View from an Energy Expert

The simulation of power system operation has always been necessary in order to ascertain the costs of production, especially fuel consumption and the expected reliability of power systems. With the coming of digital computers in the late 1960s, the techniques were improved significantly over the hand/graphical calculations that were used earlier. They were typically based on general averages or the simulation of sample days of operation and, initially, were considered accurate enough.

Later in the same decade, the problem of poor availability of large generating units forced a rethink of the approaches, aided by the availability of improved computing power. Monte-Carlo simulations of hourly operation over all days of a year, embodying detailed chronological effects, were developed. Probabilistic simulations, involving the manipulation of probability distributions to give expected values of major variables, were developed later, and proved suitable for longer term studies.

These techniques were aimed at modeling the main sources of variability affecting the utilities at the time-generating unit forced and planned outage rates, load forecasts and, for some systems, hydroelectric inflow variability. The techniques were generally quite accurate and achieved widespread use in the utility industry during the 1970s. The author of this introduction was heavily involved in this phase of development.

But with the coming of competitive markets and greatly improved generation plant performance in the 1990s, the major variables shifted to those associated with the independent bidding decisions made by multiple independent generation owners, load forecasts, now affected by individual decisions on demand management, new patterns of flow over transmission networks and the variable output of some renewable resources, especially wind farms. A new approach to power system simulation was required, but has proven difficult to achieve.

The multi-agent based simulation model representing Australia's National Electricity Market (NEM) developed by the CSIRO shows great promise in overcoming the problems of the conventional approach. Its structure is such that it is capable of representing the various decisions made by the 'agents' participating in the NEM and of the combined effect of these decisions on supply reliability, electricity costs and prices, greenhouse gas emissions, and other secondary outputs. The Australian market allows participants a greater degree of freedom compared with that of other markets and is prone to manipulation by the exercise of market power by the relatively small number of players. It is quite difficult to model correctly.

The continued development of the CSIRO model is to be supported and the progress thus far is impressive.

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11. NEMSIM: Finding Ways to Reduce Greenhouse Gas Emissions Using Multi-Agent Electricity Modelling

David Batten and George Grozev

Abstract

This chapter outlines the development of an agent-based simulation model that represents Australia's National Electricity Market (NEM) as an evolving system of complex interactions between human behaviour in markets, technical infrastructures and the natural environment. Known as NEMSIM, this simulator is the first of its kind in Australia. Users will be able to explore various evolutionary pathways of the NEM under different assumptions about trading and investment opportunities, institutional changes and technological futures, including alternative learning patterns as simulated agents grow and change. The simulated outcomes help the user to identify futures that are eco-efficient, such as maximising profits in a carbon-constrained future. Questions about sustainable development, market stability, infrastructure security, price volatility and greenhouse gas emissions can be explored with the help of the simulation system.

Introduction

For more than a decade, electricity industries have been undergoing worldwide regulatory reform, with the general aim of improving economic efficiency. In many places, these changes have culminated in the appearance of a wholesale power market. There are various, sometimes contradictory, conclusions about the performance of such restructured electricity markets. In this new context, the operation of the generating units no longer depends on centralised state or utility-based procedures, but rather on the decentralised decisions of various firms—profit-maximisers in different states of economic health with different long-term plans. Market performance depends largely on how each market participant responds to market design—including the rules, market observations, operational procedures and information revelation.

Recently, interest has grown in the use of market-based policy instruments for environmental purposes—to introduce climate change regulation into the electricity sector and reduce greenhouse gas emissions. Australia is an early adopter of both electricity industry restructuring and market-based environmental instruments. However, the mixed performance of these schemes to date illustrates the need for considerable care in the design of market-based approaches (MacGill et al. 2004). For example, the opportunities for market participants to exercise market power are real and observable (Hu et al. 2005).

