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Learning to Trade Power

by

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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 5

Nash Equilibrium Analysis

This chapter presents a simulation that examines the convergence to a Nash equilibrium of agents competing to sell electricity. Value function based and policy gradient reinforcement learning algorithms are compared in their convergence to an optimal policy using a six bus electric power system model.

5.1 Introduction

This thesis presents the first case of policy gradient reinforcement learning methods being applied to electricity trading problems. As a first step it is necessary to confirm that when using these methods, a system of multiple agents will converge to the same Nash equilibrium[1] that a traditional closed-form simulation would produce.

This is the same approach used by Krause et al. (2006) before performing the study of congestion management techniques that is reviewed in Section 3.2.2. Nash equilibria can be difficult to determine in complex systems so the experiment presented here utilises a model simple enough that it can be determined through exhaustive search.

By observing the actions taken and the reward received by each agent over the initial simulation periods it is possible to compare the speed and consistency with which different algorithms converge to an optimal policy. In the following sections the objectives of the simulations are explicitly defined, the setup of the simulations is explained and simulation results, with discussion and critical analysis, are provided.

[1]Informally, a Nash equlibrium is a point in a non-cooperative game at which no player is motivated to deviate from its strategy, as it would result in lower gain (Nash, 1950, 1951).

5.2 Aims and Objectives

Some elements of the simulations reported in this chapter are similar to those presented by Krause et al. (2006). One initial aim of this work is to reproduce their findings as a means of validating the approach. The additional objectives are to show:

- That policy gradient methods converge to the same Nash equilibrium as value function based methods and tradtional closed-form simulations,
- Differences in the characteristics of policy gradient and value function based methods by examining the nature of their convergence to an optimal policy.

Meeting these objectives aims to provide a basis for using policy gradient methods in more complex simulations, to show that they can learn basic policies and to provide guidance for algorithm parameter selection.

5.3 Method of Simulation

Learning methods are compared in this chapter by repeating the same simulation with different algorithms used by the agents. An alternative might be to use a combination of methods in the same simulation, but the approach used here is intended to be an extension of the work by Krause et al. (2006).

Each simulation uses a six bus electric power system model adapted from Wood and Wollenberg (1996, pp. 104, 112, 119, 123-124, 549). The model provides a simple environment for electricity trade with a small number of generators and branch flow constraints that slightly increase the complexity of the Nash equilibria. The buses are connected by eleven transmission lines at 230kV. The model contains three generating units with a total capacity of 440MW and loads at three locations, each of 70MW. The connectivity of the branches and the locations of the generators and loads is shown in Figure B.1. Data for the power system model was taken from a case provided with MATPOWER and is listed in Appendix B.1.

Two sets of quadratic generator operating cost functions, of the form $c(p_i) = ap_i^2 + bp_i + c$ where p_i is the output of generator i, are defined in order to create two different equilibria for investigation. The coefficients a, b and c for cost configuration 1 are listed in Table 5.1. This cost configuration defines two low cost generators that can not offer a price greater than the marginal cost of the most expensive generator when they apply the maximum possible markup. The set of coefficients for cost configuration 2 is listed in Table 5.2. This configuration

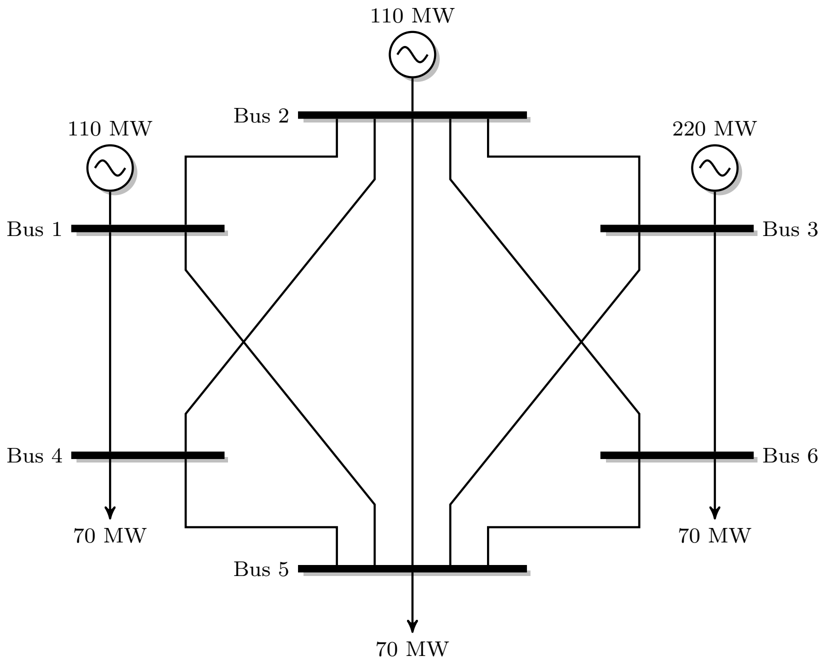

Figure 5.1: Single-line diagram for six bus power system model.

Gen	C_{down}	a	b	c
1	0	0.0	4.0	200.0
2	0	0.0	3.0	200.0
3	0	0.0	6.0	200.0

Table 5.1: Generator cost configuration 1.

narrows the cost differences such that offer prices may overlap and may exceed the marginal cost of the most expensive generator.

As in Krause et al. (2006), no load profile is defined for the simulation. The system load is assumed to be peak in all periods and only one state is defined for methods using look-up tables. Each simulation step is assumed to be one hour in length.

For all generators $P^{min} = 0$ so as to simplify the equilbria and avoid the need to use the unit de-commitment algorithm. The maximum capacity for the

Gen	C_{down}	a	b	c
1	0	0.0	5.1	200.0
2	0	0.0	4.5	200.0
3	0	0.0	6.0	200.0

Table 5.2: Generator cost configuration 2.

most expensive generator $P_3^{max} = 220$MW such that it may almost supply all of the load if dispatched. This generator is associated with a passive agent that always offers full capacity at marginal cost. For the less expensive generators $P_1^{max} = P_2^{max} = 110$MW. These two generators are each associated with an active learning agent whose activity in the market is restricted to one offer of maximum capacity in each period, at a price representing a markup of between 0 and 30% on marginal cost. Methods restricted to discrete actions may markup in steps of 10%, giving possible markup actions of 0, 10%, 20% and 30%. No capacity withholding is implemented. Discriminatory pricing (pay-as-bid) is used in order to provide a clearer reward signal to agents with low cost generators.

The algorithms which are compared are Q-learning, ENAC, REINFORCE and the modified Roth-Erev technique (See Section 2.4). Default algorithm parameter values from PyBrain are used and no attempt to study parameter sensitivity or variations in function approximator design is made.

For the Q-learning algorithm $\alpha = 0.3$, $\gamma = 0.99$ and ϵ-greedy action selection is used with $\epsilon = 0.9$ and $d = 0.98$. For the Roth-Erev technique $\epsilon = 0.55$, $\phi = 0.3$ and Boltzmann action selection is used with $\tau = 100$ and $d = 0.99$.

Both REINFORCE and ENAC use a two-layer neural network with one linear input node, one linear output node, no bias nodes and with the connection weight initialised to zero. A two-step episode is defined for the policy gradient methods and five episodes are performed per learning step. The exploration paramter σ for these methods is initialised to zero and adjusted manually after each episode such that:

$$\sigma_t = d(\sigma_{t-1} - \sigma_n) + \sigma_n \tag{5.1}$$

where $d = 0.998$ is a decay parameter and $\sigma_n = -0.5$ specifies the value that is converged to asymtotically. In each simulation the learning rate $\gamma = 0.01$ for the policy gradient methods, apart from for ENAC under cost configuration 2 where $\gamma = 0.005$. Both active agents use the same parameter values in each simulation.

