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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 thesis is to establish if *policy gradient* reinforcement learning algorithms can be used to create participant models superior to those involving 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, which 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 artificial neural networks that approximate each market participant's policy for selecting power quantities 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 they are mostly restricted to use with discrete representations of a market environment. Policy gradient methods have been proven to offer convergence guarantees in continuous environments and avoid many of the problems that mar value function based methods.

Five types of learning algorithm are compared in a series of Nash equilibrium and constraint exploitation simulations. Policy gradient methods are found to be a valid option for modelling the strategies of electricity market participants, but they are outperformed by a traditional action-value function algorithm in all of the tests. Further development of this research could provide opportunities for advanced learning algorithms to be used in descision support and automated energy trade applications.

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Chapter 1

Introduction

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

1.1 Research Motivation

Quality of life for a person is directly proportional to his or her electricity usage (Alam, Bala, Huo, & Matin, 1991). The world population is currently 6.7 billion and forecast to exceed 9 billion by 2050 (United Nations, 2003). Electricity production currently demands over one third of the annual primary energy extracted (The International Energy Agency, 2010) and as more people endeavour to improve their quality of life, finite fuel resources will become increasingly scarce. Market mechanisms, such as 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. In 1990 the UK became the first large industrialised country to introduce competitive markets for electricity generation.

The inability to store electricity, once generated, in a commercially viable quantity prevents it from being traded as a conventional commodity. Trading mechanisms must allow shortfalls in electric energy to be purchased at short notice from quickly dispatchable generators. Designed correctly, a competitive electricity market can promote efficiency and drive down costs to the consumer, while design errors can allow market power to be abused and market prices to become elevated. It is necessary to research electricity market architectures to ensure that their unique designs are fit for purpose.

The value of electricity to society makes it impractical to experiment with radical changes to trading arrangements on real systems. 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 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).

An alternative approach is to study abstract mathematical models of markets with sets of appropriate simplifying approximations and assumptions applied. Characteristics of market architectures and the consequences of proposed changes can be established by simulating the models using digital computer programs. Competition between participants is fundamental to all markets, but the strategies of humans can be difficult to model mathematically. One option is to use reinforcement learning algorithms from the field of artificial intelligence. These methods can be used to represent adaptive behaviour in competing players and have been shown to be capable of learning highly complex strategies (Tesauro, 1994). This thesis makes advances in electricity market participant modelling through the application of a relatively new genre of reinforcement learning methods called policy gradient algorithms.

1.2 Problem Statement

Individuals participating in an electricity market (be they representing generating companies, load serving entities, firms of traders etc.) must utilise multidimensional data to their advantage. This data may be noisy, sparse, corrupt, have a degree of uncertainty (e.g. demand forecasts) or be hidden from the participant (e.g. competitor bids). Reinforcement learning algorithms must be capable of operating with data of this kind if they are to successfully model participant strategies.

Traditional reinforcement learning methods, such as Q-learning, attempt to find the *value* of each available action in a given state. When discrete state and action spaces are defined, these methods become restricted by Bellman's Curse of Dimensionality (Bellman, 1961) and can not be readily applied to complex problems. Function approximation techniques, such as artificial neural networks, can allow these methods to be applied to continuous environment representations.

However, value function approximation has been shown to result in convergence issues, even in simple problems (Tsitsiklis & Roy, 1994; Peters & Schaal, 2008; Gordon, 1995; Baird, 1995).

Policy gradient reinforcement learning methods do not attempt to approximate a value function, but instead try to approximate a *policy function* that, given the current perceived state of the environment, returns an action (Peters, 2010). They do not suffer from many of the problems that mar value function based methods in high-dimensional problems. 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 (Peters & Schaal, 2008). Policy performance may be degraded by uncertainty in state data, but the learning methods do not need to be altered. They have been successfully applied in many operational settings, including: robotic control (Peters & Schaal, 2006), financial trading (Moody & Saffell, 2001) and network routing (Peshkin & Savova, 2002) applications.

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 benefit. This thesis will compare value function based and policy gradient learning methods in the context of electricity trade to explore these proposals.

