BUNN, D.W. and OLIVEIRA, F.S. 2007. Agent-based analysis of technological diversification and specialization in electricity markets. *European journal of operational research* [online], 181(3), pages 1265-1278. Available from: https://doi.org/10.1016/j.ejor.2005.11.056

Agent-based analysis of technological diversification and specialization in electricity markets.

BUNN, D.W. and OLIVEIRA, F.S.

2007

AGENT-BASED ANALYSIS OF TECHNOLOGICAL DIVERSIFICATION AND SPECIALISATION IN ELECTRICITY MARKETS

Derek W. Bunn, London Business School, dbunn@london.edu

Fernando S. Oliveira, Warwick Business School, Fernando.Oliveira@wbs.ac.uk

ABSTRACT

This paper develops a model-based analysis of technological market structure evolution in electricity markets. This is done through the development of a power plant trading game that, *via* computational learning, simulates how players coordinate their behaviour in buying and selling power generation assets. In particular, we look at the question of how market performance depends upon the different technological types of plant owned by the generators, and whether, through the strategic adaptation of their power plant portfolios, there is a tendency for the market to evolve into concentrations of specialised or diversified companies.

KEYWORDS: Agent-Based, Computational Learning, Electricity Markets, Evolutionary Games, Simulation.

AGENT-BASED ANALYSIS OF TECHNOLOGICAL DIVERSIFICATION AND SPECIALISATION IN ELECTRICITY MARKETS

1. INTRODUCTION

All capital intensive industries manifest a co-evolution of market structure and performance, but what makes electricity particularly intriguing in this respect is the instantaneous, non-storable nature of the product, delivered into a market with low demand elasticity, high requirements for security of supply and wide seasonal variations. This means that electricity is provided, at any instant, from an economic and technical mix of baseload, mid-merit and peaking plant, which in turn operate for a decreasing fraction of the year. Thus, whilst some baseload plant may be operating for 90% or more of the year (depending upon maintenance), some peaking plant may only be called into operation for a few hours. This raises the strategic issue of whether the natural tendency, in these markets, is for competing companies to evolve towards becoming diversified players, with a mix of different kinds of assets, or niche players seeking to be more dominant in the base, mid or peaking segments of the market. It is often argued, for example, that the exercise of market power in electricity markets requires the major players to own a diversity of peak, mid and baseload plant, in order to set market prices with their marginal plant and thereby reap higher profit contributions from their baseload. If so, we would expect the emergent structure under competitive plant trading to reflect this. However, we also examine the counter proposition, e.g. Borenstein et al. (1995), for example, who suggested that in the liberalised power markets, different segments would emerge, at least for baseload and peak plants, and so market-power considerations might suggest a tendency towards greater concentration in these. Furthermore, this issue may be complicated by the market rules, for example, to the extent that an administered market is introduced, based upon a single clearing price for all power at a particular point in time (e.g., the Pool model), or a multi-clearing process that facilitates discriminatory prices for the base, mid and peaking market segments (e.g. bilateral forward trading). This paper is motivated by a desire to develop a methodological framework for addressing these two inter-related questions.

Research into the strategic behaviour within power markets has typically focussed upon bidding behaviour, capacity withholding and price formation in the daily markets[1], usually under various exogenous assumptions for market structure. Yet, whilst the dynamic trading of assets between major players has been a salient feature of fully liberalised electricity markets, as seen in Australasia, North America, Great Britain and other European countries, the evolutionary development of market structure, its drivers and dependencies, has received very little research attention. Ishii and Yan (2002, September) present evidence that mandated divestment *crowded out* new investment in the California market, but this is quite a different issue from *voluntary* strategic plant trading. To address the latter, a modelling framework is needed that captures the trading of assets as an *endogenous* response to performance in the daily market(s) for electricity.

The model developed in this paper incorporates two main components: a plant trading game and an electricity market game. The plant trading game represents the interaction between electricity companies that trade generating plants. The electricity market game formulates the daily electricity market prices by assuming Cournot

[1] See for example: Abbink et al., 2003; Rassenti et al., 2003**;** Bower and Bunn, 2000; Bunn and Oliveira, 2001, 2003; Day and Bunn, 2001; Green and Newbery, 1992.

players. Essentially, we investigate the different strategies that can be used by a generator when managing its portfolio of plant to see how technological diversification or specialisation could enhance its performance. We find that the relative value of peak and baseload specialisation is influenced by the market mechanisms and that, for example, the value of peaking plants to a portfolio is higher under a single price (i.e., "Pool") clearing mechanism. We follow Borenstein et al. (1995), for example, who suggested that in the liberalised power markets there would be different markets for baseload and peak plants, and Elmaghraby and Oren (1999) who proposed a market mechanism that implies discriminatory pricing by technology. Although we develop a generalisable model and stylised insights through agent-based simulation, we are motivated in this study by salient aspects of the evolutionary history of the British electricity market from its liberalisation in 1990.

2. STRUCTURAL EVOLUTION IN ENGLAND AND WALES

During the 1990s, the privatisation of the E&W electricity industry aimed to introduce competition, through unbundling, in generation and supply, while maintaining incentive based monopoly regulation in the transmission and distribution businesses[2]. Before privatisation, the Central Electricity Generating Board (CEGB) dominated the industry structure, selling electricity in bulk to 12 area distribution boards, each of which served a closed retail supply area. The 1989 Electricity Act started the process by splitting the CEGB into three different generation companies (National Power, PowerGen and Nuclear Electric) and a transmission company (National Grid). Fossil-fuel plants, operating as base, mid-merit and peaking, were assigned to National

[2] A good source of information on the history of the electricity sector in the UK is by the Electricity Association (2000a).

Power (38 GW of capacity) and PowerGen (18 GW of capacity), and the baseload nuclear plants to Nuclear Electric (8.4 GW of capacity). In 1996, Nuclear Electric was further demerged into two companies, Magnox Electric and British Energy.

Ownership of their plants then entered a second period of change with successive divestments and the arrival of new players to the E&W market. Thus, in 1995, Edison Mission Energy entered the market buying the 2GW of peaking pumped storage capacity. In 1996, TXU Europe acquired five coal-fired power stations, from National Power and PowerGen, with a total capacity of 6 GW. Furthermore, the arrival of the new technology of combined cycle gas turbines (CCGTs) in the 1990s changed the nature of new investment and competitive entry. This technology reduced the economies of scale in electricity generation, and offered low capital costs, operational costs and short construction times. Overall, plant-trading and the new entry process gradually accelerated so that, by early 2000, there were 24 companies in the market with small Independent Power Producers (IPPs) having 21% of the installed capacity. Furthermore, vertical integration (between generation, distribution and supply), and diversification (the main electricity companies also selling gas) began to reshape the industry and its value chain.

The next major development in the E&W electricity market was a change in the spot market mechanism with the introduction of New Electricity Trading Arrangements (NETA) in March 2001. NETA replaced the mandatory daily uniform price auction, with continuous bilateral trading (up until an hour before real-time, whereupon the system operator takes over responsibility for system balancing). This major change in market mechanism fuelled an international debate upon the relative merits of pool *versus* bilateral trading systems and their relative effects upon improving market efficiency. Thus, it seems very appropriate when seeking to understand the process of endogenous strategic adaptation, which has characterised the evolution of asset ownership in the market, and presumably will continue to do so, to test the sensitivity of such models to this exogenous influence of market rule changes.

3. STRATEGIC MANAGEMENT OF PLANT PORTFOLIOS

Mergers, acquisitions and divestures, insofar as they would be expected to determine subsequent performance in the industry, are crucial for both regulatory and competition authorities (Cox, 1999). Electricity companies may use mergers and acquisitions to adapt to the new environment (e.g. risk management) or to gain market power, whereas divestments by incumbent generation companies may be mandated in order to ensure that the market becomes more competitive. Clearly, one of the strategic aims that companies have in refining the composition of their plant portfolios may be to gain a dominant position.