As in Krause et al. (2006), the point of Nash equilibrium is established by computing each agent's reward for all possible combinations of markup. The rewards for Agent 1 and Agent 2 under cost configuration 1 are given in Table 5.3. The Nash equilibrium points are marked with a *. The table shows that the optimal policy for each agent is to apply the maximum markup to each offer as their generators are always dispatched. The rewards under cost configuration 2 are given in Table 5.4. This table shows that the optimal point occurs when Agent 2 applies its maximum markup and Agent 1 offers a price just below the marginal cost of the passive agent's generator.

		G_1							
		0.0%		10.0%		20.0%		30.0%	
		r_1	r_2	r_1	r_2	r_1	r_2	r_1	r_2
G_2	0.0%	0.0	0.0	40.0	0.0	80.0	0.0	120.0	0.0
	10.0%	0.0	33.0	40.0	33.0	80.0	33.0	120.0	33.0
	20.0%	0.0	66.0	40.0	66.0	80.0	66.0	120.0	66.0
	30.0%	0.0	99.0	40.0	99.0	80.0	99.0	120.0*	99.0*

Table 5.3: Agent rewards under cost configuration 1

		G_1							
		0.0%		10.0%		20.0%		30.0%	
		r_1	r_2	r_1	r_2	r_1	r_2	r_1	r_2
G_2	0.0%	0.0	0.0	51.0	0.0	0.0	0.0	0.0	0.0
	10.0%	0.0	49.5	51.0	49.5	0.0	49.5	0.0	49.5
	20.0%	0.0	92.2	51.0	99.0	0.0	99.0	0.0	99.0
	30.0%	0.0	126.8	54.8*	138.4*	0.0	148.5	0.0	148.5

Table 5.4: Agent rewards under cost configuration 2

5.4 Simulation Results

Each action taken by an agent and the consequent reward is recorded for each simulation. Values are averaged over the ten simulation runs and standard deviations are calculated using the formula

$$SD = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N}(x_i - \bar{x})^2} \tag{5.2}$$

where x_i is the action or reward value in simulation i of N simulation runs and $\bar{x}$ is the mean of the values.

Figure 5.2 shows the average markup on marginal cost and the standard deviation over the ten simulation runs for Agent 1 under price configuration 1 using the four learning methods. The second y-axis in each plot realtes to the exploration parameter for each method. Figure 5.3 shows the same quantities for Agent 2. Plots of reward are not given as generator prices and the market are configured such that an agent's reward is directly proportional to its action. The plots are vertically aligned and have equal x-axis limits to assist algorithm comparison.

Figures 5.4 and 5.5 plot the average markup and reward over ten simulation runs for Agent 1 and Agent 2, respectively, under price configuration 2 for the variant Roth-Erev, Q-learning learning methods. The plots for REINFORCE and ENAC in these figures are for actual values in one simulation run as the num-

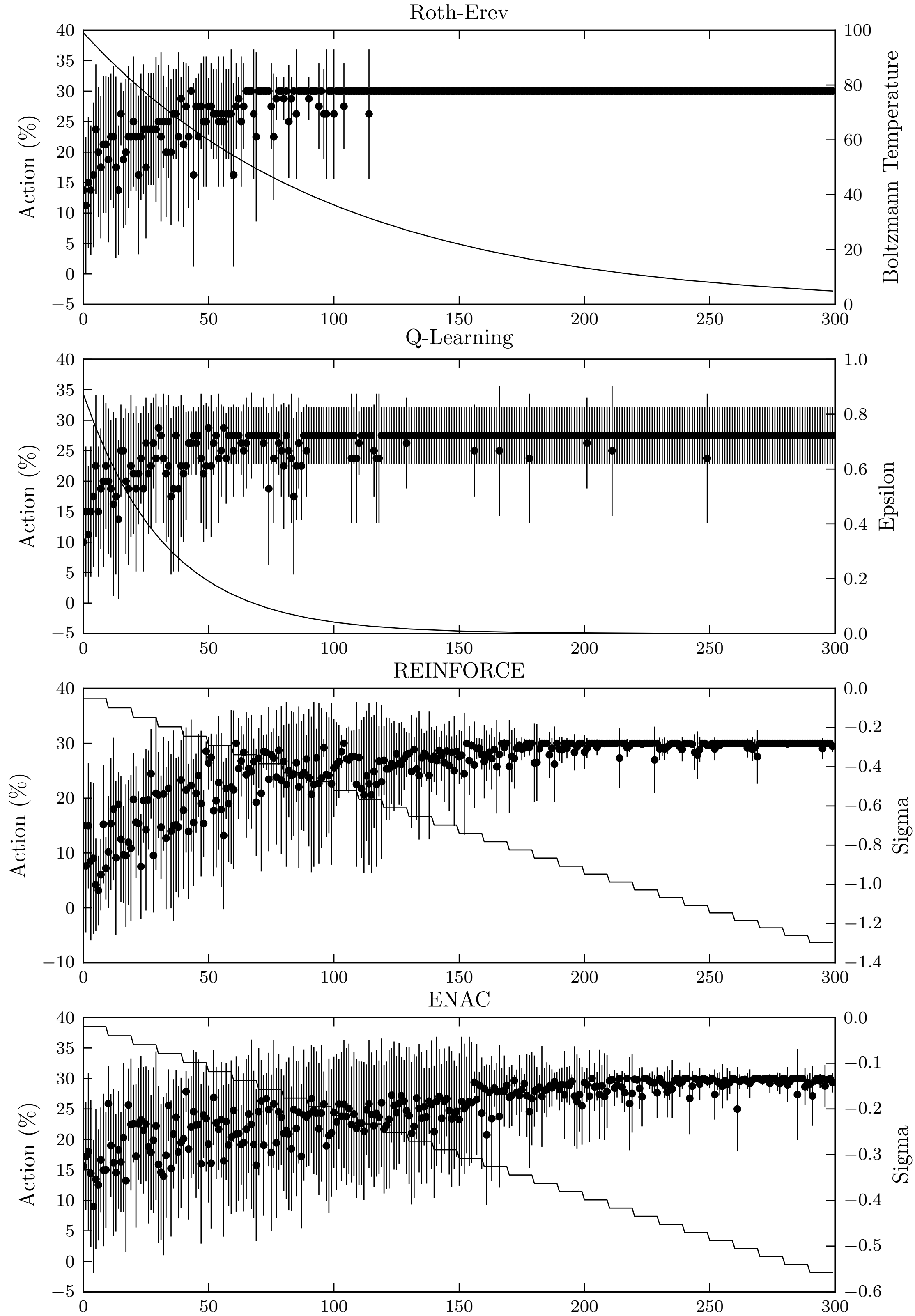

Figure 5.2: Average markup for agent 1 and standard deviation over 10 runs.

