Bidding in Non-Stationary Energy Markets

(Extended Abstract)

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ABSTRACT

The PowerTAC competition has gained attention for being a realistic and powerful simulation platform used for research on retail energy markets, in part because of the growing number of energy markets worldwide. Agents in this complex environment typically use multiple strategies, changing from one to another, posing a problem for current learning algorithms. This paper introduces DriftER, an algorithm that learns an opponent model and tracks its error rate. We compare our algorithm in the PowerTAC simulator against the champion of the 2013 competition and a state-of-the-art algorithm tailored for interacting against switching (non-stationary) opponents. The results show that DriftER outperforms the competition in terms of profit and accuracy.

Categories and Subject Descriptors

I.2.11 [Distributed Artificial Intelligence]: Multiagent Systems

General Terms

Algorithms, Experimentation

Keywords

PowerTAC; opponent modeling; non-stationary strategies; Markov decision processes; energy markets

1. INTRODUCTION

One of the consequences of shifting towards smarter energy (consumption, generation and distribution) is the deregulation of the energy supply and demand. These deregulated grids have enabled producers to sell energy to consumers by using a broker as an intermediary. However, these broker agents need to interact in a highly dynamic environment, where other agents are competing against each other. Autonomous brokers can succeed because of their computation power and fast reaction times, but are still challenged by the scenario’s complexity (rich state spaces, high dimensionality, partial observability and non-stationarity [5]) and straightforward game-theoretic, machine learning, and artificial intelligence techniques fall short. Moreover, in this complex environment, it is reasonable to expect that agents will use different strategies throughout their interaction and change from one to another.

Recent approaches based on multiagent systems have been proposed for energy markets. PowerTAC simulates a retail electrical energy market, where competing brokers (trying to maximize their profits) offer energy services to customers through tariff contracts, and must then serve those customers by trading in a wholesale market [4]. However, neither of the agents winning 2013 (TacTex [5]) nor 2014 (AgentUDE [1]) can efficiently compete against non-stationary opponents (that switch between stationary strategies), even though agents tend to change their strategy in competitions over time (e.g., to keep their opponent guessing) [2]. Some works have addressed this problem, like the MDP-CL framework [3]. One major drawback is that it has many parameters that need to be tuned by an expert. This paper’s main contribution is to introduce DriftER, Drift (based on) Error Rate, an algorithm that uses concept drift ideas for adapting quickly to non-stationary opponents and has few parameters to tune. The results show the effectiveness of our approach, obtaining better results in total profit and accuracy, relative to existing approaches.

2. DRIFTER

When facing non-stationary opponents two aspects are important: exploring the opponent actions to detect switches and tracking the opponent model. DriftER treats the opponent as a stationary (Markovian) environment and uses concept drift ideas to track the quality of the learned model as an indicator of a possible change in the opponent strategy. When a switch in the opponent strategy is detected, DriftER resets its learned model and restarts the learning. In this work, DriftER uses the same representation as TacTex [5] for modeling the wholesale market as a Markov Decision Process. Because the agent has no initial information, it must collect data to develop a transition function. It starts with exploratory actions during the first $k$ timeslots (learning phase), after which the MDP can be solved. We assume that during learning phase the opponent remains stationary.
incorrect observing i in the sequence, the error rate i.i.d. events will produce a Bernoulli process. Then, for each son can be seen as a Bernoulli trial. We assume a sequence of and can be compared with the true state, $s$ predicts the next state of the opponent $\hat{s}$. Once DriftER has learned an opponent model, it can decide to continue with the current model or change to a new one. When DriftER has learned a new MDP and a new policy which reduces the error rate consistently. Figure 1 (b) shows the error rates of MDP-CL and DriftER. We can observe that both algorithms detect the opponent's switch. However, MDP-CL performs comparisons to detect switches every $w$ steps ($w = 25$ in this case), unlike DriftER. Figure 1 shows the cumulative profit of (c) TacTex-WM and (d) DriftER against the non-stationary opponent. TacTex-WM profits decrease after the opponent's switch, while DriftER's profits increase even after the switch. Both algorithms reach similar cumulative profits, but DriftER obtained an average of 80k € more than the non-stationary opponent.

4. CONCLUSIONS AND FUTURE WORK

This paper introduces DriftER, an algorithm that learns a model of the opponent in the form of a MDP and keeps track of its error rate. DriftER's success is shown empirically by comparing with other approaches in PowerTAC, a complex energy market simulator. Future work will address using transfer learning ideas to promote a fast learning.

REFERENCES