Further, market rules have been seen to influence investment decisions. For example, Exelby and Lucas (1993) examine the link between capacity payments and capacity investment in the E&W Pool, showing that the capacity payments mechanism in use at that time, paradoxically introduced incentives to reduce the capacity available in the system.

In the E&W electricity market, before privatisation, national security and cost minimisation were the driving forces behind the strategic management of plant portfolios. The main goal of this strategy was to ensure generation technology diversity. Stirling (1994) claims that technological diversity was the basic rationale for the investment in the UK electricity market, under central planning. Diversification seemed the correct reaction to the uncertainty underlying fuel prices, environmental impacts and financial performance. Sterling also maintains that, since privatisation, the government created better conditions for technological diversity by revoking, in the late 80s, the European Community legislation forbidding the use of gas in bulk power generation. Furthermore, the need for diversification also justified the investment on nuclear plants. Moreover, he argues that in the liberalised market, the new private companies also appear to have technological diversity as one of the drivers of their behaviour as they have indeed diversified their sources of fuel. Regarding the impact of governmental intervention on the technological diversity of electricity generation in the UK, Henney (1994) suggests that, during the 70s and 80s, the policies were favourable to nuclear and coal technologies. In contrast, Newbery (1998) suggests that the UK government promoted the nuclear option as a means to combat the coal miners' power. In Henney's view, however, the protection of UK coal led to high inefficiencies and mistakes, namely over-estimating the demand for coal.

Therefore, it seems that within the public sector, a monopolistic electricity industry managed under government policy, followed technological diversity as one of the key issues of plant portfolio strategy. Essentially this was a facet of national security. The political context of the oil crises in the 70s in the UK, as elsewhere, helps to explain this preference.

However, the driving forces in the electricity industry, during the late 1980s and at the beginning of the 1990s, became much broader with the arrival of new technologies, environmental concerns and the political impetus for market mechanisms (Flavin and Lensen, 1994; Bodde ,1998). The arrival of natural gas allowed independent power producers to build small and efficient power plants, and subsequent concerns about carbon emissions served to amplify its attractiveness compared to coal. With privatisations, the logic behind the strategic management of plant portfolios changed substantially. Larsen and Bunn (1999) summarised some of these the changes. The new industry became characterised by unstable and volatile prices, the presence of new shareholders with high performance objectives, regulatory uncertainty, and information opacity. At the corporate level, the new market was characterised by a focus on shareholder value (that replaces the social optimum) and new methods of linking strategic thinking, uncertainty, and limited information (replacing the classic operational research planning).

When looking at the principles of restructuring, Kaserman and Mayo (1991) claim that the industry should generally be privatised vertically due to the presence of economies of vertical integration, and due to the exhaustion of economies of scale (caused by technological change). It is noteworthy that the evolution of the E&W electricity market seems to have supported their hypothesis. Even though privatised horizontally in 1990, ten years later by 2000, the E&W electricity industry had re-converged substantially towards vertical integration. In addition, Kennedy (1997) analyses the way vertical integration affects market power, wholesale prices, and barriers to entry. Kennedy argues that vertical integration benefits would depend on the market structure such that, if the supply is regulated and there is competition on the generation side then vertical integration reduces transaction costs.

Within the new liberalised markets, and due to the decentralisation of the long-term decisions, the investment problem is now very different from the capacity planning formulations that characterised power system economics for so long. The privatised market presents an increased risk due to price and demand uncertainty and due to competition (the investment projects are private). Skantze et al. (2000, November) address the investment problem in oligopolistic electricity markets using stochastic prices, to perform simulation-based valuation of generation assets, taking into account start-up and shutdown costs. On the same topic, Visudhiphan et al. (2001) model investment dynamics in a system with a spot and futures market, analysing how price information affects long-term supply, demand and price evolution. They simulate investment behaviour using a backward-looking strategy, wherein investment depends on past spot prices, and a forward-looking strategy in which investment depends on the prices in the market for futures. Their simulations show that a backward-looking strategy leads to investment delays and under-investment, while a forward-looking strategy leads to smaller imbalances between generation and demand. Similarly, Pineau and Murto (2003) look specifically at the special nature of modelling investment in competitive electricity markets, again from the perspective of supply adequacy, and, as in our formulation, adopt separate markets for baseload and peaking plant as one of their constructs.

Whilst the investment perspective of security of supply is clearly important for public policy, we have chosen to focus upon the apparently unresearched, but observable, phenomena of investment through asset swapping, the process of readjusting the balance of ownership for an existing stock of plant, rather than changing the overall stock of plant.

4. MODELLING THE ELECTRICITY MARKET AND THE PLANT TRADING GAME

In this paper we model the electricity market as a Cournot game (e.g., Allaz and Vila, 1993; Borenstein and Bushnell, 1999; Wei and Smeers, 1999; Hobbs, 2001). Even though other approaches are possible such as conjectural variations (e.g., Garcia-Alcalde et al., June 2002; Hernaez et al., 2003), Bertrand games (e.g., Bunn and Oliveira, 2003), or supply functions (e.g., Green and Newbery, 1992; Anderson, E. J., Philpott, 2002), we found that the simpler Cournot model with capacity constraints provides useful and novel insights into the main characteristics of oligopolistic strategic behaviour within a portfolio setting.

We have adopted and analysed two different hypotheses for these Cournot games: a single-clearing Cournot game in which there is a single clearing price for each hour of the day (which attempts to replicate the conditions of electricity trading in pool like systems), as distinct from a multi-clearing Cournot game in which there are different clearing prices for different markets, over certain times of the day (which attempts to replicate the conditions of electricity trading in bilateral markets). Therefore, these clearing-mechanisms define a theoretical model of prices and loads in electricity markets in which the behaviour of a generator is a function of the industry structure and of his portfolio of plants. Further, each one of the models captures the following stylised facts: A generator's supply function is step-shaped. A generator may receive different prices for his generation from different plants, even if these are identical. Different generators may price the same type of plant differently. A generator aims at maximising the value of his portfolio of plants as a whole.

In both models, the start-up costs and ramp rates are not explicitly taken into account[3]. However, since these technical constraints are important to define the capability of a plant to access a given market, the model exogenously defines, for each plant, the

[3] This is a simplifying assumption, which has also been adopted by other studies such as, for example, Ramos at al. (1998) and Borenstein et al. (1999).

market in which it can sell. This simplification does not change the economics of a model for the yearly trading of electricity (as it still captures the underlying stylised facts) and decreases its complexity from a non-linear to a linear complementarity problem.

Next, we formalise the electricity Cournot game. In this game, each player *i* chooses his output $Q_{i,L}$ in market *L*, which is characterised by a certain demand. Moreover, let $C_{i,L}$ stand for the marginal cost of player *i*. In this case, $C_{i,L}$ is assumed locally constant for a given plant, but it may be different for the different plants owned by a player. Thus, $C_{i,L}$ will generally be a step-function, which makes the optimisation problem computationally hard. Let A_L, α_L represent, respectively, the intercept and slope of the inverse demand function; further let D_L stand for the duration of market *L*. Moreover, let $K_{i,L}$ stand for player *i*'s total available capacity in market *L*.

The single-clearing mechanism assumes that each player receives the same price for the electricity generated by any plant selling at any given time. Therefore, each player receives a clearing price P_L for the electricity sold in each one of these markets, and the capacity constraint, for each market, is equal to the total capacity that a given player has available for market *L* (in the single-clearing mechanism at any time there is only one market). Thus, for a player *i*, the profit (π_i) maximisation problem is represented by equations (4.1).

$$
\begin{aligned}
&\max \pi_i = \sum_L \left(P_L - C_{i,L}\right) Q_{i,L} D_L \\
&st. \\
&P_L = A_L - \alpha_L . \sum_i Q_{i,L}, \ \forall L \\
&Q_{i,L} \le K_{i,L}, \ \forall L \\
&Q_{i,L} \ge 0, \ \forall L
\end{aligned}
\tag{4.1}
$$

On the other hand, the multi-clearing price mechanism aims to capture the bilateral trading of electricity by allowing a player to sell the generation from any of his plants in different markets, for a given time, possibly receiving a different clearing price in each one of them. This mechanism follows the model proposed by Elmaghraby and Oren (1999) and suggested by Borenstein et al. (1995), and aims to capture the interaction between different markets and technologies in defining the value of a plant. Thus, for a player *i*, the profit maximisation problem is similar to the one presented in equations (4.1), with the additional constraint that at each time *t* the available capacity is the sum of the available capacity in each market, i.e., $K_i = \sum_L K_{i,L}$.