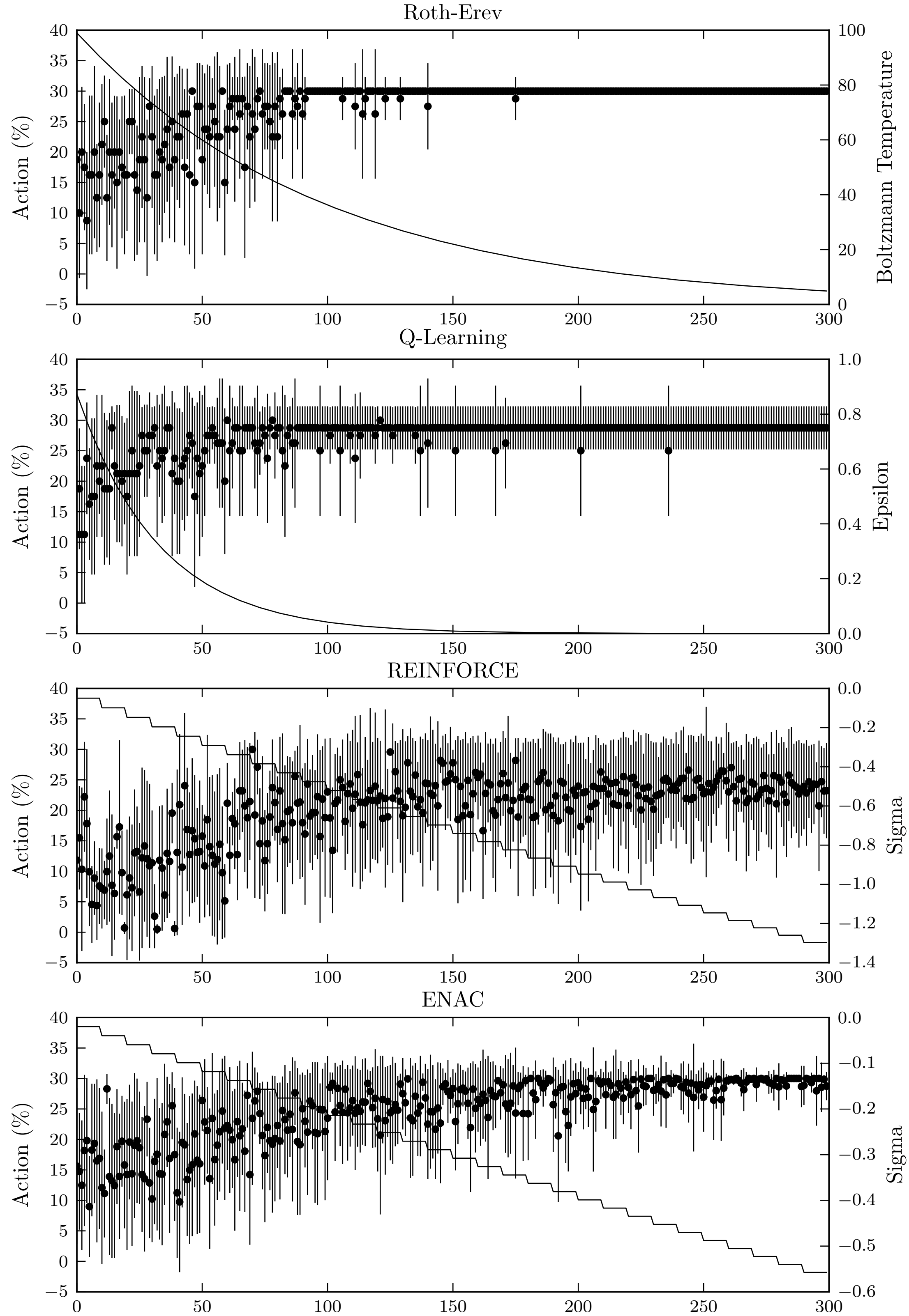

Figure 5.3: Average markup for agent 2 and standard deviation over 10 runs.

ber of interactions and variation in values makes the results difficult to observe otherwise. Not all x-axis extents are equal in these two figures.

5.5 Discussion and Critical Analysis

Under cost configuration 1 the agents face a relatively simple control task and receive a clear reward signal that is directly proportional to their markup. The results show that all of the methods consistently converge to the Nash equilibrium point. The variant Roth-Erev method shows very little variation around the mean once converged due to the use of Boltzmann exploration with a then low temperature parameter value. The constant variation around the mean that can be seen for Q-learning once it has converged is due to the use of ϵ-greedy action selection and can be removed if a Boltzmann explorer is used.

Empirical studies have also shown that the speed of convergence is largely determined by the rate at which the exploration parameter value is reduced. However, the episodic nature of the policy gradient methods requires them to make several interactions per learning step and therefore a larger number of initial exploration steps are needed. Policy gradient methods have also been found to be highly sensitive to the choice of learning rate. High values cause large changes to policy parameters to be made at each step and may cause the algorithm to fail to converge, but low values cause the algorithm to learn very slowly.

Cost configuration 2 provides a more challenging control problem in which Agent 1 must learn to undercut the passive agent. The results show that the variant Roth-Erev and Q-learning methods both consistently learn their optimal policy and converge to the Nash equilibrium. However, there is space for Agent 1 to markup its offer by slightly more than 10% and still undercut the passive agent, but methods with discrete actions are not able to exploit this and do not receive the additional profit.

The results for the policy gradient methods under cost configuration 2 show that these methods learn to reduce their markup if their offer price starts to exceed that of the passive agent and the reward signal drops. However, a chattering effect below the Nash equilibrium point can be clearly seen for ENAC and the method does not learn to always undercut the other agent. These methods also require a much larger number of simulation steps and for the exploration parameter to be decayed more slowly if they are to produce this behaviour. This is due to the need for a lower learning rate that ensures fine policy adjustments can be made and for several interactions to be performed between each learning step.