Firms engaged in these new electricity markets are exposed to higher risks, so their need for suitable decision-support models has increased. Regulatory agencies also require analysis support models so as to monitor and supervise market behaviour. The problem is that traditional electrical operational models are a rather poor fit to these new circumstances, since the new driving force for operational design—market behaviour—was excluded. Furthermore, purely economic or financial models used in other economic contexts do a relatively poor job of explaining behaviour in electricity markets. Nowadays, convincing electricity market models must consider at least 3 interrelated, dynamic processes: market participants' behaviour; the physical limitations of production and transmission assets; and the environmental outcomes associated with electricity generation, transmission and consumption.

This chapter outlines the development of an agent-based simulation model that represents Australia's NEM as an evolving system of complex interactions between human behaviour in markets, technical infrastructures and the natural environment. This simulator is the first of its kind in Australia. Users will be able to explore various evolutionary pathways of the NEM under different assumptions about trading and investment opportunities, institutional changes and technological futures, including alternative learning patterns as participants grow and change. The simulated outcomes will help the user to identify futures that are eco-efficient, for example, maximising profits in a carbon-constrained future. Questions about sustainable development, market stability, infrastructure security, price volatility and greenhouse gas emissions can be explored with the help of the simulation system.

Some physical and behavioural characteristics of Australia's NEM are outlined. This serves as a background for the following section, in which it is argued that Australia's wholesale and contract market system should be treated together as a complex adaptive system. Then we review 3 approaches to electricity market modelling: optimisation, equilibrium and simulation models. The next section argues the case for agent-based simulation models, on the grounds that markets and their participants co-evolve by adaptive learning, though all are pursuing profit-maximising goals. Our empirical work reveals that they adapt their behaviour in response to several dynamic factors, including their own costs, experiences and observed market outcomes. We then describe NEMSIM, the National Electricity Market Simulator currently under development. The greenhouse gas emissions calculator incorporated in NEMSIM is discussed. The final part describes the simulated outcomes, tables and reports that are produced by NEMSIM followed by a summary of future work.

Australia's national electricity market

The NEM in Australia was launched on 13 December 1998 and incorporates 5 States and Territories: Queensland, New South Wales, Australian Capital Territory, Victoria, and South Australia. In 2005, the Tasmanian electricity grid will be linked with the mainland if the Basslink project is completed. The NEM is not a truly national market, since Western Australia and the Northern Territory are not physically connected. It is a gross pool-type market and it operates under the administration of the National Electricity Market Management Company (NEMMCO). As such, the NEM displays many features in common with other pool-type markets after restructuring, for example, the original England/Wales pool prior to New Electricity Trading Agreements (NETA).

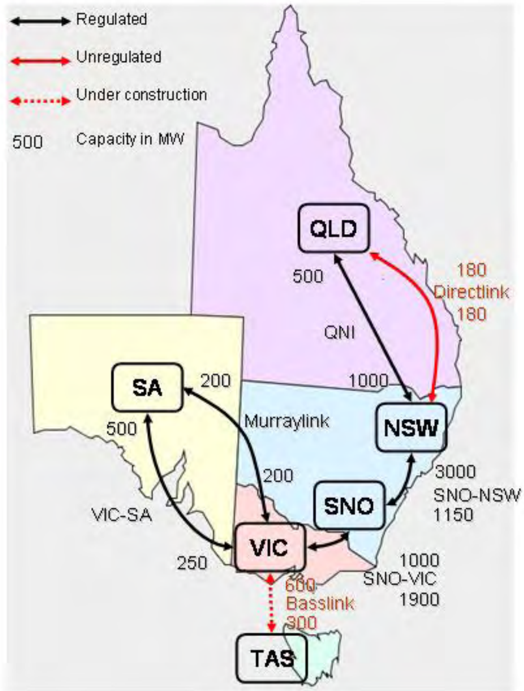
There were 89 registered market participants at the end of 2003. They include 41 generator companies, 20 network service (transmission and distribution) providers, 29 market customers and 9 traders. Several participants are registered in more than one category and some are registered as intending to participate. There are more than 350 physical generation units, of which about 190 can dispatch electricity. The total NEM installed capacity is around 37 gigawatts (GW). In the NEM, a settlement day starts at 04:00 and ends at 04:00 the next day. Each settlement interval is a half-hour period starting on the hour or half-hour. For example, settlement interval 6 denotes the period from 06:30 to 07:00. Each dispatch interval is a 5-minute interval.