Each one of this market clearing mechanisms is then used within the plant trading game. The main goal of the plant trading game is to model how the electricity market structure would evolve under the current market mechanisms, taking into account the initial conditions for the market structure. The game is repeated for a given number of iterations in order to capture its main attractors (however, we do not expect to simulate how the market will evolve over time, only to test which market structures represent an attractor, under the present conditions).

In the computational simulation of the plant trading game the simulation algorithm has five main stages: *Initialization*, *Identification*, *Adaptation*, *Trading and Updating*. Briefly, *Initialization* starts with the opening market structure and solves the Cournot game to give the initial valuations of each plant. In the second *Identification* stage, each player then infers a model representing how the system is behaving and identifies the plants that will most probably be offered for trading in the next round (ie, each player selects which plants are *likely* to be traded, in order to simplify the coordination problem). In *Adaptation*, each player computes the set of plants he will attempt to buy and sell given the inferred model (i.e., the set of plants most likely to be traded). Then, possibly, two of the players *Trade* a plant. Finally, the algorithm *Updates* the state of the game, i.e., it recalculates the capacities owned by each player, and the respective cost structures.

In order to exemplify each of these stages, we use a simple example, alongside a formal description of the simulation algorithm. Assume a system with five plants a_1, a_2, a_3, a_4, a_5 and two players P_1 and P_2, with the properties specified as in Table 4.1. Furthermore, assume that, in the initial state, player *P1* owns plants a_1, a_3, a_5, and player *P2* owns plants a_2 and a_4.

TABLE 4.1: Example: Marginal Costs and Installed Capacity

Plant	Marginal Cost (£/MWh)	Capacity MW
a_1	5	1000
a_2	5	1000
a_3	10	100
a_4	10	100
a_5	50	10

Table 4.2 presents the Identification process, and in the Appendix we have a summary of all notations used. A one dimensional table T^i is a model of the system, for each player, in which each element represents a given plant and the perceived outcome (success or not) of an action to buy a plant not owned or to sell a plant owned. At initialization, we set $T_0^{P1} = T_0^{P2} = [1,1,1,1,1]$, which implies that both players perceive all possible trades as possible. In general, as iterations develop, the players associate a probability of success for each of the possible trades and only retain those in this set of possible trades if their success probabilities are greater than a pre specified

plausibility cut-off[4] $(\theta = 0.1)$. These success probabilities are based upon a moving window (length K) of previous trades (K=4 in this example).

TABLE 4.2: Identification Algorithm

At stage zero initialise (S,T_0^i): $\forall a^i \in \Sigma^i, s(a^i) = [1,1,...,1], T_0^i(s(a^i),\theta) = 1$.

1. At any given stage t and for each player i:

1.a) For each possible action update the string of perceived outcomes of the past

$$D_t^i(a_t^i) = \begin{cases} 0 \leftarrow Trade\_not\_possible \\ 1 \leftarrow Trade\_possible \end{cases}$$

$$\forall a_t^i \in \Sigma^i, s_t^i = \phi\left(s_{t-1}^i, D_t^i\left(a_t^i\right)\right)$$

1.b) Compute $p_{i,t}^a$ the percentage of time each action is expected to be successful

Let $d_j \in s_t^i$ represent a perceived outcome in string s_t^i, such that $d_j \in \{0,1\}$.

$$\forall a_t^i \in \Sigma^i, p_{i,t}^a = \frac{\sum_{j=1}^{K} d_j}{K}$$

1.c) Let $\tau_{j,t}$ represent the perceived outcome of action a, such that $\tau_{a,t} \in \{0,1\}$: $\forall \tau_{a,t} \in T_t^i, \tau_{a,t} = \Phi^i\left(p_{i,t}^a,\theta\right)$.

2. The update operator (ϕ)

Let $D_t^i\left(a_t^i\right)$ represent the expected outcome of action a_t^i, and let $s_{t-1}^i = [d_1, d_2, ..., d_K]$ represent the vector of the past outcomes of action a^i:

$$s_t^i = \left[d_2,...,d_K, D_t^i\left(a_t^i\right)\right].$$

3. The forecast operator $\Phi(p,\theta) = \begin{cases} 1 \leftarrow p \geq \theta \\ 0 \leftarrow p < \theta \end{cases}$

[4] The plausibility parameter helps to speed up the best-response algorithm as it enables the players to direct the best-response algorithm to analyze the set of actions that is more likely to lead to a trade.

Thus each player maintains a K-element string in S (the set of strings representing the possible outcomes of the bids and offers for each plant, as perceived by each player) and these are initially set as $s_0^{P1}\left(a_1^1\right)=\ldots=s_0^{P1}\left(a_5^1\right)=s_0^{P1}\left(a_1^2\right)=\ldots=s_0^{P1}\left(a_5^2\right)=[1,1,1,1]$, in which each string $s_{time}^{Player}\left(a_{number\_plant}^{Player}\right)$ has a size $K = 4$. This means that at the start of the game these prior parameters $[1,1,1,1]$ ensure that all actions start with equal probability of success.

In step 1.a) for each possible action, and for each player, the perceived outcomes (D^{P1}, D^{P2}) are updated. The perceived outcomes are trade-possible (1) or not trade-possible (0). A trade is possible if the player wants to sell (buy) plant and there are buyers (sellers) in the market for that plant. We restrict the number of offers and/or bids into the market, by any player, to W at each time (W = 2 in this example). Assume that in our example the set of actions at time one were $A_0^{P1}=\{a_2,a_4\}$ and $A_0^{P2}=\{a_1,a_4\}$ respectively for player $P1$ and $P2$. These action sets imply that player $P1$ wishes to buy plants a_2,a_4; and that player $P2$ wishes to buy plant a_1 and sell plant a_4. Therefore, at this step each player would update his strings of perceived outcomes. Hence, for player $P1$, $s_1^{P1}\left(a_1^1\right)=s_1^{P1}\left(a_4^1\right)=[1,1,1,1]$ and $s_1^{P1}\left(a_2^1\right)=s_1^{P1}\left(a_3^1\right)=s_1^{P1}\left(a_5^1\right)=[1,1,1,0]$, and for player $P2$: $s_1^{P2}\left(a_1^2\right)=s_1^{P2}\left(a_4^2\right)=[1,1,1,1]$ and $s_1^{P2}\left(a_2^2\right)=s_1^{P2}\left(a_3^2\right)=s_1^{P2}\left(a_5^2\right)=[1,1,1,0]$.

Thus, in step 1.b) we compute the probability that a given action is a success $\left(p_{player,t}^{action}\right)$ at time t. Therefore, in this example, given the observed strings, for both players $P1$ and $P2$ (here represented as PJ) the probabilities of success are $p_{PJ,t}^{a1}=p_{PJ,t}^{a4}=1$ and $p_{PJ,t}^{a2}=p_{PJ,t}^{a3}=p_{PJ,t}^{a5}=0.75$.

Finally, in step 1.c) we update the tables T^{P1} and T^{P2}. Each element of the tables is computed using the forecast operator $\Phi\left(p_{Player,t}^{action},\theta\right)$. Thus, for a given action, if the perceived probability of a trade being made is greater than θ, then this action is considered to be a plausible trade. In this example, at the end of iteration one, since all the $p_{Player,1}^{action} > 0.1$ the updated models will be $T_1^{P1} = T_1^{P2} = [1,1,1,1,1]$.