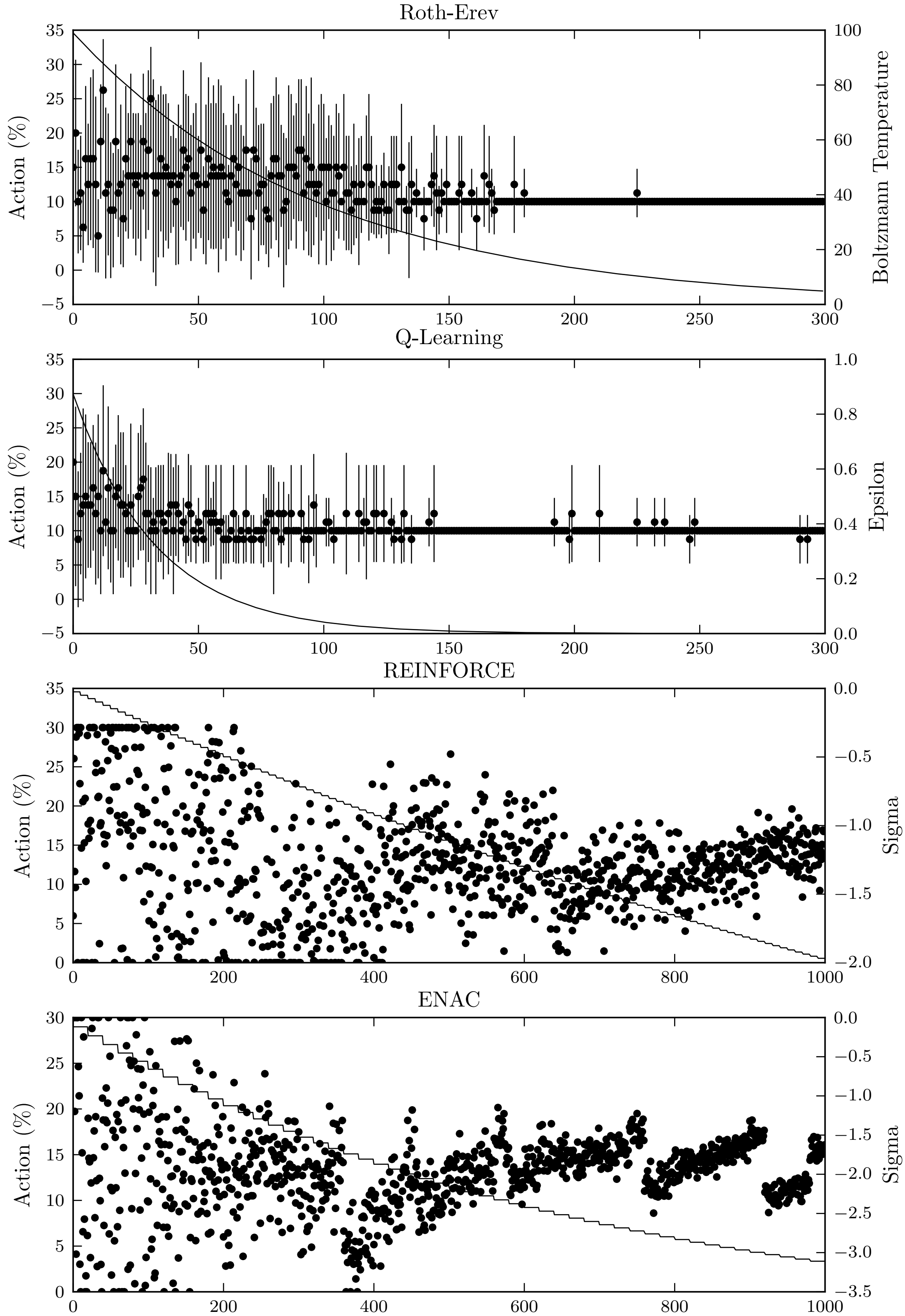

Figure 5.4: Average markup for agent 1 and standard deviation.

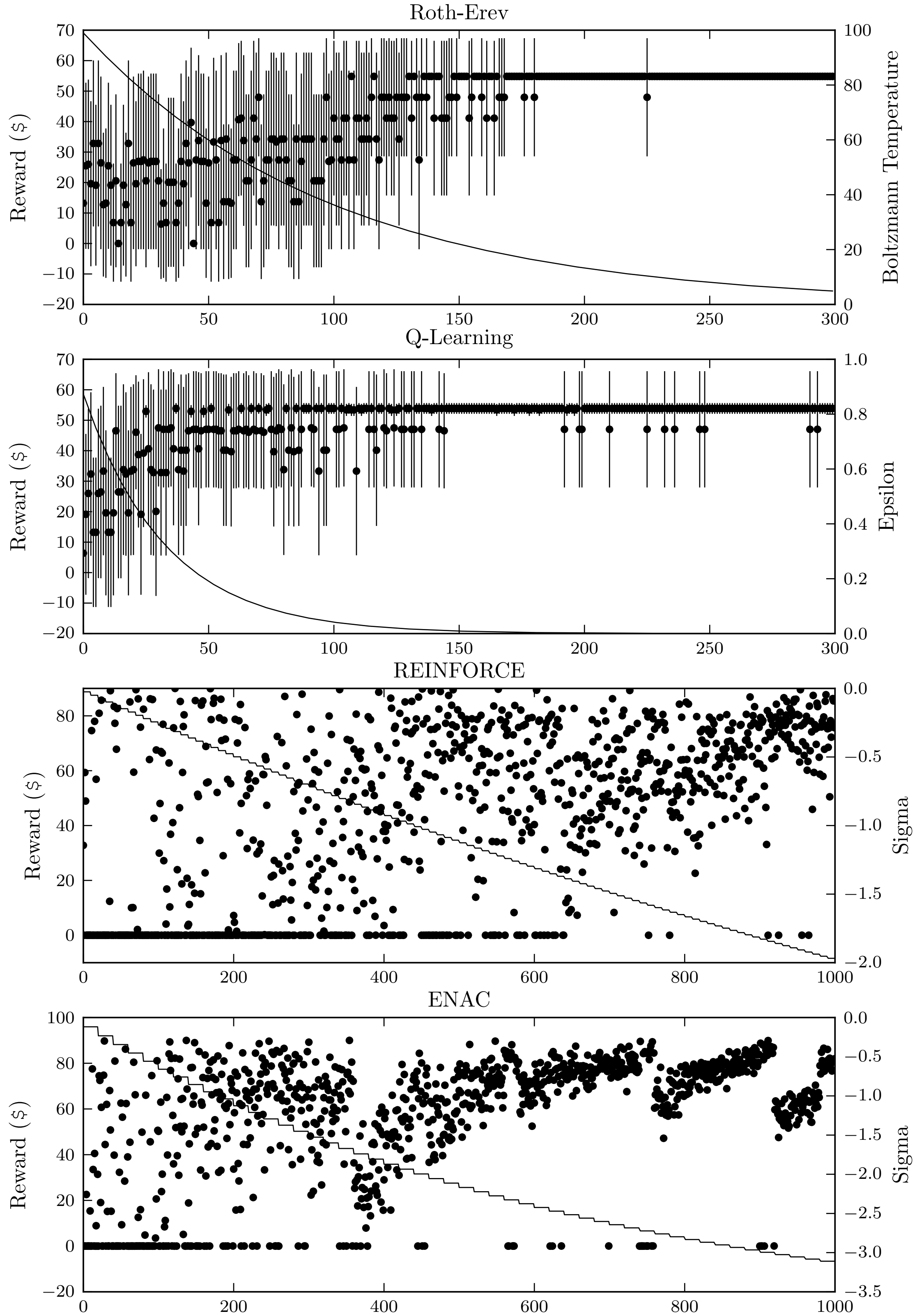

Figure 5.5: Average reward for agent 1 and standard deviation.

5.6 Summary

By observing the state to which a multi-learning-agent system converges, it is possible to verify that algorithms produce the same Nash equilibrium that closed-form simulations provide. The results presented in this chapter closely correspond with those from Krause et al. (2006) for Q-learning and show equivalent behaviour for the variant Roth-Erev method. The simulations illustrate how challenging unsupervised learning in a continuous environment can be, even for simple problems. Tasks in which a large reward change can occur for a very small change in policy prove difficult for policy gradient methods to learn and require low learning rates and lengthy periods of exploration. The operation of policy gradient methods with noisy, multi-dimensional state data is not examined in this chapter and deserves investigation.

Chapter 6

System Constraint Exploitation

This chapter explores the exploitation of constraints by learning agents in a dynamic electricity trading environment. Value function based and policy gradient reinforcement learning methods are compared using a modified version of the 24-bus power system model from the IEEE Reliability Test System.

6.1 Introduction

Having examined the basic learning characterisitics of four algorithms in Chapter 5, this chapter extends the approach to examine their operation in a complex dynamic environment. It explores the ability of policy gradient methods to operate with multi-dimensional, continuous state and action data in the context of *learning to trade power*.

A reference electric power system model from the IEEE Reliability Test System (Application of Probability Methods Subcommittee, 1979) provides a realistic environment in which agents compete with diverse portfolios of generating plant to supply dynamic demand. System constraints change as agents adjust their behaviour and loads follow a daily profile that is varied in shape over the course of a simulated year. By observing profits at different times of day, the ability of methods to successfully observe and exploit constraints is examined.

6.2 Aims and Objectives

This experiment aims to compare policy gradient and traditional learning methods in a dynamic electricity trading environment. Specifically, the objectives are to determine:

- If the policy gradient methods can achieve greater profitability under dynamic system constraints.
- The value of using an AC optimal power flow formulation in agent based electricity market simulation.

Meeting these objectives aims to demonstrate some of the value of using policy gradient methods in electricity market participant modelling and to determine if they warrant further research in this domain.

