huge early withdrawal penalties, to prevent customers from exploiting this sign up payments and prevent them from signing in and leave and repeat.

3.4 Balancing Market

From the multiple scientific papers analyzed it was clear that even the better agents and most of the PowerTAC winners were being heavily charged by the balancing market fees.

As such, it was for us a priority to try and balance them. Although we did not have much success, the following described strategy was applied.

Essentially, if for a given time slot we've noticed we had excess energy, we would place a sell order for that amount below our market price prediction, to ensure it was bought and we were balanced. If for a given time slot we had lack of energy, we would place a buying order for that amount slightly above market price, again to ensure we would be balanced.

4 Simulation and Experimental Results

In this section, we provide a detailed analysis on the results of the team's experiments with agent TNE19 versus other agents. To test our agent we conceived two different scenarios.

In the first scenario, we ran a simulation with our agent, the default and sample brokers. This simulation looks to test our agent in the most simple and less competitive scenario possible. The results will serve as a control group and means of comparison versus other scenarios.

In the second scenario, we ran a simulation with our agent, the default broker and AgentUDE17, the winner of the 2017 PowerTAC. This simulation elevates the complexity and competitiveness of the game to the maximum. This tests our agent in the hardest environment possible.

The first simulation scenario included our agent, the default and the sample PowerTAC brokers. Below is the color code used for the graphics presented regarding this first scenario.

Fig. 4. Simulation1 agent's labels

Before applying our retail strategy, that is, with only a wholesale strategy, we were able to win in the wholesale market, as show below in terms of profit.

Fig. 5. Wholesale profit with no retail strategy

However, we overall lost money despite our huge gains in the wholesale market. This is due to the fact that we buy energy when below average market price and sell it when higher. However, in the mean time, we have to store it, causing an imbalance in the system and being heavily penalized by the balancing market fees. Below is a graphic of the cumulative profits in the simulation.

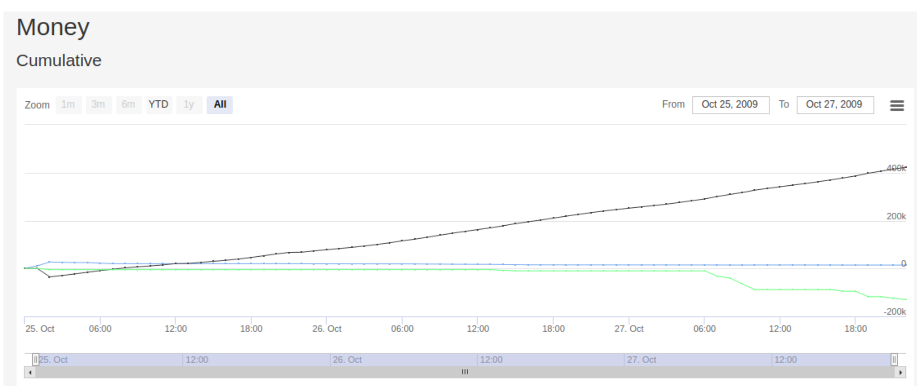

Fig. 6. Cumulative loss with no retail strategy

We observed that the wholesale strategy by itself was not enough. Thus we required a retail strategy as well. As previously explained in section 3.3, our retail strategy traded early game profits by a more long run stable income. We attempted to steal customers early using a Tit-For-Tat strategy.

In *Fig. 7* we see the number of customers each agent has contracts with at the given time slots.