Operating the NEM

The NEM is operated as follows (Figure 11.1):

- Scheduled generators submit offers in 10 price bands, stacked in an increasing order in 10 incremental quantity bands over a settlement day. These quantity offers correspond to the 10 price bands for each of the 48 settlement intervals, and must be received by NEMMCO before noon of the previous day (i.e., a day before the real dispatch).
- Regional network operators prepare demand forecasts, whereupon NEMMCO runs a linear program to dispatch generation and meet demand every 5 minutes. This program aims to maximise the value of trade based on dispatch bids or offers from market participants along with other ancillary services, subject to constraints on the physical network and the generating units. Thus less expensive generating units are dispatched first, but the price offered by the most expensive generating unit dispatched determines the price for that dispatch interval.
- The settlement price for each settlement interval is the average of all prices over the six dispatch intervals in the settlement interval.

Figure 11.1. Inter-connectors in Australia's National Electricity Market



The price cap (or VOLL—value of the lost load) in the NEM is currently \$10000/MWh, an increase from \$5000/MWh from April 2002 onward.[1] In practical terms, generators can bid their price bands up to this figure, knowing that the market price is capped by this limit.

Market information plays an important role in participant's decision making and in ensuring reliable dispatch operations. NEMMCO provides market participants with information such as load forecasts, pre-dispatch (and price sensitivity analysis) data, dispatch data, as well as medium- (7 days) and long-term (2 years) forecasting of supply scenarios or system adequacy. Market participants are permitted to adjust their bids in response to the latest information. For example, they can rebid the quantity for a previously bid settlement interval up to 5 minutes before dispatch, although the price bands are fixed for the entire settlement day.

On its website,[2] NEMMCO publishes the bidding and dispatch data for all scheduled generating units shortly after the end of a settlement day. Yesterday's files contain bids/offers and rebids made by generating units and dispatchable

[1] Prices are in Australian dollars.

[2] www.nemmco.com.au

loads for each day's settlement intervals. They also record rebid explanations, since early 2002. The daily dispatch files include regional information such as regional reference prices, total demand and dispatchable generation. Although Barmack (2003) has expressed concerns about the revelation of bidding data to the public, in some earlier work we have demonstrated that there are several positive aspects of such data revelation (Hu et al. 2005).

Several other researchers have studied the market's performance during this period of restructuring. Wolak (1999) examined the first 3 months of the NEM's operation and observed that wholesale prices in Victoria and NSW dropped initially compared with those prevailing prior to the introduction of the NEM. Outhred (2000) concluded that the extent of competition is high and that the market performs well. By way of contrast, Short and Swan (2002) reported a mixed performance based upon their calculation of Lerner indices—defined as the ratios of the difference of bid price and marginal price to the bid price—for the regions in the NEM.

Some of our recent research identified various strategies used by generators in the market. The data we examined showed that two-thirds of the generating units are relatively inactive in terms of changing bidding strategies. However, the minority of generators that do respond actively to changes in market conditions are base-load units that tend to dominate the supply side. These 30-or-so active generating units are the *giants* in their regions. Their greater size affords them more opportunities to try different combinations of capacity offers in different price bands. Also, their sheer size renders them a more secure and confident position. They can more easily afford to try different strategic bids since part of the bulk of their capacity can be committed to very low price bands, safe in the knowledge that it is almost certain to be dispatched. This releases the remainder of their capacity for experimental bidding in strategic price bands.

Also, our research shows that larger generators are more likely to use quantity offers rather than price offers to improve their market positions. This is especially true in periods of peak demand. In terms of traditional game theory, such a result suggests that NEM generators may behave more like players in Cournot competition (by using quantity as a strategic variable). We shall return to this issue when we discuss several modelling and simulation approaches in sections 4 and 5.