6.3 Method of Simulation

Learning methods are compared by repeating simulations of competitive electricity trade with alternative algorithms used by the competing agents. Some simplification of the state and action representations for value function based methods is required, but generation portfolios and load profiles are the same for each algorithm test.

The IEEE Reliability Test System (RTS) provides a reference power system model and load profiles that are used in each simulation. The model has 24 bus locations that are connected by 32 transmission lines, 4 transformers and 2 underground cables. The transformers tie a 230kV area to an area at 138kV. The original model has 32 generators of 9 different types with a total capacity of 3.45GW. To reduce the size of the discrete action domain, five 12MW and four 20MW generators are removed. This is deemed reasonable as their combined capacity is only 4.1% of the original total generation capacity and the remaining capacity is more than sufficient to meet demand. To further reduce action space sizes all generators of the same type at the same bus are aggregated into one generating unit. This can be considered to be the representation of each power station in the market, rather than each synchronous machine stage. The model has loads at 17 locations and the total demand at system peak is 2.85GW.

Again, generator marginal costs are quadratic functions of output and are defined by the parameters in Table 6.1. Figure 6.1 shows the cost functions for each of the seven types of generator and illustrates their categorisation by fuel type. Generator cost function coefficients were taken from a website hosted by Georgia Tech Power Systems Control and Automation Laboratory[1] which assumes Coal costs of 1.5 \$/MBtu[2], Oil costs of 5.5 \$/MBtu and Uranium costs

[1] http://pscal.ece.gatech.edu/testsys/

[2] 1 Btu $\approx$ 1055 Joules

Code	c_{down}	a	b	c	Type
U50	0	0.0	0.001	0.001	Hydro
U76	0	0.01414	16.0811	212.308	Coal
U100	0	0.05267	43.6615	781.521	Oil
U155	0	0.00834	12.3883	382.239	Coal
U197	0	0.00717	48.5804	832.758	Oil
U350	0	0.00490	11.8495	665.109	Coal
U400	0	0.00021	4.4231	395.375	Nuclear

Table 6.1: Generator types and cost parameters for the simplified IEEE Reliability Test System.

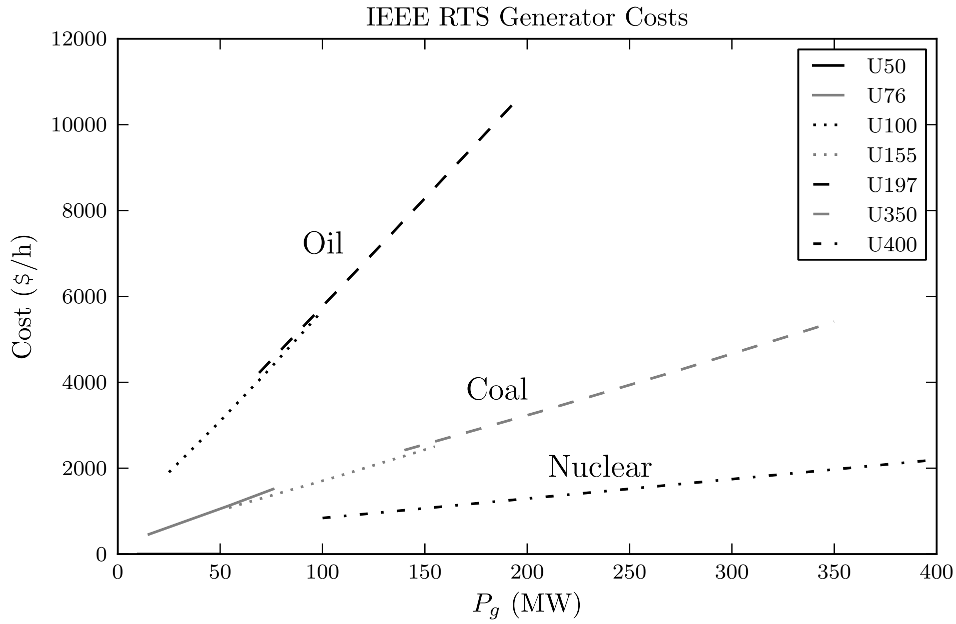

Figure 6.1: Generator cost functions for the IEEE Reliability Test System

of 0.46 \$/MBtu. Data for the modified model is provided in Appendix B.2 and the connectivity of branches and the location of generators and loads is illustrated in Figure 6.3.

The generating stock is divided into 4 portfolios (See Table 6.2) that are each endowed to a learning agent. Portfolios were chosen such that each agent has: a mix of base load and peaking plant, approximately the same total generation capacity and generators in different areas of the network. The generator labels in Figure 6.3 specify the associated agent. The synchronous condenser is associated with a passive agent that always offers 0 MW at 0 \$/MWh (the unit can be dispatched to provide or absorb reactive power).

Markups on marginal cost are restricted a maximum of 30% and discrete

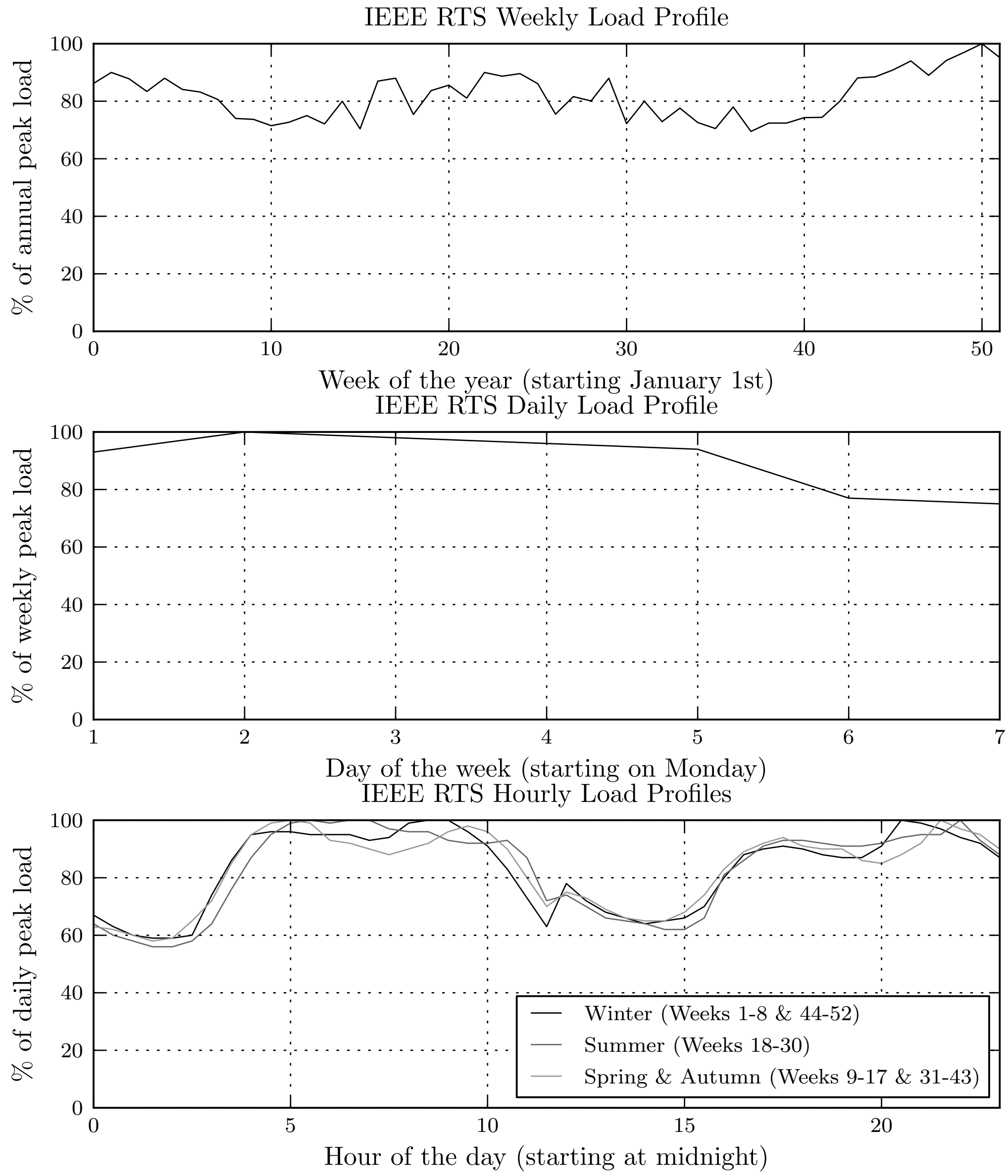

Figure 6.2: Hourly, daily and weekly load profile plots from the IEEE Reliability Test System