The plant trading game proceeds with the *Adaptation* procedure, Table 4.3, which models how players co-evolve their best response strategies on the basis of some stochastic search and learning. There are several behavioural elements to this including *inertia*, w_t^i, which denotes in the probability[5] of player *i* to stay with existing strategies at time *t* rather than search for new ones.

Assume in our example that the inertia variables are $w_0^{P1} = 0.5$ and $w_0^{P2} = 1$, and so after drawing two random numbers, suppose they are 0.8 and 0.9 respectively for *P1* and *P2*. Therefore, it follows from 1.a) that player *P1* will have to compute a new set of actions, whilst player *P2* will keep choosing the same actions $A_1^{P2} = A_0^{P2} = \{a_1, a_4\}$. Thus, player P1 selects a new portfolio of actions using a dynamic programming algorithm. In our example, as the state space and table T^{P1} are the same at times zero and one the optimal set of actions will not change and therefore $Z_1^{P1} = \{a_2, a_4\}$. Moreover, as $\# Z_1^{P1} = W = 2$, there is no need to complete the adaptation model, and therefore $A_1^{P1} = Z_1^{P1} = \{a_2, a_4\}$. Otherwise, player *P1* would choose the best possible action from the set of unlikely trades (in addition to the ones in Z_1^{P1}) and use them in the auctions, in order to attract another player to that deal.

[5] We allow inertia to decline over time through an updating parameter $(\sigma = 0.9)$.

TABLE 4.3: Adaptation Algorithm

1. Each player i decides to adapt

1.a) Applies the Inertia principle, for a given w_t^i

$$\begin{cases} Z_t^i = BR\left(\Omega_t, T_t^i, \rho_i\right) \leftarrow r \geq w_t^i \\ \qquad Z_t^i = A_{t-1}^i \leftarrow r < w_t^i \end{cases}$$

1.b) Algorithm Best-Response $Z_t^i = BR\left(\Omega_t, T_t^i, \rho_i\right)$:

Compute the optimal policy, Z_t^i:

$$\forall t = 1, \ldots, h,$$

$$Z_t^i = \arg\max_{a_t^i}\left[u\left(\Omega_t, a_t^i\right) + \rho_i V_{t+1}^i\left(\Omega_{t+1}, T_{t+1}^i\right)\right]$$

$$s.t.$$

$$T_1^i = T_0^i, \Omega_1 = \Omega_0$$

$$\forall \tau_{j,t+1} \in T_{t+1}^i, \tau_{j,t+1} = \delta^i\left(\tau_{j,t}, a_t^i\right)$$

$$\Omega_{t+1} = \left\{\Omega_t \setminus \left(a, i\right)\right\} \bigcup \left\{(a, j)\right\}$$

$$\delta^i\left(\tau_{j,t}, a_t^i\right) = \begin{cases} \tau_{j,t} \leftarrow j \neq a_t^i \\ 0 \ \leftarrow j = a_t^i \end{cases}$$

2. Complete Adaptation Model

If $\# Z_t^i < W$

Let $\Lambda_t^i = \left\{a_t^i : \tau_{j,t} \in T_t^i, \tau_{j,t} = 0\right\}$

$$\overline{Z_t^i} = BR\left(\Omega_t, \Lambda_t^i, \rho_i\right)$$

else $\overline{Z_t^i} = \{\ \}$

3. Define the set of actions to bid into the auction

$$A_t^i = Z_t^i \cup \overline{Z_t^i}$$

The game continues with the plant *Trading Auction* (Table 4.4). There is a separate auction for every plant, simultaneously: a trade is possible only if simultaneously there are one or more buyers and a seller, and the price bid by the buyers ($B_{a,i}$, for player i attempting to buy asset a) is higher than the seller's offer ($O_{a,i}$, for player i attempting to sell asset a). Then, after computing the set of possible trades, the auctioneer chooses which transaction actually takes place, as the one with the largest difference between bid and offer (there are only positive-valued trades since a seller always has the option to close a plant at no cost). The algorithm proceeds by computing the transaction price for the chosen trade as a simple average of the seller's bid price and the buyers' highest offered price.

TABLE 4.4: The Trading Auction

1. For every asset a find T_a

$$T_a = \left\{ \left(B_{a,i}, O_{a,j} \right) : i \neq j, B_{a,i} > O_{a,j} \right\}$$

$$B_a = \left\{ B_{a,i} : \left(B_{a,i}, O_{a,j} \right) \in T_a \right\}$$

2. Find T:

For every asset a find a viable trade $\left(B^{+}_{a,i}, O^{+}_{a,j} \right)$:

$$O^{+}_{a,j} = O_{a,j} \text{ and } B^{+}_{a,i} = \sup B_a$$

Find the set of all viable trades:

$$T = \bigcup_a \left(B^{+}_{a,i}, O^{+}_{a,j} \right)$$

3. Find the asset to be traded $\left(B^{*}_{a,i}, O^{*}_{a,j} \right)$

Let g stand for a function from T into R :

$$g = \left\{ \left(\left(B_{a,i}, O_{a,j} \right), G_a \right) \in T \times R \mid G_a = B_{a,j} - O_{a,j} \right\}$$

The asset to be traded is the one with the largest difference between offer and bid prices

$$\left(B^{*}_{a,i}, O^{*}_{a,j} \right) = \underset{\left(B_{a,i}, O_{a,j} \right)}{argmax}\ g$$

4. Compute the transaction price

Let $B^{++}_{a,z}$ represent the second highest bid for asset a:

$$B^{++}_{a,z} = \sup \left\{ B_a \setminus B^{*}_{a,i} \right\}$$

$$P_{a,t} = \max \left(\frac{B^{*}_{a,i} + O^{*}_{a,j}}{2}, B^{++}_{a,z} \right)$$

We now consider the case of a third player a third player P3, who owns no plant, and is attempting to buy plants a_3 or a_4, i.e., $A_1^{P3} = \{a_3, a_4\}$. In our example the sets of possible trades would be $T_{a1} = T_{a2} = T_{a3} = T_{a5} = \{\ \}$, i.e, for these plants no trade is possible, but for plant a_4 we have $T_{a4} = \{(B_{a4,P1}, O_{a4,P2}), (B_{a4,P3}, O_{a4,P2})\}$.

Assume that in our example $B_{a4,P1} = 160£/KW$, $B_{a4,P3} = 155£/KW$ and that $O_{a4,P2} = 140£/KW$. Then $B_{a4,P1} = 160£/KW$ is the winning bid and ${B^{++}}_{a4,P1} = 155£/KW$ and the trading price equals the maximum of the simple average of the highest bid and the second highest offered price[6], i.e., $Pa_{4,1} = \max\left(\frac{160+140}{2}, 155\right) = 155£/KW$. In this case player *P1* buys plant a_4 for 155£/ *KW*.

Next, after a successful trade, the algorithm computes a new state of the game. Table 4.5 describes this procedure, which can be illustrated in our example as follows. First we update the state of the industry Ω for the trade of plant a_4:

$$\Omega_0 = \{(a_1, P1), (a_2, P2), (a_3, P1), (a_4, P2), (a_5, P1)\}$$

$$\Omega_1 = \{(a_1, P1), (a_2, P2), (a_3, P1), (a_4, P1), (a_5, P1)\}.$$

Then, the inertia variables $w_0^{P1} = 0.5$ and $w_0^{P2} = 1$ are updated using the inertia updating parameter $\sigma = 0.9$: $w_1^{P1} = 0.5 \times 0.9 = 0.45$ and $w_1^{P2} = 1 \times 0.9 = 0.9$.

Then, in order to solve the Cournot game (step 3) the algorithm computes the marginal costs and capacities of each player in each auction. Each player updates the capacities and marginal costs iteratively, taking into account the past performance of

[6] This is a standard procedure of the single-call auction, Cason and Friedman (1997). The simple average is just one of the possible criteria from which to select the trading price; for as long as the trading price falls between the highest and the second highest bids the auction solution will always be the same, and any price in this range is an acceptable outcome of the auction, as it will not change the trajectory of ownership in the game.

each plant. Note that the marginal cost of a given player is the highest one among all the plants he submits to a given market: see Ramos at al. (1998) and Borenstein et al. (1999).

