University of Strathclyde

Department of Electronic and Electrical Engineering

Learning to Trade Power

by

Richard W. Lincoln

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

Doctor of Philosophy

2010

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.

Signed: Date: August 20, 2010

Acknowledgements

I wish to thank Professor Jim McDonald for giving me the opportunity to study at The Institute for Energy and Environment and for giving me the freedom to pursue my own research interests. I also wish to thank my supervisors, Professor Graeme Burt and Dr Stuart Galloway, for their guidance and scholarship. I wish to offer very special thanks to my parents, my big brother and my little sister for all of their support throughout my PhD.

This thesis makes extensive use of open source software projects developed by researchers from other institutions. I wish to thank Dr Ray Zimmerman from Cornell University for his work on optimal power flow, researchers from the Dalle Molle Institute for Artificial Intelligence (IDSIA) and the Technical University of Munich for their work on reinforcement learning algorithms and artificial neural networks and Charles Gieseler from Iowa State University for his implementation of the Roth-Erev reinforcement learning method.

This research was funded by the United Kingdom Engineering and Physical Sciences Research Council through the Supergen Highly Distributed Power Systems consortium under grant GR/T28836/01.

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.

Contents

List of Figures

List of Tables

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 and Conclusions

This thesis has introduced the use of policy gradient reinforcement learning algorithms for modelling electricity market participant strategies. Over the last two decades markets have become an essential component in the electricity supply industries of many large countries. They will play an important role in the future as the world population grows and finite primary energy fuel resources become increasingly scarce. Electricity market design are unique amongst commodity markets and new architectures are expensive and risky to implement.

Computational simulation is a well established for evaluating market design concepts and an agent-based approach allows large complex systems to be simulated. The literature includes many examples of learning algorithms being used to model electricity market participants, but policy gradient methods have not been previously applied. They *have* been used successfully in other market related research and in robotic control and network routing applications.

To examine the properties of policy gradient methods and to compare them with previously applied value function based methods a modular simulation framework has been defined and implemented. The framework includes a power exchange auction market model with nodal marginal pricing that provides an environment in which agents learn to trade electricity competitively.

The framework is first used in a simulation that compares the convergence to a Nash equilibrium of four learning algorithms. The simulation reproduces the findings of Krause et al. (2006) produced similar results for policy gradient methods. These methods were found to require a larger number of interactions before learning an optimal policy and learning rate and exploration rate decay parameters had to be set low for the more complex equilibrium to be approached.

In a second simulation the same algorithms were compared in a complex dynamic electricity trading environment. A reference electric power system model for reliability analysis that experiences a variety of constraint conditions as load follows an annual profile was used. The algorithms were compared in their ability to observe and exploit systems constraints. Policy gradient methods were found to . . .

In conclusion, policy gradient methods are a valid alternative to previously applied methods that require discrete environment representations. They have been shown to develop similar policies as value function based methods in simple problems. It has been how even moderately complex electricity market simulations produce state and action spaces that are too large for value function based methods to explore. Policy gradient methods have been shown to produce consistent behaviour in increasingly complex dynamic trading problems. Further developement of this research could opens the opportunity for policy gradient methods to be used in descision support and automated energy trading applications.

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

The simulations presented in this thesis use typical algorithm parameters that are either the default values from PyBrain or taken from the literature. However, the sensitivity of the results to parameters changes deserves investigation. There are also other function approximation and back-propagation techniques that could be used with policy gradient methods. Parameter sensitivity analysis is typically conducted by the algorithm developers using standard benchmark problems, such as mazes and pole balancing tasks, to allow results to be compared. The shortage of published results and lack of standardised electricity trading models would limit the benefit of using this domain for general sensitivity analysis.

7.2.2 Delayed Reward

The reward received by each agent in all of the simulations presented in this thesis is a direct result of its previous action. In reality, payment for electricity generation is delayed considerably in the settlement process. Time did not permit analysis of value function based methods with eligibility traces (See Section **??**) or policy gradient methods under delayed reward.

Actions in previous states not only effect the reward signal, but the current range of possible actions. The rate at which generator types can ramp up or ramp down production is a typical constraining factor in this regard. Multi-period optimal power flow formulations may incorporate such constraint, but are challenging to implement and solve.

7.2.3 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.

7.2.4 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.

7.2.5 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.

7.2.6 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.

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.

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.

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.

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.

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.

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. (2007, May 23-25). Unit commitment and system stability under increased penetration of distributed generation. In Proceedings of the 4th International Conference on the European Energy Market, 2007. EEM 2007. Cracow, Poland.

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).

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).

Maei, H. R., & Sutton, R. S. (2010). Gq(λ): A general gradient algorithm for temporal-difference prediction learning with eligibility traces. In 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. (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., & 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.

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.

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.