Agent	U50 Hydro	U76 Coal	U100 Oil	U155 Coal	U197 Oil	U350 Coal	U400 Nuclear	Total (MW)
1		2×		1×			1×	707
2		2×		1×			1×	707
3	6×				3×			891
4			3×	2×		1×		960

Table 6.2: Agent portfolios.

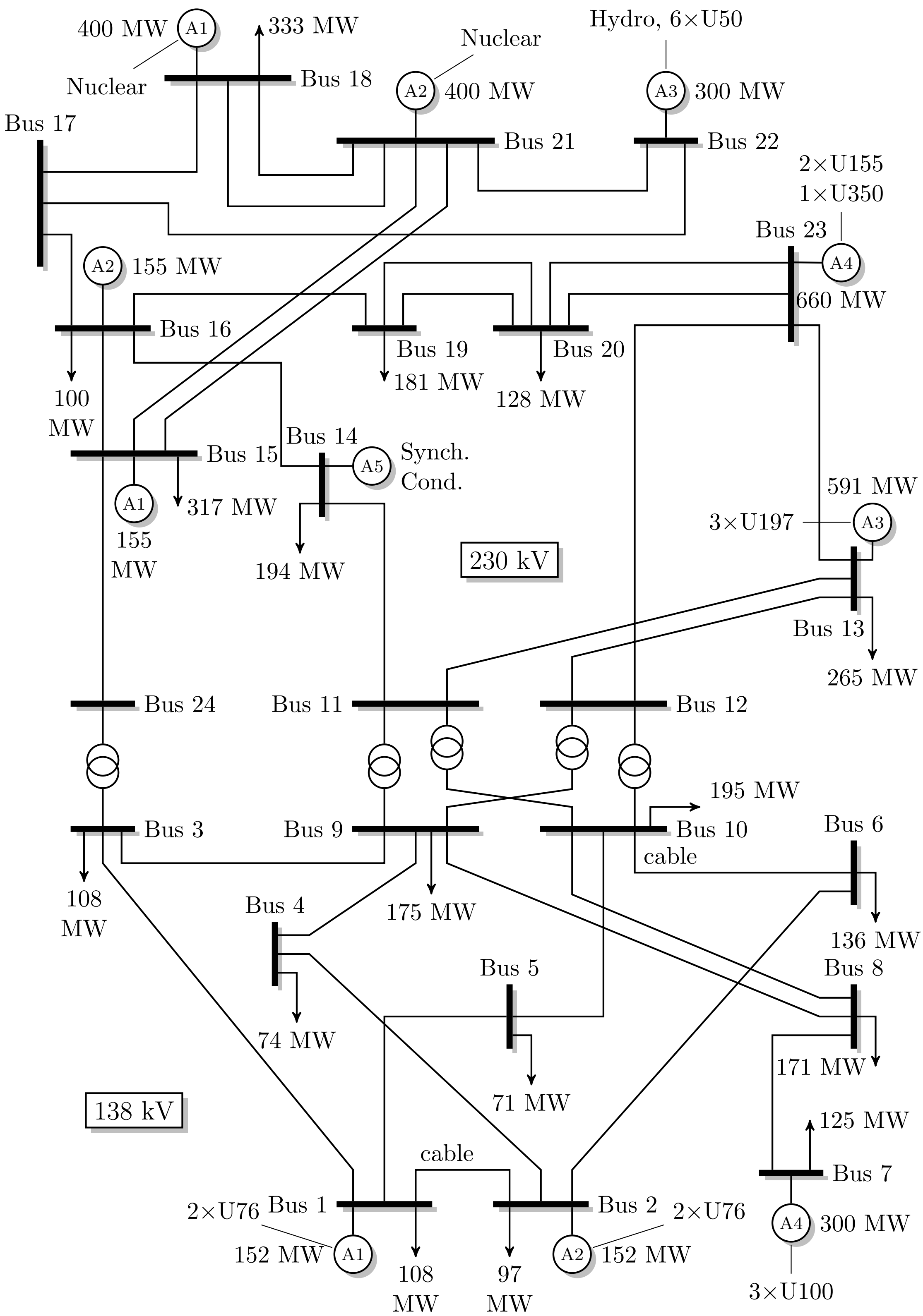

Figure 6.3: IEEE Reliability Test System

markups of 0, 15% or 30% are defined for value function based methods. Upto 20% of the total capacity of each generator can be withheld and discrete withholds of 0 or 20% are defined. Initially only one offer per generator is required, but this is later increased to two in order to explore the effect of a larger action space.

The environment state for all algorithm tests consists of a forecast of the total system demand for the next period. The system demand follows an hourly profile that is adjusted according to the day of the week and the time of year. The profiles are taken from the RTS and are illustrated in Figure 6.2. For tests of value function based methods and the Roth-Erev learning algorithm, the continuous state is divided into 3 discrete states, between minimum and maximum total system load, that correspond to low, medium and peak demand.

To investigate the exploration of constraints, AC optimal power flow is used and the state vector for agents using policy gradient methods can be adjusted to contain a combination of voltage constraint Lagrangian multipliers for all generator buses and the voltage magnitude at all other buses. Lagrangian multipliers are used as generators typically fix the voltage at their associated bus. Branch flows are not included in the state vector as the flow limits in the RTS are high and are not reached at peak demand. Generator capacity limits are binding in most states of the RTS, but the output of other generators is deemed to be hidden from agents.

The nodal marginal pricing scheme is used in which cleared offer prices are determined by the Lagrangian multiplier on the power balance constraint for the bus at which the generator associated with the offer is connected.

Typical parameter values are used for each of the algorithms. Learning rates are set low and exploration parameters decay slowly due to the length and complexity of each simulation. For Q-learning $\alpha = 0.2$, $\gamma = 0.99$ and ϵ-greedy action selection is used with $\epsilon = 0.9$ and $d = 0.999$. For Roth-Erev learning $\epsilon = 0.55$, $\phi = 0.3$ and Boltzmann action selection is used with $\tau = 100$ and $d = 0.999$.

Two-layer neural networks with linear input and output nodes, no bias nodes and randomised initial connection weights are used for policy function approximation. The initial exploration rate $\sigma = 0$ for both policy gradient methods and decays according to Equation (5.1) with $d = 0.995$ and $\sigma_n = -0.5$. Constant learning rates are used in each simulation with $\gamma = 0.01$ for REINFORCE and $\gamma = 0.005$ for ENAC.