TABLE 4.5: Update State of the Game

1. Update state of the industry Ω_t

$$\Omega_{t+1} = \{\Omega_t \setminus (a,i)\} \bigcup \{(a,j)\}$$

$$w_{t+1}^z = \begin{cases} w_t^z.\sigma \leftarrow otherwise \\ 1 \quad \leftarrow \quad z = i, j \end{cases}$$

2. Update cost structure and capacities bid in each auction:

$\forall L, \forall i$:

$K_{i,L} := 0$

$\forall a$, $K_{(a,i),L} := 0$

2.1: For all available asset a

$$\textit{if } C_{(a,i),L} \leq C_{i,L} \text{ or } \left[not(a,i,t), C_{(a,i),L} \leq C_{i,L+1} \right]$$

$$K_{i,L} := K_{i,L} + K_{(a,i)}$$

$$C_{i,L} := \max\left[C_{i,L}, C_{(a,i),L} \right]$$

$$K_{(a,i),L} := K_{(a,i)}$$

$$\textit{if multi-clearing and } \text{if } K_{(a,i),L} > 0 \textit{ then } K_{(a,i)} := 0$$

3. Solve Cournot game

4. Compute value of plant

$\forall i, a$:

$$OP(a,i) = \sum_L \left[\left(P_{L,t} - C_{(a,i),L} \right) .Q_{(a,i),L} .D_L \right]$$

$$OP(i) = \sum_{(a,i)} OP(a,i)$$

In our example assume that the quantities generated at time zero are the ones represented in Table 4.6. Therefore, following step 2 in Table 4.5 we can compute the marginal costs and capacities submitted by each player for each market.

We start with player *P1*. As at iteration zero: in the baseload market he will offer the full capacity of plant a_1; in the shoulder market he will offer the full capacity of plant a_1 and a_3; in the peak market he will offer the full capacity of plant a_1, a_3, and a_5.

Furthermore, this time he also owns plant a_4. As he did not owned this plant at iteration zero, this time he will also offer the generation of plant a_4 in the baseload market (which will also attempt to sell in the shoulder and peak markets) as it follows from step 2.1. Then player P2 decides to offer the generation of his only plant a_2 in all the markets. Finally, the algorithm solves the Cournot game and computes the operational profit of each plant and player.

TABLE 4.6: Example: Generation per plant and Market at Time Zero

	Generation		
Plant	Baseload	Shoulder	Peak
a_1	1000	1000	1000
a_2	500	1000	1000
a_3	0	80	100
a_4	0	50	100
a_5	0	0	5

The simulation then repeats and advances in *t*. Clearly the main goal of the evolutionary simulation is to model how the electricity market structure would develop under the two market mechanisms, taking into account the initial conditions for the market structure. The game is repeated for a given number of iterations in order to capture its main attractors. This is not intended to simulate how the market will actually evolve over time, only to test which market structures reveal attractors, under the present conditions.

5. MODELLING THE IMPACT OF MARKET DESIGN ON STRATEGIC OWNERSHIP

This section now describes a large scale application of the above model to analyse the impact of market design on the strategic ownership of plant portfolios through simulating the evolution of a stylised version of the England and Wales Market, as it was in 2000, under various hypothetical initial conditions for the market structure. The specific market structure used is represented in Table 5.1 [Electricity Association (1999, 2000 a, b, c)].

TABLE 5.1: England and Wales Generating Capacity in 2000

Capacity of each Company (% of Total, 59 GW) in 2000				
	Total	Nuclear	Large Coal+CCGT	Small Coal +OCGT + OIL + Pump. Storage
PG	16.5		19.7	24.9
NP	13.9		16.3	22.5
BE	12.4	54.0	4.9	
Edison	10.6		10.1	30.7
TXU	9.7		11.6	14.7
AES	7.8		10.1	6.8
EDF	4.7	17.3	2.0	
Magnox	3.9	19.9		
Others	20.5	8.8	25.3	0.4
Total GW	59.1	11.4	40.7	7.0

The analysis proceeds by comparing the results under single and multi clearing mechanisms. These experiments simulated trading at a genset level (using the 137 gensets which defined the E & W system in 2000), but distributed hypothetically among three different players. In these experiments the demand functions were parameterised by defining the same elasticity, prices, and traded quantities in each one of the two clearing mechanisms, in the three simulated markets (baseload, shoulder and peak). The elasticities used were 0.5, 0.35 and 0.25 respectively for the baseload, shoulder and peak market[7]. Whilst, in the multi-clearing mechanism the durations for

[7] The choice of these elasticities follows the elasticities used previously in the literature: Wei and Smeers (1999) use 0.4 and 0.53 for residential and industrial clients respectively, in simulating the

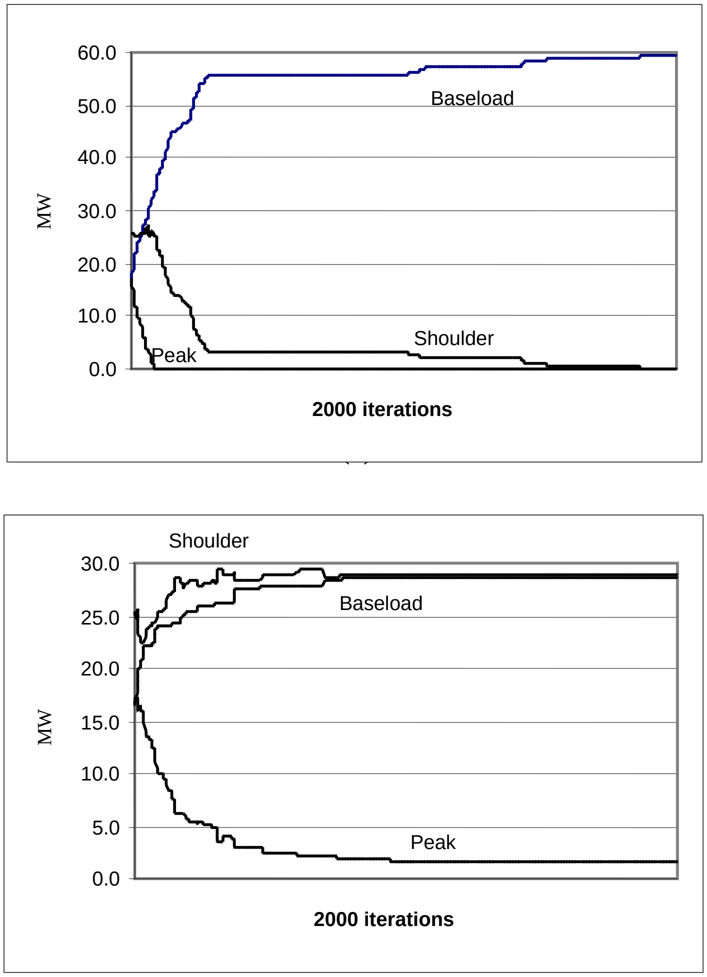
the baseload, shoulder and peak markets were specified as 8760, 5500 and 500 hours; these durations in the single-clearing mechanism were equivalently defined as 3260, 5000 and 500 hours. Further, all the experiments presented in this section simulate 2000 iterations in each different scenario.

Moreover, we used a plausibility cut-off of $\theta = 0.1$, a discount factor of $\rho = \rho_{P1} = \rho_{P2} = 0.9$ and an inertia updating of $\sigma = 0.9$. The specific values of these parameters are not crucial. However, the plausibility cut-off should be low (even equal to zero, if speed is not a concern), the inertia updating should be close to one (the closer to one the higher the required number of iterations will be) and the discount factor reflects both the value of money in time and the accuracy of the dynamic programming algorithm used to estimate the optimal policy (the closer to one, the higher the accuracy, but the algorithm can become very slow).