1.3 Research Contributions

The research presented in this thesis pertains to the academic fields of electrical power engineering, artificial intelligence and economics. The principle contributions made by this thesis are:

1. The first application of policy gradient reinforcement learning methods in simulated electricity trade. A relatively new class of unsupervised learning algorithms, designed for operation in multi-dimensional, continuous, uncertain and noisy environments, are applied in dynamic techo-economic simulations.

2. The first application of a non-linear AC optimal power flow formulation in agent based electricity market simulation. The constraining assumptions of linearised DC models not being applied provides more accurate electric

power systems models in which reactive power flows and voltage magnitude constraints are considered.

3. A new Stateful Roth-Erev reinforcement learning method for application in complex environments with dynamic state.

4. A comparison of policy gradient and value function based reinforcement learning methods in their convergence to states of Nash equilibrium. Results from published research for value function based methods are reproduced and extented to provide a foundation for the application of policy gradient methods in more complex electric power trade simulations.

5. An examination of the exploitation of electric power system constraints by policy gradient reinforcement learning methods. The superior multi-dimensional, continuous data handling abilities of policy gradient methods are tested by exploring their ability to observe voltage constraints and exploit them to achieve increased profits.

6. The delivery of an extensible open source multi-learning-agent-based power exchange auction market simulator for electric power trade research. Sharing software code can dramtically accelerate research of this kind and an extensive suite of the tools developed for this thesis has been released under a liberal open source license.

7. The concept of applying Neuro-Fitted Q-Iteration and GQ(λ) in simulations of competitive energy trade. New unsupervised learning algorithms developed for operation in continuous environments could be utilised in electric power trade simulation and some of the most promising examples have been identified.

The publications that have resulted from this thesis are:

- Lincoln, R., Galloway, S., & Burt, G. (2009, May 27-29). Open source, agent-based energy market simulation with Python. In Proceedings of the 6$^{\text{th}}$ International Conference on the European Energy Market, 2009. EEM 2009. (p. 1-5).

- Lincoln, R., Galloway, S., & Burt, G. (2007, May 23-25). Unit commitment and system stability under increased penetration of distributed generation. In Proceedings of the 4$^{\text{th}}$ International Conference on the European Energy Market, 2007. EEM 2007. Kraców, Poland.

- Lincoln, R., Galloway, S., Burt, G., & McDonald, J. (2006, 6-8). Agent-based simulation of short-term energy markets for highly distributed power systems. In Proceedings of the 41st International Universities Power Engineering Conference, 2006. UPEC '06. (Vol. 1, p. 198-202).

This thesis also resulted in invitations to present at the tools sessions of the Common Information Model (CIM) Users Group meetings in Genval, Belgium and Charlotte, North Carolina, USA in 2009.

1.4 Thesis Outline

This thesis is organised into nine chapters. Chapter 2 provides background information on electricity 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 algorithms that are later compared. The chapter is intended to enable readers unfamiliar with this field of research to understand the techniques used in the subsequent chapters.

In Chapter 3 the research in this thesis is described in the context of previous work related in terms of application field and methodology. Publications on agent based electricity market simulation are reviewed with emphasis on the participant behavioural models used. Previous applications of policy gradient learning methods in other types of market setting are also covered. The chapter illustrates the movement in this field towards more complex participant behavioural models and highlights some of the gaps in the existing research that this thesis aims to fill.

Chapter 4 describes the power exchange auction market model and the multi-agent system used to simulate electricity trade. It defines the association of learning agents with portfolios of generators, the process of offer submission and the reward process. The chapter describes the common components that are then applied in specific simulations.

Simulations that examine 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 used and results for four learning algorithms under two cost configurations are presented and analysed. The chapter confirms that policy gradient methods can be used in electric power trade simulations, in the same way as value function based methods and provides a foundation for their application in more complex experiments.

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 chapter is used to determine if the multi-dimensional continuous data handling abilities of policy gradient methods can be exploited by agents to learn more complex electricity trading policies than those operating in discrete trading environment representations.

The primary conclusions drawn from the results in this thesis are summarised in Chapter 7. Shortcomings of the approach are noted and the broader implications are addressed. Some ideas for further work are also outlined, including alternative reinforcement learning methods and potential applications of a model of the UK transmission system.

Bibliography

Alam, M. S., Bala, B. K., Huo, A. M. Z., & Matin, M. A. (1991). A model for the quality of life as a function of electrical energy consumption. Energy, 16(4), 739-745.