Market power issues in the NEM are also of interest. Whether deliberate or otherwise, the strategy of capacity withholding by generators has the effect of raising prices. Such outcomes have been observed in several deregulated electricity markets, like California (Borenstein et al. 2002), Britain (Green and Newbury 1992; Wolfram 1999) and Australia (Short and Swan 2002). In the NEM, capacity withholding can be accomplished by offering capacity only in very high price bands, or making one or more generating units unavailable. Our research shows that capacity withholding is used by several larger firms who own the larger generating units (Hu et al. 2005). Since these generating units have the capability to influence regional prices, this may partly explain why they are engaged in strategic bidding.

Generators are allowed to rebid their capacity commitment in response to load changes and other factors. Via rebidding, they can take advantage of the information provided by NEMMCO in the pre-dispatch phases to improve revenue streams. There is concern over rebidding, partly because it may help certain generators to exercise market power. Some peaking units use rebidding to adapt to changes in market conditions, instead of using the daily offer/bid opportunities. They offer identical quantity bands through all settlement intervals and then rebid at short notice. Moreover, these rebids can occur several times within a single settlement interval. This action highlights the volatility of demand and the rapidity of changes in market prices, which are not easy to predict and are further compounded by the technical advantages of those generating units that can startup rapidly.

Electricity markets are complex adaptive systems

Nowadays, the NEM faces a number of additional challenges. It is not only the exercise of market power that can cause dramatic price fluctuations from day to day. Temperature variations and network congestion play a similar role. Since retail prices are pegged, some retailers and market customers find their profit margins squeezed. Each generating unit (coal-fired, gas-fired, hydroelectric or renewable) has different start-up costs, start-up times and performance variables. In a climate of uncertainty, choosing a generator unit and figuring out a profitable price at which to service newly posted demand is a challenging and risky business.

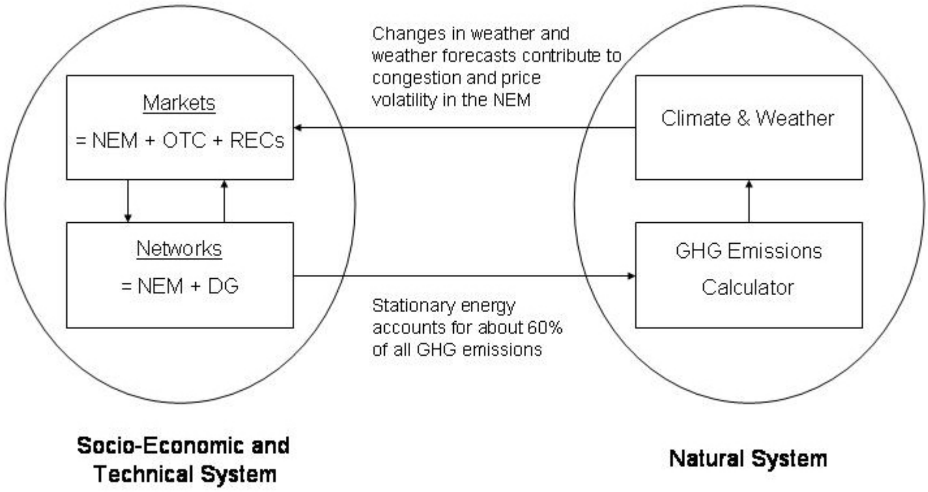
Clearly, the market for electricity has become more complex. In an evolving world of power generation, transmission and distribution, individual firms make use of increasingly specific and timely feedback of bid prices, costs, realised demand and operating information to enhance managerial decisions. Just possessing information holds little competitive advantage. Private firms and government organisations invest in various analytical and decision-making tools, as well as other sophisticated devices to gather pertinent information. Faster feedback requires faster adaptive reaction. Those who receive and respond to feedback more quickly gain competitive advantage (for example, revising their bids or choosing not to bid at a time of volatile price movements). The challenge is to respond to information quickly yet profitably.