5.1. Analyzing the Specialisation Scenario

In the experiments presented in Figures 5.1 and 5.2 the baseload, shoulder and peak plants were separated out among the three different players (they are called, respectively, Baseload, Shoulder and Peak). Figure 5.1 shows that the single clearing mechanism leads to higher concentrations: whilst in the single-clearing mechanism, a single player becomes a monopolist, in the multi-clearing mechanism several players do survive. The main reason for this behaviour relates to the impact of capacity withholding on market prices and generation, under the two different market clearing mechanisms.

Belgium, France, Germany and Italy market; whilst Ramos et al. (1998) use an elasticity of 0.6 in simulating the Spanish market.



(b)

FIGURE 5.1: Capacity by player. (a) Single-clearing mechanism. (b) Multi-clearing mechanism.

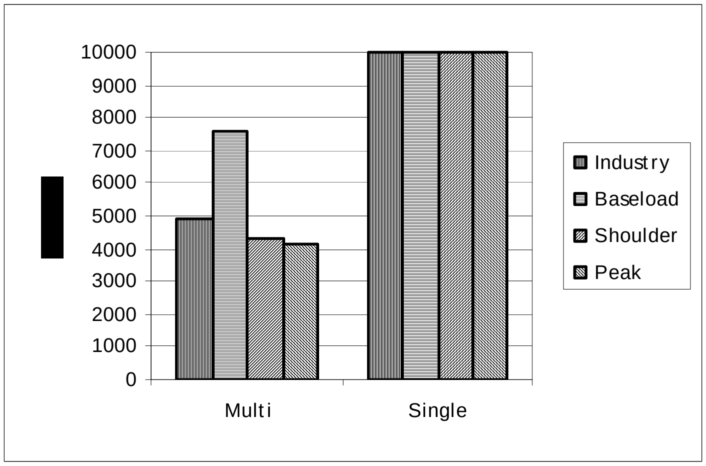
Under single-clearing, the Baseload player (which receives the same price as the Shoulder and Peak players for the electricity sold at shoulder and peak times) has a very strong incentive to withhold capacity. Consequently, by reducing the generation from shoulder and peak plants this player is able to increase the value of his baseload portfolio. Therefore, the winning strategy of this player is to buy the Shoulder and Peak players out of the market. This scenario most clearly shows that the evolutionary attractors of the industry, under single-clearing, tend to lead towards the low generation and high prices which characterise monopolistic behaviour.

Under multi-clearing, on the other hand, every player receives the same price for selling in a given market, however, as baseload plants cannot sell their generation in the shoulder or peak markets, and as shoulder plants cannot sell their generation in the peak markets, then capacity withholding is less profitable. In this second case, the evolutionary attractor drives the market structure towards specialization in different markets (and technologies). This specialization, however, also leads to high prices and lower generation as the players can benefit from selling in a segmented market.

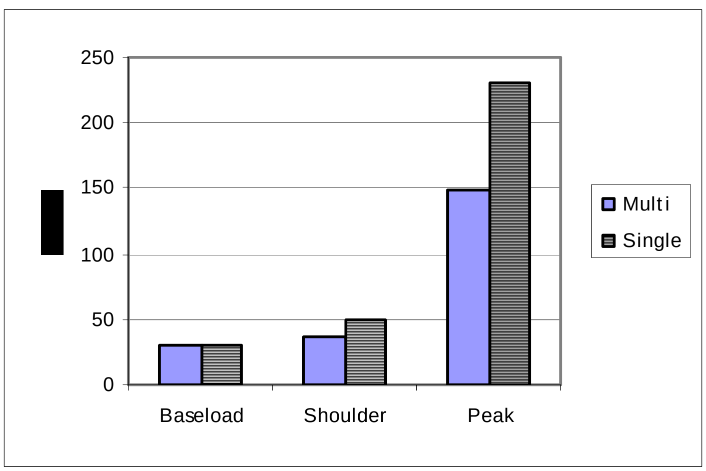
Furthermore, looking at Figure 5.2, again the concentration indices in the single-clearing mechanism are higher than in the multi-clearing mechanism. In the multi-clearing case, the concentration index of the baseload technology is the highest. As the initial values for these concentration indices were, respectively 5200, 3360 and 5000 (in Figure 5.2.a), in the multi-clearing mechanism the baseload player buys baseload plant, and the shoulder player buys shoulder plant: this is a direct consequence of the effect of capacity withholding on their respective portfolios.

Moreover, it is very important to note that even with only three players the multi-clearing game does not converge to a monopoly. This observation suggests that the structure of an industry that had been privatised with specialized players is only sustainable, in the long run, if accompanied by the multi-clearing pricing mechanism.

Additionally, the analysis of Figure 5.2.b) tells us, straight away, that prices in the single-clearing mechanism tend to be higher than under the multi-clearing mechanism. However, and most surprisingly, the prices in the baseload are the same in both mechanisms; and the prices in the shoulder market are very similar in both mechanisms as well: the reason being the market specialization by each player.



(a)



(b)

FIGURE 5.2: Concentration and Prices. (a) HHI Concentration Indices: Multi (Single) represents the concentration index in the multi-clearing (single-clearing) mechanism. (b) Electricity Prices (in the Baseload, Shoulder and Peak markets).

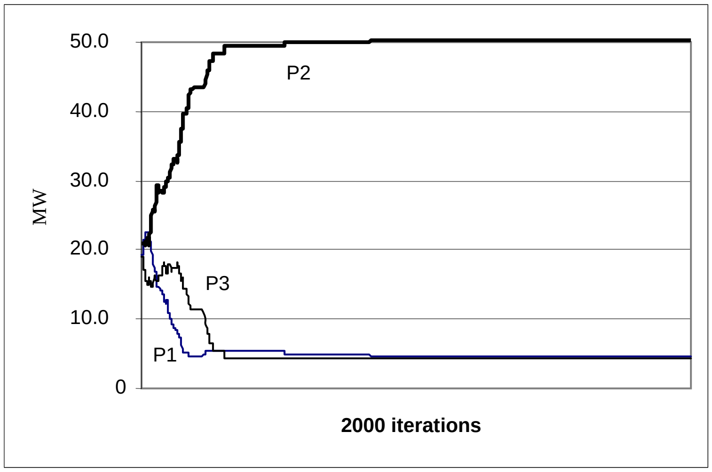
Furthermore, still in Figure 5.2.b), regarding the relation between market concentration and the HHI, these experiments have interesting findings. Even though the concentration indices of the two markets are very different (10000 vs. 5000) only in the small part of the market that reflects the Peaks, were the electricity prices significantly different (approx 230 vs. 150). In the baseload market, even though the concentration ratios are different (10000 vs. 7800) the prices are the same. In the shoulder market, the difference in the HHI (10000 vs. 4100 approx.) does not correspond to the same level of difference between prices.

These results show that the HHI is a measure of concentration that does not indicate well the ability of players to manage market prices. Furthermore, this set of experiments clearly shows that the clearing-mechanism has implications for the evolutionary properties of the market structure. Under single-clearing, technological specialization is not stable and the market converges towards concentration, whereas, under multi-clearing, technological specialization is viable, and more players can survive in their own market segments.

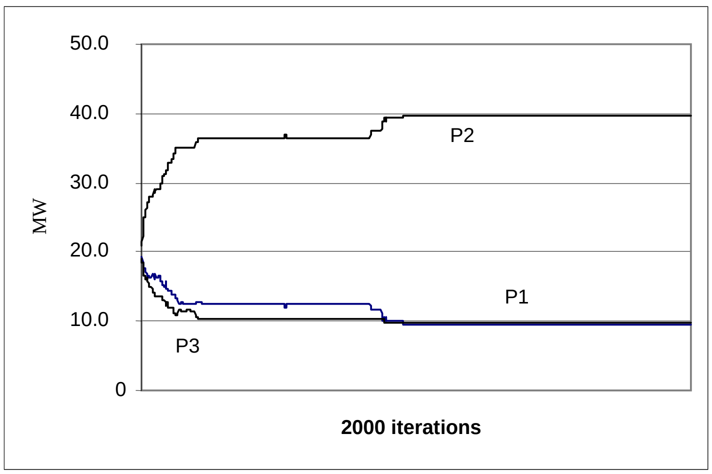
5.2. *Analyzing the Diversification Scenario*

As a second variation on the interaction of market design and the strategic management of plant portfolios, in the experiments represented in Figures 5.3 and 5.4 the plants were assigned (one by one) to each one of three players (called P1, P2 and P3) by increasing order of marginal cost. Thus, in these experiments the initial portfolios are similar for all the three players.