Aleksandrov, V., Sysoyev, V., & Shemeneva, V. (1968). Stochastic optimization. Engineering Cybernetics, 5, 11-16.

Amerongen, R. van. (1989, May). A general-purpose version of the fast decoupled load flow. Power Systems, IEEE Transactions on, 4(2), 760-770.

Application of Probability Methods Subcommittee. (1979, November). IEEE reliability test system. Power Apparatus and Systems, IEEE Transactions on, PAS-98(6), 2047-2054.

Auer, P., Cesa-Bianchi, N., Freund, Y., & Schapire, R. E. (2003). The non-stochastic multiarmed bandit problem. SIAM Journal of Computing, 32(1), 48-77.

Baird, L. (1995). Residual algorithms: Reinforcement learning with function approximation. In Proceedings of the Twelfth International Conference on Machine Learning (p. 30-37). Morgan Kaufmann.

Bellman, R. E. (1961). Adaptive control processes – A guided tour. Princeton, New Jersey, U.S.A.: Princeton University Press.

Bertsekas, D. P., & Tsitsiklis, J. N. (1996). Neuro-dynamic programming. Belmont, MA: Athena Scientific.

Bhatnagar, S., Sutton, R. S., Ghavamzadeh, M., & Lee, M. (2009). Natural actor-critic algorithms. Automatica, 45(11), 2471–2482.

Bishop, C. M. (1996). Neural networks for pattern recognition (1st ed.). Oxford University Press, USA. Paperback.

Bower, J., & Bunn, D. (2001, March). Experimental analysis of the efficiency of uniform-price versus discriminatory auctions in the england and wales electricity market. Journal of Economic Dynamics and Control, 25(3-4), 561-592.

Bower, J., Bunn, D. W., & Wattendrup, C. (2001). A model-based analysis of strategic consolidation in the german electricity industry. Energy Policy, 29(12), 987-1005.

Boyd, S., & Vandenberghe, L. (2004). Convex optimization. Cambridge University Press. Hardcover.

Bunn, D., & Martoccia, M. (2005). Unilateral and collusive market power in the electricity pool of England and Wales. Energy Economics.

Bunn, D. W., & Oliveira, F. S. (2003). Evaluating individual market power in electricity markets via agent-based simulation. Annals of Operations Research, 57-77.

Carpentier, J. (1962, August). Contribution à l'étude du Dispatching Economique. Bulletin de la Society Francaise Electriciens, 3(8), 431-447.

Cole, S. (2010, February 4). MatDyn [Computer software manual]. Katholieke Universiteit Leuven.

Department of Energy and Climate Change. (2009). Digest of United Kingdom Energy Statistics 2009. In (chap. 5). National Statistics – Crown.

Erev, I., & Roth, A. E. (1998). Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria. The American Economic Review, 88(4), 848-881.

Ernst, D., Minoia, A., & Ilic, M. (2004, June). Market dynamics driven by the decision-making of both power producers and transmission owners. In Power Engineering Society General Meeting, 2004. IEEE (p. 255-260).

Fausett, L. (Ed.). (1994). Fundamentals of neural networks: architectures, algorithms, and applications. Upper Saddle River, NJ, USA: Prentice-Hall, Inc.

Gieseler, C. (2005). A Java reinforcement learning module for the Repast toolkit: Facilitating study and implementation with reinforcement learning in social science multi-agent simulations. Unpublished master's thesis, Department of Computer Science, Iowa State University.

Glimn, A. F., & Stagg, G. W. (1957, April). Automatic calculation of load flows. Power Apparatus and Systems, Part III. Transactions of the American Institute of Electrical Engineers, 76(3), 817-825.

Glynn, P. W. (1987). Likelilood ratio gradient estimation: an overview. In WSC '87: Proceedings of the 19th conference on winter simulation (p. 366-375). New York, NY, USA: ACM.

Goldfarb, D., & Idnani, A. (1983). A numerically stable dual method for solving strictly convex quadratic programs. Mathematical Programming, 27, 1-33.

Gordon, G. (1995). Stable function approximation in dynamic programming. In

Proceedings of the Twelfth International Conference on Machine Learning (p. 261-268). Morgan Kaufmann.

Grainger, J., & Stevenson, W. (1994). Power system analysis. New York: McGraw-Hill.

