University of Strathclyde

Department of Electronic and Electrical Engineering

Learning to Trade Power

by

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A thesis presented in fulfilment of the requirements for the degree of

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Abstract

In Electrical Power Engineering, learning algorithms can be used to model the strategies of electricity market participants. The objective of this work is to establish if *policy gradient* reinforcement learning methods can provide superior participant models than previously applied *value function based* methods.

Supply of electricity involves technology, money, people, natural resources and the environment. All of these aspects are changing and electricity market designs must be suitably researched to ensure that they are fit for purpose. In this thesis electricity markets are modelled as non-linear constrained optimisation problems that are solved with a primal-dual interior point method. Policy gradient reinforcement learning algorithms are used to adjust the parameters of multi-layer feed-forward neural networks that approximate each market participant's policy for selecting power quantities and prices that are offered in a simulated marketplace.

Traditional reinforcement learning methods that learn a value function have been previously applied in simulated electricity trade, but are largely restricted to discrete representations of a market environment. Policy gradient methods have been proven to offer convergence guarantees in continuous environments, such as in robotic control applications, and avoid many of the problems that mar value function based methods.

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Chapter 7

Conclusions and Further Work

This chapter summarizes the conclusions that can be drawn from the results that are presented in this thesis and presents several ideas for further development of the contributions that have been made.

7.1 Summary Conclusions

7.2 Further Work

This section introduces some relatively new learning algorithms that have also been developed for operation in continuous multi-dimensional domains and might also be used to simulate electricity trade. It also explains is how data from National Grid Ltd. could be used in practical simulations of the UK electricity market and some of the possibilities that AC optimal power flow brings to to electric power market simulation.

7.2.1 Parameter Sensitivity Analysis

7.2.2 Alternative Learning Algorithms

This thesis has concentrated on traditional value function based and two policy gradient reinforcement learning methods. However, there have been some interesting new learning algorithms presented recently and they might also be examined in the domain of electric power trade.

Riedmiller (2005) presented Neuro-Fitted Q-Iteration (NFQ) algorithms that attempt to overcome many of the problems experienced when implementing Q-learning methods with value function approximation using neural networks. They store all transition experiences and perform off-line updates using supervised learning techniques such as RProp (Riedmiller & Braun, 1993). The method has been shown to be robust against parameterization and to learn quickly in standard benchmark tests and in real-world applications (Kietzmann & Riedmiller, 2009).

The GQ(λ) algorithm by Maei and Sutton (2010) is another extension of the Q-learning method for operation in continuous spaces. Convergence guarantees have been shown and the scaling properties suggest it is suitable for large-scale reinforcement learning applications. Software implementations of GQ(λ) are reportedly in development and due to be made available soon.

Four new Natural Actor-Critic algorithms are presented in Bhatnagar, Sutton, Ghavamzadeh, and Lee (2009). They all use function approximation techniques, making them suitable for large-scale applications of reinforcement learning. Three of the algorithms are extensions to ENAC (Peters & Schaal, 2008), but are fully incremental: the gradient computation is never reset while the policy is updated at every simulation step. The authors state a need to assess the ultimate utility of these algorithms through application in real-world problems.

This thesis provides a framework that would allow implementations of these interesting new algorithms to be assessed and used to examine aspects of electricity markets.

7.2.3 UK Transmission System

Some of the more ambitious agent-based electricity market simulations have used stylised models of national transmission systems (Rastegar, Guerci, & Cincotti, 2009; Weidlich & Veit, 2006). This work has often been motivated by recent or expected changes to the arrangements in the associated regions.

Several of the the UK's largest power stations are due to be decommissioned around 2015 in accordance with EU Large Combustion Plant Directive. The ability of the market to sufficiently incentivize new investment in generation that will cover the resulting shortfall is in question. The concern extends to the need for long-term investment in new nuclear power plant that is deemed necessary for the UK to meet the legally binding obligations, made in the Climate Change Bill, to cut greenhouse gas emissions by 80% by 2050, compared to 1990 levels.

Examination of the situation could be enhanced by the advanced participant behavioural models and the accurate electric power system simulations presented in this thesis. Figure **??** illustrates a model of the UK transmission system that has been derived from data provided in National Electricity Transmission System Operator (2010). This model has been converted into a PSS/E version 30 raw file and is distributed with the code developed for this thesis (See Appendix A.9).

It is currently too computationally expensive for this model to be solved repeatedly in an agent-based simulation. However, optimisation efforts might allow for it to be used to examine issues pertinent to the UK energy industry.

7.2.4 AC Optimal Power Flow

To the best of the author's knowledge this is the first application of AC optimal power flow in agent-based electricity market simulation. AC optimal power flow formulations are more difficult to implement and the problems are more computationally expensive than than their linearised DC counterparts. The additional time and effort does not always bring sufficient value to electricity market simulations. However, the option to use an AC formulation offers some interesting possibilities for further work.

The inclusion of reactive power costs in the objective function of an AC optimal power flow problem means that parallel auctions for voltage support could be added to simulations. This could be open to agents associated with reactive compensation equipment such as that commonly needed for wind farm developments. Reactive power markets have traditionally been largely academic, but as the UK makes greater use of wind power the topic could become of increasing interest.

Bus voltages are not all assumed to be 1 per-unit in AC optimal power flow problems, but are part of the vector of optimisation variables. Adjusting phase shift angles, θ_{ph}, offers a degree of control over the direction of power flows. The control the transformer tap ratios, τ, and the shift angles by learning agents could be of interest in the evaluation of congestion management techniques.

7.2.5 Multi-Market Simulation

The global economy is a holistic system of systems and the analysis of markets independently must be of limited value. Recent agent-based electricity market simulations studies have investigated the interaction between electricity, gas and emission allowances markets (Kienzle, Krause, Egli, Geidl, & Andersson, 2007; J. Wang, Koritarov, & Kim, 2009). The information on the UK gas network provided in National Electricity Transmission System Operator (2010) is relatively limited to that of the electricity transmission system, but suitable models could be used in conjunction to study the the relationships between gas and electricity markets. As in Kienzle et al. (2007), actions in the gas market would constrain the generators options to sell power in subsequent electricity auctions. Add to this the option to trade in carbon markets and the agent's state and action spaces would quickly become very large and suitable learning methods would be required.

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