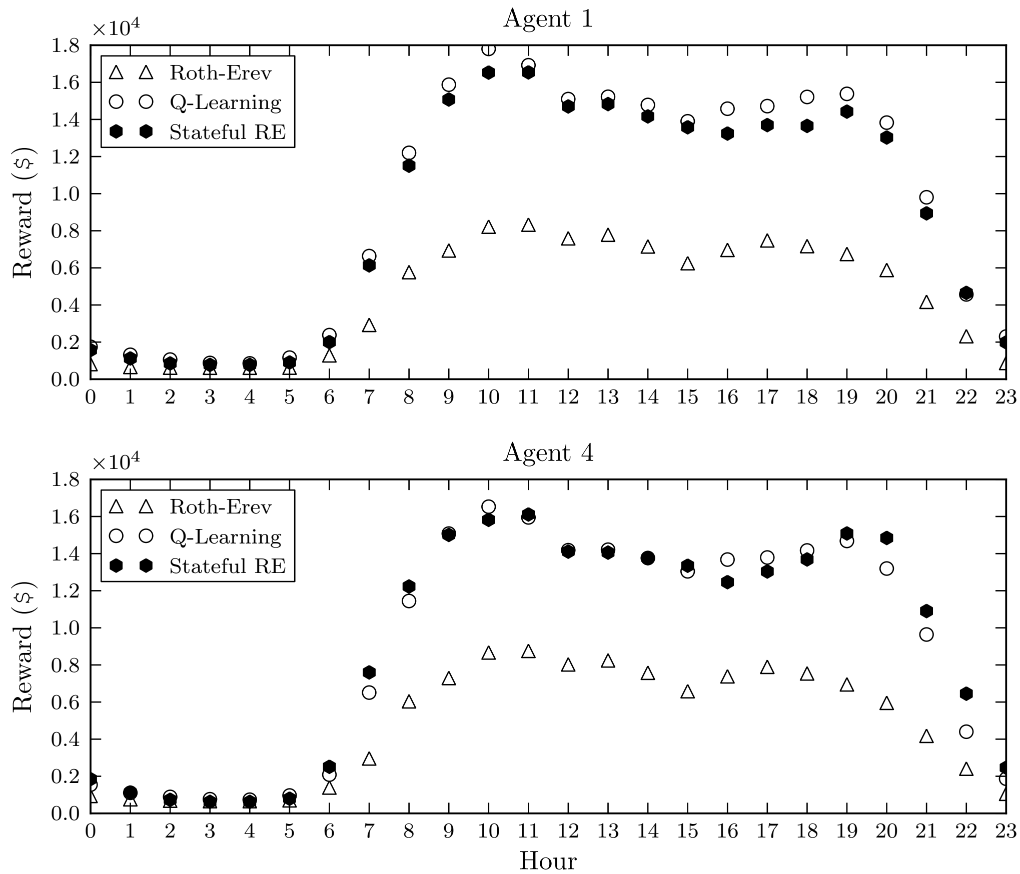

Figure 6.4: Modified Roth-Erev compared with Stateful Roth-Erev.

6.4 Simulation Results

Each agent's rewards are recorded for a simulated year of 364 trading episodes, each consisting of 24 interactions. To compare algorithms, the average reward for each hour of the day is calculated for each agent and plotted in the same Figure. Only results for agents 1 and 4 are given as agents 1 and 2 have identical portfolios and most of agent 3's portfolio consists of Hydro plant with zero cost. The method of applying percentage markups on marginal cost does not work for generators with zero cost and almost identical results are found for all algorithms.

Figure 6.4 compares the Modified Roth-Erev method with the Stateful Roth-Erev method. The plots show average rewards for agents 1 and 4 when using Q-learning and the two Roth-Erev variants.

Figure **??** compares policy gradient methods under two state vector configurations. The first two plots concern agent 1 and show the average reward received for a state vector consisting solely of a demand forecast and for a combined forecast and bus voltage profile state vector. The bottom two plots show rewards for agent 4 under these configurations also.

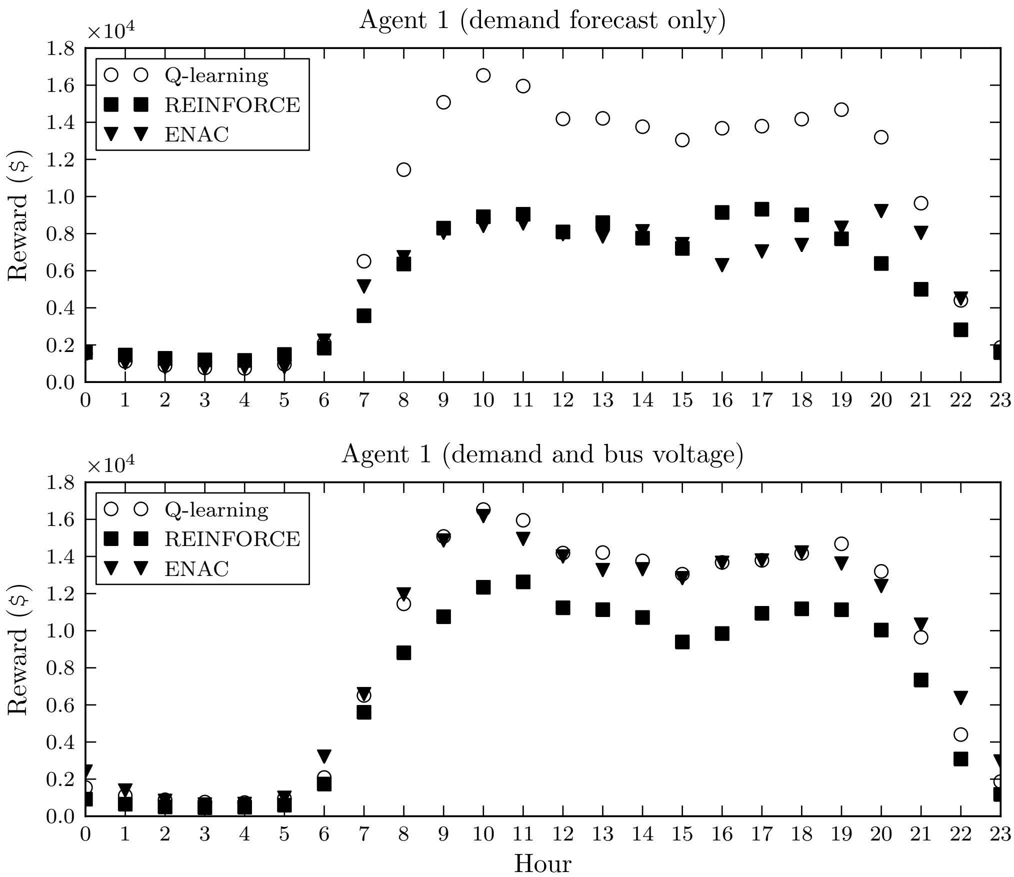

Figure 6.5: Average rewards for agent 1 under two state configurations.