Guo, M., Liu, Y., & Malec, J. (2004, October). A new Q-learning algorithm based on the metropolis criterion. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 34(5), 2140-2143.

ICF Consulting. (2003, August). The economic cost of the blackout: An issue paper on the northeastern blackout. (Unpublished)

IEEE Working Group. (1973, November). Common format for exchange of solved load flow data. Power Apparatus and Systems, IEEE Transactions on, 92(6), 1916-1925.

Kallrath, J., Pardalos, P., Rebennack, S., & Scheidt, M. (2009). Optimization in the energy industry. Springer.

Kienzle, F., Krause, T., Egli, K., Geidl, M., & Andersson, G. (2007, September). Analysis of strategic behaviour in combined electricity and gas markets using agent-based computational economics. In 1st European workshop on energy market modelling using agent-based computational economics (p. 121-141). Karlsruhe, Germany.

Kietzmann, T. C., & Riedmiller, M. (2009). The neuro slot car racer: Reinforcement learning in a real world setting. Machine Learning and Applications, Fourth International Conference on, 0, 311-316.

Kirschen, D. S., & Strbac, G. (2004). Fundamentals of power system economics. Chichester: John Wiley & Sons.

Krause, T., & Andersson, G. (2006). Evaluating congestion management schemes in liberalized electricity markets using an agent-based simulator. In Power Engineering Society General Meeting, 2006. IEEE.

Krause, T., Andersson, G., Ernst, D., Beck, E., Cherkaoui, R., & Germond, A. (2004). Nash equilibria and reinforcement learning for active decision maker modelling in power markets. In Proceedings of 6th IAEE European Conference 2004, modelling in energy economics and policy.

Krause, T., Beck, E. V., Cherkaoui, R., Germond, A., Andersson, G., & Ernst, D. (2006). A comparison of Nash equilibria analysis and agent-based modelling for power markets. International Journal of Electrical Power & Energy Systems, 28(9), 599-607.

Li, H., & Tesfatsion, L. (2009a, July). The ames wholesale power market test bed: A computational laboratory for research, teaching, and training. In

IEEE Proceedings, Power and Energy Society General Meeting. Alberta, Canada.

Li, H., & Tesfatsion, L. (2009b, March). Capacity withholding in restructured wholesale power markets: An agent-based test bed study. In Power systems conference and exposition, 2009 (p. 1-11).

Lincoln, R., Galloway, S., & Burt, G. (2009, May). Open source, agent-based energy market simulation with Python. In Proceedings of the 6th International Conference on the European Energy Market, 2009. EEM 2009. (p. 1-5).

Maei, H. R., & Sutton, R. S. (2010). Gq(λ): A general gradient algorithm for temporal-difference prediction learning with eligibility traces. In Proceedings of the third conference on artificial general intelligence. Lugano, Switzerland.

McCulloch, W., & Pitts, W. (1943, December 21). A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biology, 5(4), 115-133.

Micola, A. R., Banal-Estañol, A., & Bunn, D. W. (2008, August). Incentives and coordination in vertically related energy markets. Journal of Economic Behavior & Organization, 67(2), 381-393.

Micola, A. R., & Bunn, D. W. (2008). Crossholdings, concentration and information in capacity-constrained sealed bid-offer auctions. Journal of Economic Behavior & Organization, 66(3-4), 748-766.

Minkel, J. R. (2008, August 13). The 2003 northeast blackout–five years later. Scientific American.

Momoh, J., Adapa, R., & El-Hawary, M. (1999, Feb). A review of selected optimal power flow literature to 1993. I. Nonlinear and quadratic programming approaches. Power Systems, IEEE Transactions on, 14(1), 96-104.

Momoh, J., El-Hawary, M., & Adapa, R. (1999, Feb). A review of selected optimal power flow literature to 1993. II. Newton, linear programming and interior point methods. Power Systems, IEEE Transactions on, 14(1), 105-111.

Moody, J., & Saffell, M. (2001, July). Learning to trade via direct reinforcement. IEEE Transactions on Neural Networks, 12(4), 875-889.

Moody, J., Wu, L., Liao, Y., & Saffell, M. (1998). Performance functions and reinforcement learning for trading systems and protfolios. Journal of Forecasting, 17, 441-470.