Figure 5.3 represents the results of this set of experiments, showing that in the single-clearing mechanism the structure converged to a more concentrated configuration than in the multi-clearing mechanism.



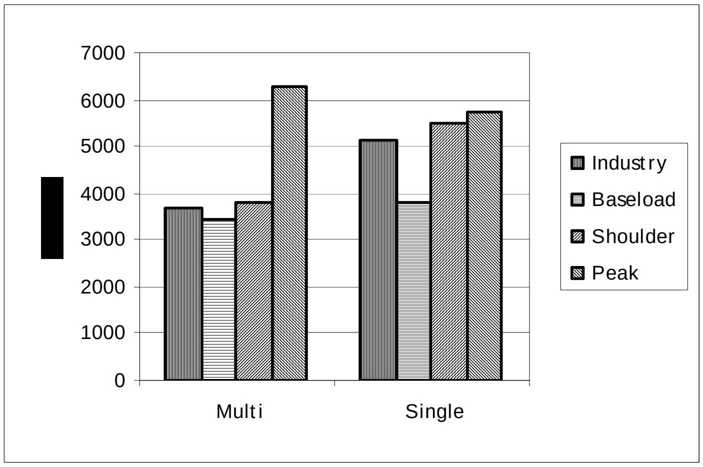
(a)



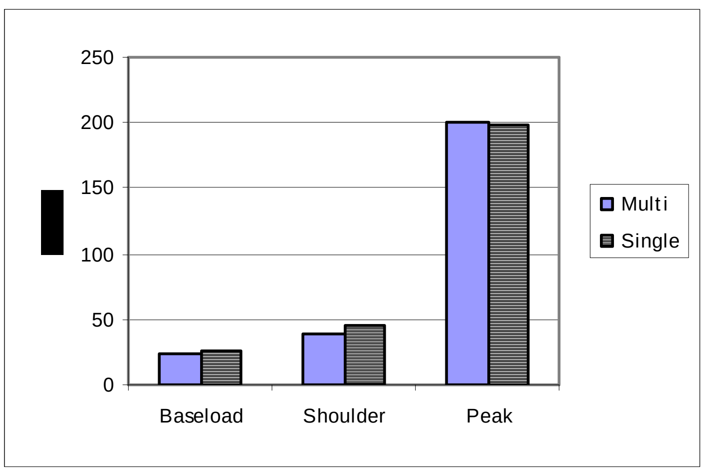
(b)

FIGURE 5.3: Capacity by player. Experiment with three homogeneous players (P1, P2, P3). (a) Single-clearing mechanism. (b) Multi-clearing mechanism.

Moreover, the analysis of Figure 5.4 shows that the industry as a whole is a little more concentrated in the single clearing market: see Figure 5.4a. As a general observation, the prices in both types of clearing mechanism are very similar, which implies that under diversification the type of market clearing-mechanism is not a crucial determinant of the evolutionary attractors of the industry's structure. The evolution of market structure again did not converge on the monopolistic solution and, even though the market concentration increased, the final equilibrium is a stable diversification.



(a)



(b)

FIGURE 5.4: Concentration and Prices. Experiment with 3 homogeneous players (P1, P2, P3). (a) HHI Concentration Indices. (b) Electricity Prices. For the Baseload, Shoulder and Peak markets, presented as a function of Clearing-Mechanism.

Furthermore, the comparisons of Figure 5.1 (5.3) and Figure 5.2 (5.4) suggest that independently of the type of the clearing mechanism, a restructuring in which all the players are diversified tend to lead to less concentration. Most importantly, these results seem to indicate that the management of a portfolio of generation plants is a function not only of the market clearing mechanism, but also of the initial state of the industry's structure. Consequently, if the industry is at a state of great diversification it will tend to remain so, independently of the market-clearing mechanism.

6. CONCLUSIONS

The issue of market structure evolution in liberalised electricity markets and its relationship with the management of portfolios of generation plants is still an open research question. Therefore, a better understanding of this evolutionary process will have important implications on both regulatory policy and strategic behaviour. The research presented in this paper has provided initial insights on this elusive issue through a plant trading game, which enables market structure evolution to occur endogenously.

Furthermore, through the simulations of this game, a number of preliminary interesting insights into the interaction between market design and strategic portfolio management have become evident. Restructuring with similarly diversified, rather than technologically specialised, players leads to more competition, less concentration and lower prices. The assumption that this would lead to relatively higher market power has not been supported. Liberalisation through bilateral markets can lead to market power in the market segments. However, it can also ensure the survival of more companies. In the bilateral markets, the existence of segment market power, due to the technical features of generation, can lead to prices that are very high, even in the presence of multiple companies. In general, the value of power plants does depend upon the ownership portfolios in which they belong, and more surprisingly, upon the market rules within which competition takes place.

Moreover, this study has some interesting implications for the strategic management of portfolios of generation plants. Market specialization leads to higher profits than diversification. Therefore, a player should invest in the same type of technology (i.e., that sells in the same market segment) as the one it currently owns. Moreover, new entrants should specialize in a given technology, instead of diversifying their portfolios by acquiring (or investing) in different types of technology. When trading plants, the incumbents should sell the technologies in which they are not specialized. Moreover, preferably they should sell to companies that are specialists in that technology. The reason for this is that, as we have seen before, the more concentrated the industry segments the higher the prices. Therefore, by selling a plant in which a player does not dominate a given technology he is in fact charging a small part of the premium that the buyer will have on the traded plant. Independent power producers will tend to flourish in industries where the incumbent players are not specialized and where there is bilateral trading. All of these observations relate simply to competition and market structure. Clearly, many other factors influence such conclusions in practice, eg economies of scale, operational synergies, etc, but in the context of these, our results do provide substantially new insights into some basic principles of market structure and design.

Moreover, despite the computational intensity of this model, this study represents quite a stylised approach to the modelling of evolutionary electricity markets. There are some possible extensions to this model that may bring very interesting and complementary new insights, such as the inclusion of transmission networks and regional interconnections, new entry and investment in new plants, as well as the impact of risk aversion on the firms' strategies.

APPENDIX – Notation

:= operator representing a process of iterative updating

a: Any given plant that may be auctioned

(a,i): Plant *a* is owned by player *i*

$not(a,i,t)$: Plant *a* is not owned by player *i*, at time *t*

a_t^i: action of player *i* at time *t*

i, *j*: players offering (attempting to sell) or bidding (attempting to buy) assets in an auction

h: number of steps of look-ahead

θ: plausibility cut-off parameter, $0 \le \theta \le 1$

ρ_i: discount factor for agent *i*, $0 \le \rho_i \le 1$

r: random generated number from a uniform distribution, such that $r \in [0,1]$

$\mu(\Omega_t, a_t^i)$: utility (profit or reward) of player *i* at time *t*, for a given action a_t^i in state Ω_t

w_t^i: inertia variable such that $w_t^i \in [0,1]$, at time *t*.