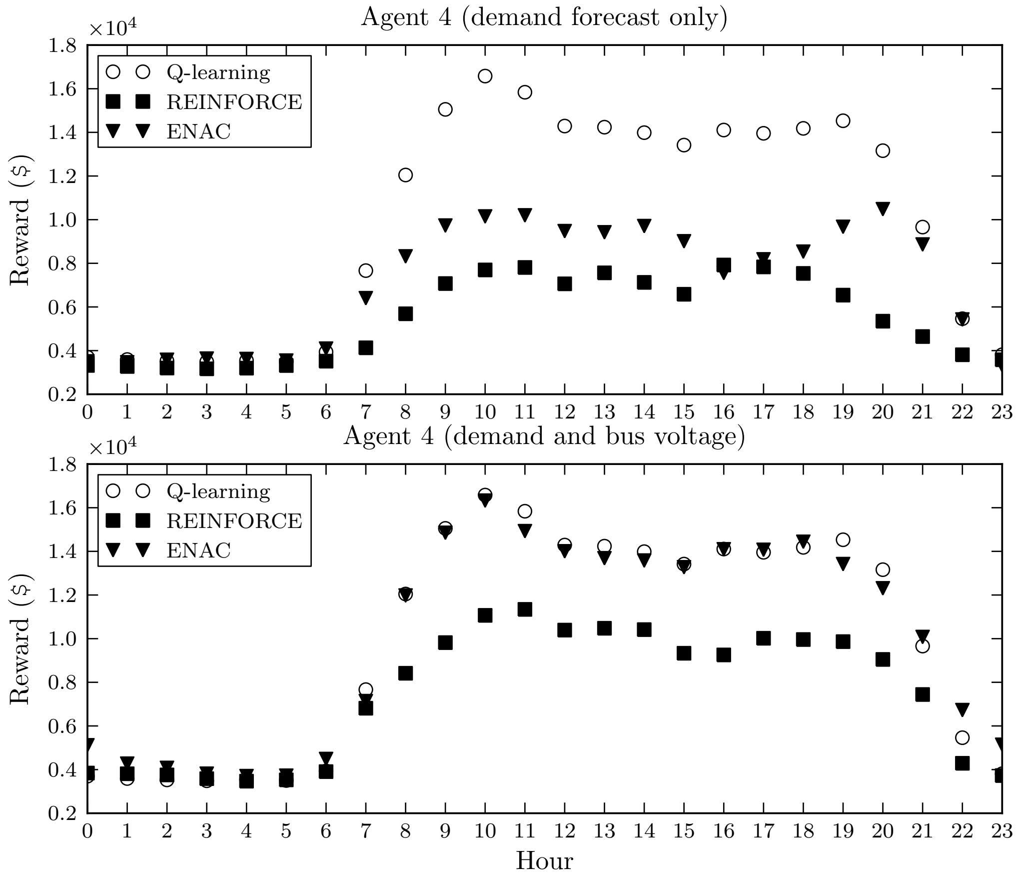

Figure 6.6: Average rewards for agent 4 under two state configurations.

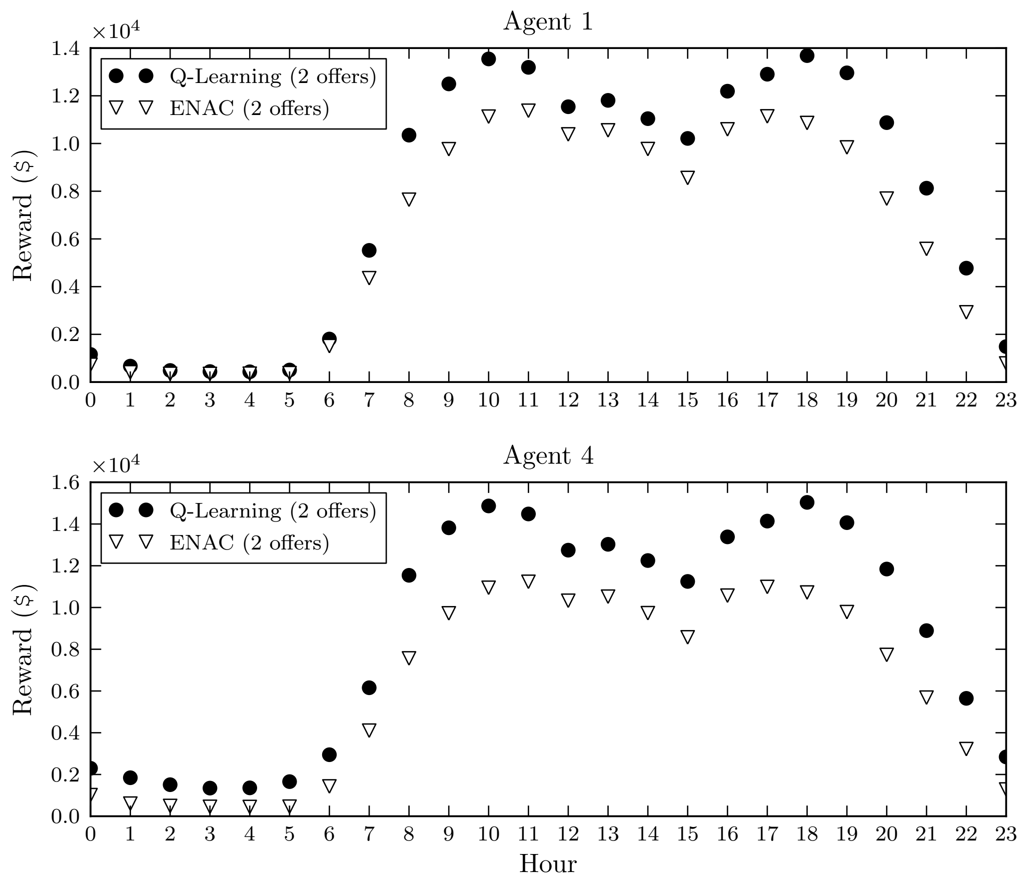

Figure 6.7: Average rewards for two offers per generator.

Figure 6.7 shows average rewards for agents 1 and 4 from a repeat of the bus voltage profile state simulation, but with two offers required per generator. Due to time constraints and limited simulation resources only results for Q-learning and ENAC are given.

6.5 Discussion and Critical Analysis

Agents with a discrete environment have 216 possible actions to choose from in each state when required to submit one offer per generator. Figure 6.4 shows that, using Q-learning, the agents are able to learn an effective policy that yields greater profits that under passive behaviour for two different portfolios. The importance of utilising environment state data in a dynamic electricity setting is illustrated by the differences in average reward received by the Modified Roth-Erev method and the Stateful Roth-Erev method. The optimal action for an agent depends upon the current system load and Modified Roth-Erev is unable to interpret this. Stateful Roth-Erev is able to achieve roughly the same performance as Q-learning.

Including bus voltage constraint data in the state for a discrete environment would result in a state space of impractical size, but including it in a continuous environment was straight-forward. The results show that ENAC achieves greater profits when presented with a combined demand forecast and bus voltage state vector. REINFORCE performs less well than ENAC, but also shows improvement over the pure forecast case. ENAC achieves equivalent, but not greater performance than Q-learning in all periods of the trading day when using the voltage data. It is not able to use the additional state information to any advantage, but does learn a profitable policy.

Simply changing the number of offers required to be submitted for each generator from 1 to 2, increases the number of discrete action possibilities in each state to 46,656. Figure 6.7 shows that Q-learning is still able to achieve a level of reward the same as that achieved under the one offer case. ENAC achieves lower average reward when required to produce a larger action vector and is not able to use the increased flexibility in its offer structure to any advantage.

6.6 Summary

No evidence has been found to suggest that policy gradient methods can be used to exploit complex constraints in a power system model. However, they have been shown to operate well with a large state vectors. Limitations of the

Modified Roth-Erev method in an dynamic environment have been demonstrated. Q-learning was able to produce an effective policy in all simulations, including one involving a relatively large action space that saw degraded performance from a policy gradient method.

AC optimal power flow adds enormously to simulation times when analysing an entire year of trading interactions. The addition of bus voltage data to the state vector improved the performance of the policy gradient methods, but it has not been show if the same could not be achieved by perhaps using bus voltage angles from a DC optimal power flow.

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