Naghibi-Sistani, M., Akbarzadeh-Tootoonchi, M., Javidi-D.B., M., & Rajabi-Mashhadi, H. (2006, November). Q-adjusted annealing for Q-learning of bid selection in market-based multisource power systems. Generation, Transmission and Distribution, IEE Proceedings, 153(6), 653-660.

Nash, J. F. (1950, January). Equilibrium points in n-person games. Proceedings of the National Academy of Sciences of the United States of America, 36(1), 48-49.

Nash, J. F. (1951, September). Non-cooperative games. The Annals of Mathematics, 54(2), 286-295. Available from http://dx.doi.org/10.2307/1969529

National Electricity Transmission System Operator. (2007, September). Large combustion plant directive (Tech. Rep.). National Grid Electricity Transmission plc. (GCRP 07/32)

National Electricity Transmission System Operator. (2010, May). 2010 National Electricity Transmission System Seven Year Statement (Tech. Rep.). National Grid Electricity Transmission plc.

Nicolaisen, J., Petrov, V., & Tesfatsion, L. (2002, August). Market power and efficiency in a computational electricity market with discriminatory double-auction pricing. Evolutionary Computation, IEEE Transactions on, 5(5), 504-523.

Nicolaisen, J., Smith, M., Petrov, V., & Tesfatsion, L. (2000). Concentration and capacity effects on electricity market power. In Evolutionary Computation. Proceedings of the 2000 Congress on (Vol. 2, p. 1041-1047).

Overbye, T., Cheng, X., & Sun, Y. (2004, Jan.). A comparison of the AC and DC power flow models for LMP calculations. In System sciences, 2004. Proceedings of the 37th annual Hawaii international conference on (p. 9-).

Peshkin, L., & Savova, V. (2002). Reinforcement learning for adaptive routing. In Neural Networks, 2002. IJCNN 2002. Proceedings of the 2002 International Joint Conference on (Vol. 2, p. 1825-1830).

Peters, J. (2010). Policy gradient methods. (Available online: www.scholarpedia.org)

Peters, J., & Schaal, S. (2006, October). Policy gradient methods for robotics. In Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on (p. 2219-2225).

Peters, J., & Schaal, S. (2008). Natural actor-critic. Neurocomputing, 71(7-9), 1180-1190.

Rastegar, M. A., Guerci, E., & Cincotti, S. (2009, May). Agent-based model of the Italian wholesale electricity market. In Energy Market, 2009. 6th International Conference on the European (p. 1-7).

Riedmiller, M. (2005). Neural fitted Q iteration - first experiences with a data efficient neural reinforcement learning method. In In 16th European conference on machine learning (pp. 317–328). Springer.

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster backpropagation learning: the rprop algorithm.

Robbins, H. (1952). Some aspects of the sequential design of experiments. Bulletin American Mathematical Society, 58(5), 527-535.

Roth, A. E., Erev, I., Fudenberg, D., Kagel, J., Emilie, J., & Xing, R. X. (1995). Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term. Games and Economic Behavior, 8(1), 164-212.

Schaul, T., Bayer, J., Wierstra, D., Sun, Y., Felder, M., Sehnke, F., et al. (2010). PyBrain. Journal of Machine Learning Research, 11, 743-746.

Schweppe, F., Caramanis, M., Tabors, R., & Bohn, R. (1988). Spot pricing of electricity. Dordrecht: Kluwer Academic Publishers Group.

Sharpe, W. F. (1966, January). Mutual fund performance. Journal of Business, 119-138.

Sharpe, W. F. (1994). The Sharpe ratio. The Journal of Portfolio Management, 49-58.

Stott, B., & Alsac, O. (1974, May). Fast decoupled load flow. Power Apparatus and Systems, IEEE Transactions on, 93(3), 859-869.

Sun, J., & Tesfatsion, L. (2007a). Dynamic testing of wholesale power market designs: An open-source agent-based framework. Computational Economics, 30(3), 291-327.

Sun, J., & Tesfatsion, L. (2007b, June). Open-source software for power industry research, teaching, and training: A DC-OPF illustration. In Power Engineering Society General Meeting, 2007. IEEE (p. 1-6).

Sutton, R. S., & Barto, A. G. (1998). Reinforcement learning: An introduction. MIT Press. Gebundene Ausgabe.