Economic volatility is only one aspect of the problem. A growing need to mitigate ecological impacts—especially greenhouse gas emissions—has highlighted a need to develop methods capable of addressing economic and ecological uncertainties consistently within an integrated framework. It is now believed that greenhouse gases contribute significantly to global warming. In Australia, the stationary energy sector accounts for almost 50 per cent of these emissions. Electricity generation dominates this sector, with 64 per cent of the emissions, and is thus the major culprit in terms of total emissions.

An additional complexity is that day-to-day bidding strategies in the NEM are affected by hedged positions in other contract markets, such as the Over the Counter (OTC) Electricity Market (mainly Swaps and Caps, with some Swaptions and other Options) and the use of Renewable Energy Certificates (RECs). Other jurisdictional schemes designed to reduce greenhouse gas emissions have been introduced by the States (MacGillet al. 2004). In order to understand planning and decision making over different time horizons, these new schemes must be considered. Interdependencies between the spot (NEM) and contract markets are an important factor in determining hedging decisions of generators, retailers and other market participants. Such hedged positions are important because they influence incremental investment in the medium term and thus the closure decisions of agents.

Nowadays, electricity markets are an evolving system of complex interactions between nature, physical structures, market rules and participants (Figure 11.2). Participants face risk and volatility as they pursue their goals, and make decisions based on limited information and their mental models of how they believe the system operates. There is a wide diversity of agents; they use different strategies; they have different capacities; they use different generation technologies; they have different ownership; they are physically located at different locations, and they face different grid constraints. In summary, their objectives, beliefs and decision processes vary markedly. Such a diversity of inputs may be expected to lead to a rich diversity of market outcomes.

Figure 11.2. The NEM as a Complex Adaptive System



The NEM possesses all the intrinsic features of a complex adaptive system: a largish number of intelligent and reactive agents, interacting on the basis of limited information and reacting to changes in demand (due to weather and consumer needs). As no single agent is in control, some (for example, generator agents) may profit more than others. The result may be a considerable price degree of price volatility, inadequate reserves, demand uncertainty and higher levels of greenhouse gas emissions.

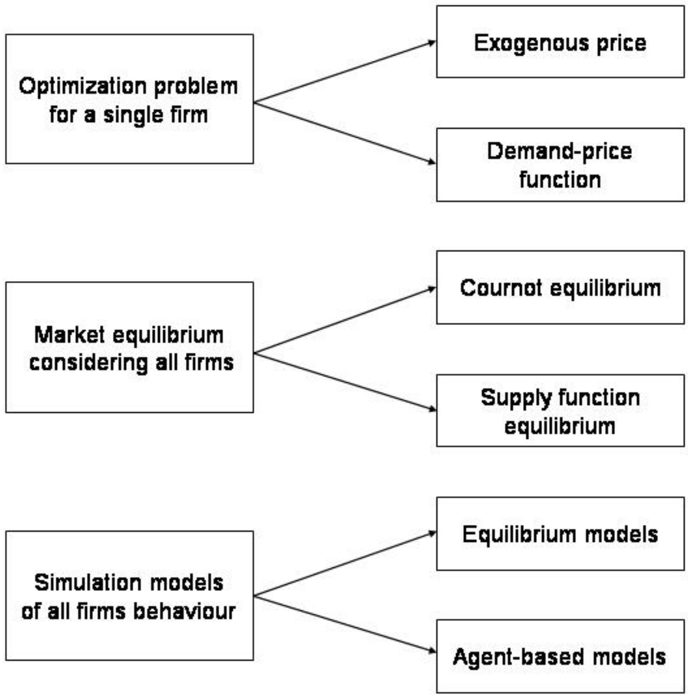
A key question then arises: what kinds of energy-economy models (if any) are capable of handling all these complexities? In the next section, we shall review several approaches in an attempt to answer this question.

Approaches to electricity market modelling

A large number of papers have been devoted to modelling the operation of deregulated power systems. In this section, we draw upon some earlier reviews to compare and contrast the main approaches based upon model attributes. Such attributes can help us to understand the advantages and limitations of each modelling approach.