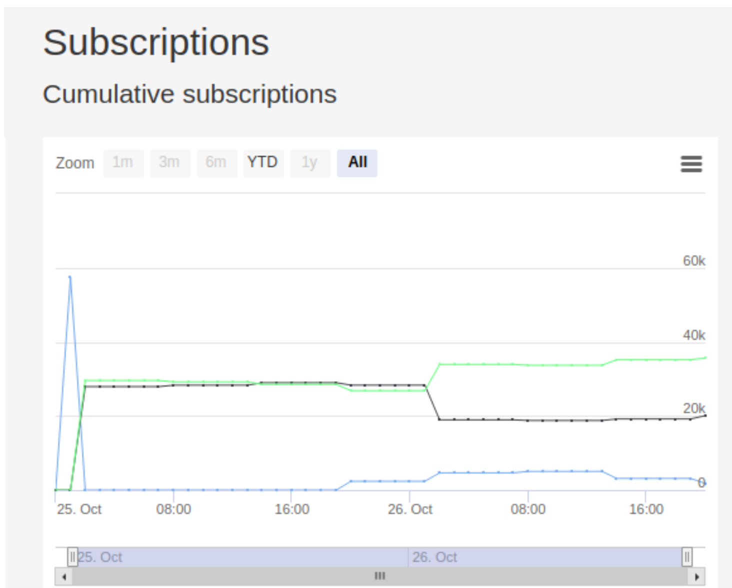

Fig. 7. Customer subscriptions

An interesting aspect is that after a certain time slot we effectively manage to steal most of the sample broker's customers. This is achieved, as already explained, with huge sign up payment bonuses. By giving these huge sums of money we end up losing in the early game. Below is a graphic of the total money each agent had for the given time slots. Despite having more customers, we have an initial set back in terms of total profit.

Fig. 8. Early game drawback

After some iterations, we successfully win the retail market. Such can be seen below.

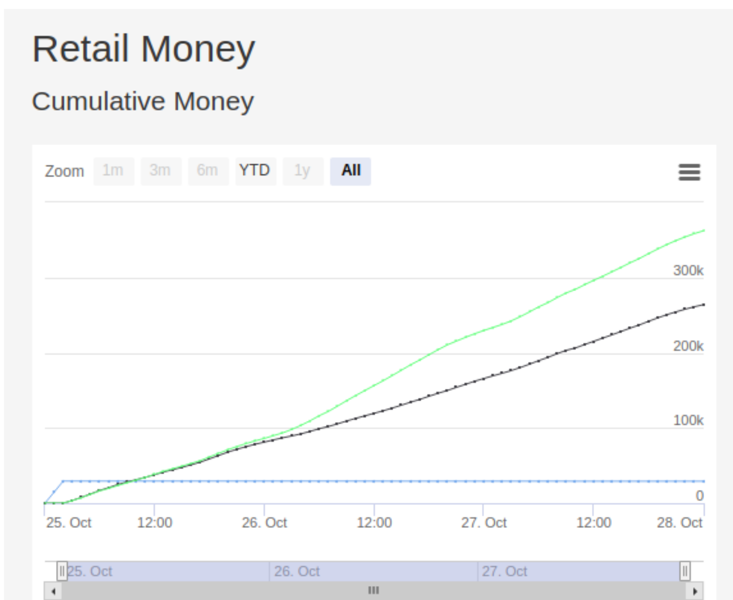

Fig. 9. Retail highest profitability

Effectively, by applying and combining our wholesale strategy with this Tit-For-Tat retail strategy, we managed to beat the sample and default brokers. An end game graph of the simulation and TNE19 agent victory is visible below.

Fig. 10. Victory in a simulation versus default and sample brokers

The second simulation scenario included our agent, the default broker and the PowerTAC 2017 champion, AgentUDE17. Figure 11 displays the color code used for the graphics presented regarding this second scenario. This is the toughest scenario from the two simulation scenarios. We are directly competing with AgentUDE17, the winner of multiple PowerTAC editions.

Fig. 11. Simulation2 agent's labels

In figure 12 we see how early on our agent is actually ahead in terms of cumulative money. At first, this might seem a good indicator that we are on the right track. However, it is clear that this differential is due to AgentUDE's strategy of early investment and offering of ridiculously low tariffs to attract customers.

Fig. 12. Early game advantage as UDE invests

In fact, in figure 13, we see the impact on customer subscriptions. Even though we attempt to steal customers from other rivals, AgentUDE's employs such aggressive retail strategies that we actually lose the customers.