Sutton, R. S., McAllester, D., Singh, S., & Mansour, Y. (2000). Policy gradient methods for reinforcement learning with function approximation. In Advances in neural information processing systems (Vol. 12, p. 1057-1063).

Tellidou, A., & Bakirtzis, A. (2007, Novemeber). Agent-based analysis of capacity withholding and tacit collusion in electricity markets. Power Systems, IEEE Transactions on, 22(4), 1735-1742.

Tesauro, G. (1994). TD-Gammon, a self-teaching backgammon program, achieves master-level play. Neural Computation, 6(2), 215-219.

Tesfatsion, L., & Judd, K. L. (2006). Handbook of computational economics, volume 2: Agent-based computational economics (handbook of computational economics). Amsterdam, The Netherlands: North-Holland Publishing Co.

The International Energy Agency. (2010, Septemeber). Key world energy statistics 2010. Paris.

Tinney, W., & Hart, C. (1967, Novemeber). Power flow solution by Newton's method. Power Apparatus and Systems, IEEE Transactions on, 86(11), 1449-1460.

Tsitsiklis, J. N., & Roy, B. V. (1994). Feature-based methods for large scale dynamic programming. In Machine learning (p. 59-94).

United Nations. (2003, December 9). World population in 2300. In Proceedings of the United Nations, Expert Meeting on World Population in 2300.

U.S.-Canada Power System Outage Task Force. (2004, April). Final report on the august 14, 2003 blackout in the United States and Canada: Causes and recommendations (Tech. Rep.). North American Electric Reliability Corporation.

Veit, D., Weidlich, A., Yao, J., & Oren, S. (2006). Simulating the dynamics in two-settlement electricity markets via an agent-based approach. International Journal of Management Science and Engineering Management, 1(2), 83-97.

Vengerov, D. (2008). A gradient-based reinforcement learning approach to dynamic pricing in partially-observable environments. Future Generation Computer Systems, 24(7), 687-693.

Visudhiphan, P. (2003). An agent-based approach to modeling electricity spot markets. Unpublished doctoral dissertation, Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology.

Visudhiphan, P., & Ilic, M. (1999, February). Dynamic games-based modeling of electricity markets. In Power Engineering Society 1999 Winter Meeting, IEEE (Vol. 1, p. 274-281).

Wang, H., Murillo-Sanchez, C., Zimmerman, R., & Thomas, R. (2007, Aug.). On computational issues of market-based optimal power flow. Power Systems, IEEE Transactions on, 22(3), 1185-1193.

Wang, J., Koritarov, V., & Kim, J.-H. (2009, July). An agent-based approach to modeling interactions between emission market and electricity market. In Power Energy Society General Meeting, 2009. PES 2009. IEEE (p. 1-8).

Weidlich, A., & Veit, D. (2006, July 7-10). Bidding in interrelated day-ahead electricity markets - insights from an agent-based simulation model. In Proceedings of the 29th IAEE International Conference.

Weidlich, A., & Veit, D. (2008, July). A critical survey of agent-based wholesale electricity market models. Energy Economics, 30(4), 1728-1759.

WG 31.04. (1983). Electric power transmission at voltages of 1000 kV and above plans for future AC and DC transmission. Electra. (ELT_091_3)

Williams, R. J. (1992). Simple statistical gradient-following algorithms for connectionist reinforcement learning. In Machine learning (p. 229-256).

Wood, A. J., & Wollenberg, B. F. (1996). Power Generation Operation and Control (second ed.). New York: Wiley, New York.

Yao, J., Adler, I., & Oren, S. S. (2008). Modeling and computing two-settlement oligopolistic equilibrium in a congested electricity network. Operations Research, 56(1), 34-47.

Yao, J., Oren, S. S., & Adler, I. (2007). Two-settlement electricity markets with price caps and cournot generation firms. European Journal of Operational Research, 181(3), 1279-1296.

Zimmerman, R. (2010, March 19). MATPOWER 4.0b2 User's Manual [Computer software manual]. School of Electrical Engineering, Cornell University, Ithaca, NY 14853.

Zimmerman, R., Murillo-Sánchez, C., & Thomas, R. J. (2009, July). MATPOWER's extensible optimal power flow architecture. In IEEE PES General Meeting. Calgary, Alberta, Canada.