From a structural viewpoint, the approaches to electricity market modelling reported in the technical literature can be classified according to the scheme shown in Figure 11.3. They fall into three main classes: optimisation, equilibrium, and simulation models. Optimisation models focus on the profit maximisation problem for a single firm competing in the market, while equilibrium models represent the overall market behavior—taking into consideration competition among all participants. Simulation models are regarded increasingly as an alternative to equilibrium models when the problem under consideration is too complex (for example, too nonlinear or dynamic) to be addressed within a traditional equilibrium framework.

Figure 11.3. Some trends in electricity market modelling



Source: Ventosa et al. 2005

Various assumptions are often made on the objectives, strategies, beliefs and capabilities of market participants. In game theory models, for example, participants are assumed to be rational in the sense that they can obtain and explore all the relevant information in order to deduce the best outcome. As we shall see shortly, some of these rigid assumptions can be relaxed with the help of agent-based simulation, since participants may employ different strategies and be subject to different sets of rules to guide their behaviour. They may have access to different information and possess different computational capabilities. The challenge then is how to assign a particular agent the appropriate set of behavioural rules and computational capabilities.

Previous review articles (Kahn 1998; Day et al. 2002; Ventosa et al. 2005) have focused mostly on the equilibrium models found in game theory. Kahn's survey was limited to 2 types of equilibrium resulting from firms in oligopolistic competition: *Cournot equilibrium* , where firms compete on a quantity basis; and

Supply Function Equilibrium (SFE), where they compete on both quantity and price. Although both models are based on the Nash equilibrium concept, the Cournot approach is usually regarded as being more flexible and tractable.

Day et al. (2002) conducted a more detailed survey of the modelling literature, listing the strategic interactions that have been, or could be, included in power market models as:

- Pure Competition;
- Generalized Bertrand Strategy (Game in prices);
- Cournot Strategy (Game in quantities);
- Collusion;
- Stackelberg (Leader-follower games);
- Supply Function Equilibria;
- General Conjectural Variations; and
- Conjectured Supply Function Equilibria.

Their conclusion was that the CSF approach to modelling oligopolistic competition is more flexible than the Cournot assumption, and more computationally feasible for larger systems than the standard supply function equilibrium models. We shall discuss the CSF approach further in the next section.

Trends reported in Ventosa et al. (2005) followed similar lines, noting that most models used to evaluate the interaction of agents in wholesale electricity markets have persistently stemmed from game theory's concept of the Nash equilibrium. For the first time, however, some simulation models were included (albeit briefly). We shall discuss simulation models further in following sections.

Cournot equilibrium models

Previously, we revealed that larger generators in the NEM use quantity offers rather than price offers to improve their market positions, especially in peak periods. In other words, they seem to act like players in Cournot competition. The assumptions underlying a Cournot solution correspond to the Nash equilibrium in game theory. At the solution point, the outputs (quantities dispatched) fall into an intermediate zone between fully competitive and collusive solutions. In effect, a second firm becomes a monopolist over the demand not satisfied by the first firm, a third over the demand not satisfied by the second, and so on.

Since the Cournot solution represents a kind of imperfect collusion technique, we must ask if this equilibrium concept approximates the reality of Australia's NEM? Although generators are forbidden from changing bid prices in the rebidding process, by shifting quantity commitments up or down between different price bands they can achieve a similar effect to changing prices directly. In reality, therefore, both quantity (directly) and price (indirectly) serve as decision variables. Thus the Cournot assumption may not be appropriate for NEM generators. Furthermore, by expressing generators' offers in terms of quantities only (instead of offer curves), equilibrium prices are determined by the demand function. This shortcoming tends to reinforce the idea that Supply Function Equilibrium (SFE) approaches may be a better alternative to represent competition in the NEM (Rudkevich et al. 1998).

In an electricity market context, a Cournot solution posits rather shortsighted behaviour on the part of generating agents. It implies that each of them modifies its bids in response to the bids and dispatches of others, without allowing for the fact that others may react in a similar manner. There is no evidence that most NEM generating agents behave in this manner, although small groups of them may do so.