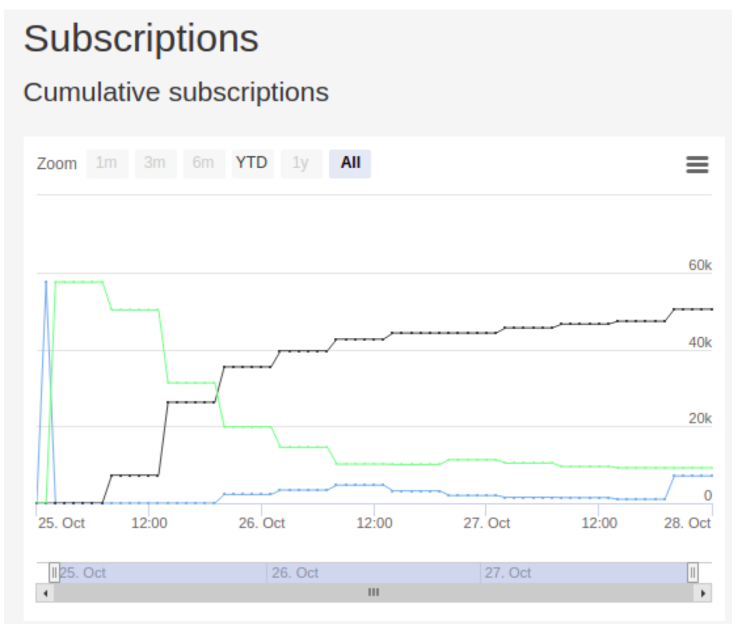

Fig. 13. Subscriptions lost to UDE

As a result, AgentUDE obtains huge retail profit. After effectively taking all of our customers AgentUDE profit skyrocket and overcome ours by a large amount. This can be verified by examining figure 14.

Fig. 14. Resultant retail loss

Toward the mid and end game the tendency continues. AgentUDE possesses most of the customers throughout the game and as seen in figure 15 dominates the game with the highest total profit. This tendency does not seem to stop based on multiple runs of this simulation scenario.

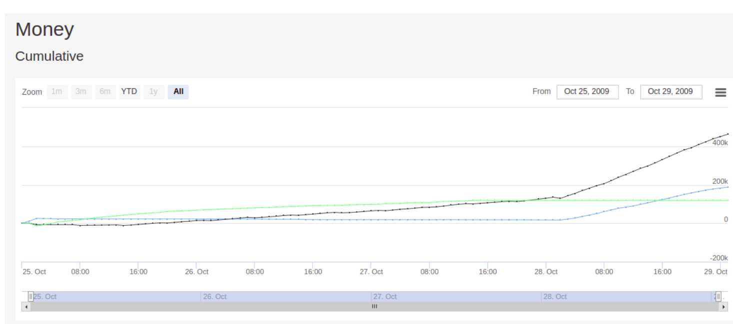

Fig. 15. Overtaken by UDE

After a wide approach to both Retail and Wholesale Market, we verified that the way customers choose a tariff is important in order to keep a stable market share as well as allowing predictions to work fine. Having said that, we think that a better analysis of the customer choosing function could be a real improvement in the broker since it could allow one to understand whether a tariff is worth to be created or updated regarding the existent tariffs on the market as well as the way customers will evaluate that tariff.

In fact, while on a competition a customer follows a utility function u_i that could be used by brokers to verify whether a tariff could bring him more reliable clients, regarding the per-KWH payment $p_{v,i}$, periodic payments $p_{p,i}$, the signup $p_{signup,i}$ and withdrawal payment $p_{withdraw,i}$ as well as an inconvenience factor X_i to account for inconvenience of switching subscriptions, and of dealing with time-of-use or variable prices or capacity controls [3]:

$$u_i = f(p_{v,i}, p_{p,i}, p_{signup,i}, p_{withdraw,i}, x_i)$$

Futhermore, each customer only evaluates a maximum number of tariffs for each broker so it is important to a broker not to create unnecessary tariffs since it will be expensive and it could not even be considered by any customer.

5 Conclusion and Future Work

In this paper, we presented a novel agent strategy for a broker in the context of the PowerTAC simulation platform focused on Wholesale Market price and quantity predictions using distributed systems to create market predictions. We conclude that a wholesale strategy by itself is not enough and thus the Power TAC competition is well designed because a broker cannot win without providing good customer services.

We observed that with a simple Tit-for-Tat Customer Market strategy, it is possible to win against the default and sample brokers, but not versus a more complex and winning broker like Agent UDE17.

Results show the use of distributed systems to make predictions in a highly dynamic environment, dealing with a huge number of variables in a short amount of time, without any disadvantage compared to a monolithic architecture.

As future work, we plan to use the customer utility function to generate better market tariffs instead of using a Tit-for-Tat approach, to explore reinforcement learning models with a distributed architecture as well as participating in the real PowerTAC competition. Regarding the wholesale market, we plan to improve the price prediction by trying to predict the price median and volatility, like Agent UDE.

We want as well to further explore the use of distributed systems using reinforcement learning models to predict wholesale market prices and quantities needed for each timeslot.

Besides this analysis and since throughout the last years, Powertac competition has created new power types mainly on the green energy field, these changes should also be taken in consideration. In fact, they now intend to change customers profiles in order to make this kind of power types more important in the competition as it has been happening in the real world, so it could be important to put some effort into the creation of good green energy tariffs.

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