University of Strathclyde

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Learning to Trade Power

by

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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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 models of market participants 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 the markets for electricity must be suitably researched to ensure that their designs are fit for purpose. In this thesis electricity markets are modelled as non-linear constrained optimisation problems that are solved using 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 quantities of power and prices that are offered in the 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.

The benefits of using policy gradient methods in electricity market simulation are explored and the results demonstrate their superior trading ability when operating in large constrained networks. By advancing the use of learning methods in electricity market simulation, this work provides the opportunity to revisit previous research in the field and creates the possibility for policy gradient methods to be used in decision support and automated energy trading applications.

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Chapter 1

Introduction

This thesis examines learning algorithms in the domain of electric power trade. In this chapter the motivation for research into electricity trade is explained, the problem under consideration is defined, the principle research contributions of this thesis are stated and an outline the remaining chapters is given.

1.1 Research Motivation

The average total demand for electricity in the United Kingdom (UK) is approximately 45GW and the cost of buying 1MW for one hour is around £40 (Department of Energy and Climate Change, 2009). This equates to yearly transaction values of £16 billion. The value of electricity to societies becomes particularly apparent when supply fails. The New York black-out in August 2003 involved a loss of 61.8GW of power supply to approximately 50 million consumers. The majority of supplies were restored within two days, but the event is estimated to have cost more than $6 billion (Minkel, 2008; ICF Consulting, 2003).

Quality of life for a person has been shown to be directly proportional to that person's electricity usage (Alam, Bala, Huo, & Matin, 1991). The world population is currently 6.7 billion and forecast to exceed 9 billion by the year 2050 (United Nations, 2003). As people endeavour to improve their quality of life, finite primary energy fuel resources will become increasingly scarce and market mechanisms (e.g. auctions), where the final allocation is based upon the claimants' willingness to pay for the goods, provide a device for efficient allocation of resources in short supply.

Commercialisation of large electricity supply industries began two decades ago in the UK. The inability to store electricity, once generated, in a commercially viable quantity prevents trade as a conventional commodity. Trading mechanisms must allow shortfalls in electric energy to be purchased at short notice from quickly dispatchable generators. Different market structures that facilitate this have been implemented in countries and states around the world. Designed correctly, a competitive electricity market promotes efficiency and drives down costs to the consumer, while design errors can allow market power abuse and elevated market prices.

The value of electricity to societies makes it infeasible to experiment with radical changes to trading arrangements on real systems. A practical alternative is to study abstract mathematical models (with sets of simplifying approximations and assumptions) and, where possible, to find analytical solutions using digital computer programs. Competition is a fundamental component of all markets, but accurate participant strategy models are difficult to create. Reinforcement learning methods can be used to represent the adaptive behaviour of competing players and have been shown to be capable of learning complex strategies (Tesauro, 1994).

1.2 Problem Statement

Individuals participating in an electricity market (be they representing generating companies, load serving entities, firms of traders etc.) must utilise multi-dimensional data, mostly continuous in nature. Certain data, such as demand forecasts, exhibits a degree of uncertainty and other market information, such as the bids of competitors, is hidden.

Traditional reinforcement learning methods accociate a value with each available action in a given state. When these values are stored in look-up tables, these methods become restricted by Bellman's Curse of Dimensionality (Bellman, 1961) and can not be applied to complex problems with high-dimensional state and action spaces. When used with function approximation techniques (e.g. artificial neural networks) to allow operation in continuous environments, these methods have been shown to have poor convergence properties, even in simple problems (Gordon, 1995; Baird, 1995; Tsitsiklis & Roy, 1994).

Policy gradient reinforcement learning methods do not attempt to approximate a value function, but use function approximation techiniques to represent a policy for seleting actions and search directly in the space of its parameters. They do not suffer from many of the problems that mar value-function based methods in high-dimensional domains. They have strong convergence properties, do not require that all states be continuously visited and work with state and action spaces that are continuous, discrete or mixed. Policy performance may be degraded by uncertainty in state data, but the learning methods need not be altered. Policy gradient methods have been successfully applied in many operational settings (Sutton, McAllester, Singh, & Mansour, 2000; Peters & Schaal, 2006; Moody & Saffell, 2001; Peshkin & Savova, 2002).

It is proposed in this thesis that agents which learn using policy gradient methods may outperform those using value function based methods in simulated competitive electricity trade. It is further proposed that policy gradient methods may operate better under dynamic electric power system conditions, achieving greater profit by exploiting constraints to their financial benefit. This thesis will use electricity market simulation techniques to compare value function based and policy gradient learning methods and explore these proposals.

1.3 Research Contributions

The research presented in this thesis pertains to the academic fields of Electric Power Engineering, Artificial Intelligence and Economics. The principle contributions made by this thesis in these fields are:

- The first application of policy gradient reinforcement learning methods in simulated energy trade.
- The first application of a non-linear optimal power flow formulation in agent based electricity market simulation.
- A new stateful formulation of the Roth-Erev reinforcement learning method.
- Simulation results which show how policy gradient reinforcement learning methods converge more slowly than value function based methods when learning simple power trade policies.
- Simulation results which show how agents using policy gradient reinforcement learning methods achieve greater profitability than those using value function methods when when competing to supply electric power on equal terms.
- An implementation of a multi-agent system for electricity market simulation with discrete and continuous sensor and action space representations.
- The idea of applying Neuro Fitted Q Iteration and GQ(λ) in simulations of competitive energy trade.

- The idea of using data from the National Grid seven year statement to simulate the UK electricity market.

The publications that have resulted from this thesis are: Lincoln, Galloway, and Burt (2009).

1.4 Thesis Outline

The presentation of this thesis is organised into nine chapters. Chapter 2 provides background information on electric power supply, wholesale electricity markets and reinforcement learning. It describes how optimal power flow formulations can be used to model electricity markets and defines the reinforcement learning methods that are later examined.

In Chapter 3 the research in this thesis is described in the context of previous work that is related in terms of application field and methodology. Publications on agent based electricity market simulation are reviewed with emphasis on the reinforcement learning methods utilised. Previous applications of policy gradient learning methods in other market settings are also discussed.

Chapter 4 describes the power exchange auction market model and the multi-agent system used to simulated electricity trade. It defines the association of learning agents with portfolios of generators, the process by which offers are submitted and the reward calculation process. Finally, it explains how look-up tables, used with value function based methods, and artificial neural networks, used for policy function approximation, are are structured.

An experiment that examines the convergence to a Nash equilibrium of systems of multiple electric power trading agents is reported in Chapter 5. A six bus test case is described and results for four learning algorithms are presented and compared.

Chapter 6 examines the ability of agents to learn policies for exploiting constraints in simulated power systems. The 24 bus model from the IEEE Reliability Test System provides a complex environment with dynamic loading conditions.

The primary conclusions drawn from the results in this thesis are summarised in Chapter 7.2. Shortcommings of the approach are noted and the broaded implications are addressed. Some ideas for futher work are also outlined. Alternative reinforcement learning methods that could be used in a similar study are listed. A model of the UK transmission system, constructed from data in the National Grid Seven Year Statement, is described and ideas for how the model could be combined with the advances made in this thesis are explained. Opportunities provided by the use of AC optimal power flow in agent based electricity market simulation are also explored. Finally, the possibilties for using policy gradient methods in multi-market studies that include gas and emissions trade are recognised.

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