$\sigma \in]0,1[$ is the parameter for inertia updating

A_t^i: set of actions actually bid by player *i*, in state *t*, with size *W; such that* $A_t^i \subseteq \Sigma^i$

B_a: set of all acceptable bids for asset *a*

$B_{a,i}$: price bid by player *i* attempting to buy asset *a*

$C_{(a,i),L}$: marginal cost of plant a, owned by player i, for market L

$C_{i,L}$: marginal cost of player i in market L

D^i: perceived outcomes of the player's actions in the path of his automaton,

$$D^i \equiv \{0,1\}$$

D_L : duration of market L

K: Length of the strings in S, a set containing all the prefixes of D^i

$K_{i,L}$: capacity of player i assigned to market L

$K_{(a,i)}$: available capacity of asset a, owned by player i

$K_{(a,i),L}$: capacity of asset a offered in market L in the previous iteration

$O_{a,i}$: price offered by player i attempting to sell asset a

$OP(a,i)$, $OP(i)$: Operational profit of plant a and player i, respectively

$P_{a,t}$: transaction price of asset a at time t

$P_{L,t}$: electricity price in market L, at time t

$Q_{(a,i),L}$: total generation of plant i sold in market L

Σ^i : set of actions a^i available to player i

$S \equiv$ all prefixes of D^i with a length less of equal than $K> W$

T_t^i : plausibility Table, a one-dimensional table of dimension M *(number of plants)*

T_a: set of all possible trades for asset a

T: set of the all winning trades (at the most one per asset)

Ω_t : state of the industry at time t

V_t^i : value of i's portfolio at time t

W: Size of the set of actions A_t^i actually bid by any player i.

REFERENCES

ABBINK, K., J. BRANDTS, AND T. MCDANIEL (2003): "Asymmetric Demand Information in Uniform and Discriminatory Call Auctions: An experimental Analysis Motivated by Electricity Markets," *Journal of Regulatory Economics*, 23 (2), 125 – 144.

ALLAZ, B., AND J.-L. VILA (1993): "Cournot Competition, futures markets and efficiency," *Journal of Economic Theory*, 59 (1), 1-16.

ANDERSON, E. J., AND A. B. PHILPOTT (2002): "Using Supply Functions for Offering Generation into an Electricity Market," *Operations Research*, 50 (3), 477-489.

BODDE, D. L. (1998): "Strategic thinking about nuclear energy: implications of the emerging market structure in electricity generation," *Energy Policy*, 26 (12), 957-962.

BORENSTEIN, S., J. BUSHNELL, E. KAHN, AND S. STOFT (1995): "Market power in California electricity markets," *Utilities Policy*, 5 (3-4), 219-236.

BORENSTEIN, S., AND J. BUSHNELL (1999): "An Empirical Analysis of the Potential for Market Power in California's Electricity Industry," *The Journal of Industrial Economics*, XLVII (3), 285-323.

BOWER, J., AND D. W. BUNN (2000): "A Model-Based Comparison of Pool and Bilateral Market Mechanisms for Electricity Trading," *The Energy Journal*, 21 (3), 1-29.

BUNN, D. W., AND F. S. OLIVEIRA (2001): "Agent-based Simulation: An Application to the New Electricity Trading Arrangements of England and Wales." *IEEE Transactions on Evolutionary Computation*, 5 (5): 493-503.

BUNN, D. W., AND F. S. OLIVEIRA (2003): "Evaluating Individual Market Power in Electricity Markets Via Agent-Based Simulation," *Annals of Operations Research*, 121, 57-77.

CASON, T. N., AND D. FRIEDMAN. 1997. Price formation in Single Call Markets. *Econometrica* 65 (2), 311-345.

COX, A. J. (1999): "Mergers, Acquisitions, Divestures, and Applications for Market-Based Rates in a Deregulated Electric Utility Industry," *The Electricity Journal*, 12 (4), 27-36.

DAY, C. J., AND D. W. BUNN (2001): "Divestiture of generation assets in the electricity pool of England and Wales: A computational approach to analysing market power," *Journal of Regulatory Economics*, 19 (2), 123-141.

ELECTRICITY ASSOCIATION (1999): "The UK Electricity System," www.electricity.org.uk.

ELECTRICITY ASSOCIATION (2000a): "Electricity Companies in the United Kingdom – a brief chronology," www.electricity.org.uk.

ELECTRICITY ASSOCIATION (2000b): "List of Power Stations." www.electricity.org.uk.

ELECTRICITY ASSOCIATION (2000c): "Who owns whom in the UK electricity industry." www.electricity.org.uk.

ELMAGHRABY, W., AND S. S. OREN (1999): "The Efficiency of Multi-Unit Electricity Auctions," *The Energy Journal*, 20 (4), 89-116.

EXELBY, M. J., AND N. J. D. LUCAS (1993): "Competition in the UK Market for Electricity Generating Capacity, A Game Theory Analysis," *Energy Policy*, April: 348–354.

FLAVIN, C., AND N. LENSSEN (1994): Reshaping the electricity power industry. *Energy Policy*, 22 (12): 1029–1044.

GARCIA-ALCALDE, A., M. VENTOSA, M. RIVIER, A. RAMOS, AND G. RELANO (2002, June): “Fitting Electricity Market Models. A Conjectural Variations Approach,” 14th PSCC, Sevilha.

GREEN, R. G., AND D. NEWBERY (1992): “Competition in the British Electricity Spot Market,” *Journal of Political Economy*, 100(5), 929-953.

HENNEY, A. (1994): “Energy markets and energy policies after the White Paper,” *Energy Policy*, January: 5-116.

HERNAEZ, E. C., J. B. GIL, J. I. LEÓN, A. M. S. ROQUE, M. V. RODRÍGUEZ, J. G. GONZÁLEZ, A. M. GONZÁLEZ, AND A. M. CALMARZA (2003): "Competitors' Response Representation for Market Simulation in the Spanish Daily Market," in Bunn (ed.), *Modelling Prices in Competitive Electricity Markets*, Wiley.

HOBBS, B. F. (2001): “Linear Complementarity Models of Nash-Cournot Competition in Bilateral and POOLCO Power Markets,” *IEEE Transactions on Power Systems*, 16 (2), 194-202.

ISHII, J., AND J. YAN (2002, September): “The “Make or Buy” Decision in U.S. Electricity Generation Investments,” CSEM WP 107, UCEI, www.ucei.org.

KASERMAN, D. L., AND J. W. MAYO (1991): “The measurement of vertical economies and the efficient structure of the electricity utility industry,” *The Journal of Industrial Economics*: 483–502.

KENNEDY, D. (1997): “Merger in the English electricity industry,” *Energy Policy*, 25 (4): 393–399.

LARSEN, E. R., AND D. W. BUNN (1999): "Deregulation in electricity: understanding strategic and regulatory risk," *Journal of the Operational Research Society*, 50: 337-344.

NEWBERY, D. M. (1998): "Freer electricity markets in the UK: a progress report," *Energy Policy*, 26 (10): 743-749.

PINEAU, P.-O., AND P. MURTO (2003): "An Oligopolistic Investment Model of the Finnish Electricity Market," *Annals of Operations Research*: 121, 123-148.

RAMOS, A., M. VENTOSA, AND M. RIVIER (1998): "Modelling competition in electric energy markets by equilibrium constraints," *Utilities Policy*, 7, 233-242.

RASSENTI, S. J., V. L SMITH, AND B. J. WILSON (2003): "Discriminatory Price Auctions in Electricity Markets: Low Volatility and the Expense of High Price Levels," *Journal of Regulatory Economics*, 23 (2), 109 – 123.

SKANTZE, P., P. VISUDHIPHAN, AND M. ILIC (2000, November): "Valuation of Generation Assets with Unit Commitment Constraints under Uncertain Fuel Prices," Working Paper MIT_EL 00-006.

STIRLING, A. (1994): "Diversity and ignorance in the electricity supply investment," *Energy Policy*, March: 195–201.

VISUDHIPHAN, P., P. SKANTZE, M. ILIC (2001, July): "Dynamic Investment in Electricity Markets and Its Impact on System Reliability," Working paper MIT_EL 01-012WP.

WEI, J.-Y., AND Y. SMEERS (1999): "Spatial Oligopolistic Electricity Models With Cournot Generators and Regulated Transmission Prices," *Operations Research*,. 47 (1), 102-112.