Supply Function Equilibrium Models

In the absence of uncertainty and knowing competitors' strategic variables, Klemperer and Meyer (1989) showed that each firm has no preference between expressing its decisions in terms of a quantity or a price, because it faces a unique residual demand. When a firm faces a range of possible residual demand curves, however, in general it expects a greater profit in return for exposing its decision tool in the form of a supply function (or offer curve) indicating those prices at which it is willing to offer various quantities to the market. This SFE approach, originally developed by Klemperer and Meyer (1989), has proven to be an attractive line of research for the analysis of equilibrium in wholesale electricity markets.

To calculate an SFE requires solving a set of *differential equations* , instead of the typical set of algebraic equations that arises in traditional equilibrium models, where strategic variables take the form of quantities or prices. Thus SFE models have considerable limitations concerning their numerical tractability. In particular, they rarely include a detailed representation of the generation system under consideration. Originally developed to address situations in which supplier response to random or highly variable demand conditions is considered, perhaps their attraction nowadays is the possibility of obtaining reasonable medium-term price estimations with the SFE methodology.

Conjectural variations approaches

A recent strategy has been to employ the Conjectural Variations (CV) approach described in traditional microeconomic theory. The CV approach can introduce some variation into Cournot-based models by changing the conjectures that generators may be expected to assume about their competitors' strategic decisions, in terms of the possibility of future reactions (CV). Day et al. (2002) suggest taking this approach in order to improve Cournot pricing in electricity markets. For example, one could assume that firms make conjectures about their residual demand elasticities or about their rivals' supply functions (Day et al. 2002). In the context of electricity markets, the latter is called the Conjectured Supply Function (CSF) approach. The CV approach can be viewed as generalising Stackelberg models (in that the conjectured response may not equal the true response). Also, superficially it resembles the SFE method described above.

Discussion

It has been argued that Cournot and Bertrand assumptions may be inappropriate for pool-type auction markets like the NEM, in which every firm bids a supply function for each generating unit. In this case, the decision variable is the bid function's parameters. For this reason, SFE has been chosen as the basis of many power market models. The resulting equilibria represent an intermediate level of competition, lying between Bertrand and Cournot solutions. However, a few additional problems remain: some equilibria are not unique; a large range of outcomes is possible; and equilibria for SFE models are difficult to calculate—indeed, none may exist.

Equilibria for SFE models have proven particularly difficult to calculate for large systems with transmission networks and a significant number of generators with limited capacity. The reasons are that the generating firm's optimisation problem on a network is inherently non-convex (and hence a challenge to solve) and an equilibrium solution may not exist. Unless strong restrictions are placed on the form of the bid functions (such as linear with only the slope or intercept being a variable), modellers have been forced to make unrealistic assumptions such as all firms having identical marginal cost functions.

Although the asserted realism of the SFE conjecture makes it attractive for markets without significant transmission constraints, it is not a practical modelling method if realistic details on demand, generation, and transmission characteristics are desired. This rules out the SFE approach for any serious representation of the NEM. Needless to say, most SFE studies have been designed for very simple systems (for example, 1–4 nodes). Alternatively, when larger networks are considered, SFE models search over only a handful of strategies to find the optimal strategy for each of 2 firms, or bids are restricted to a linear function with either fixed slope or intercept.

Simulation models

As discussed above, equilibrium models impose limitations on the representation of competition between agents in an electricity market. In addition, the resulting set of equations is frequently difficult or impossible to solve. The fact that power systems are based on the operation of generation units with complex physical constraints further complicates the situation. Simulation models are an alternative to equilibrium models when the problem under consideration is too complex to be addressed within a formal equilibrium framework. This is certainly the case in the medium to long-term, when investment decisions, hedging strategies and learning processes become important endogenous variables.

Simulation models typically represent each agent's strategic decision dynamics by a set of sequential rules that can range from scheduling generation units to constructing offer curves that include a reaction to previous offers submitted by competitors. The great advantage of a simulation approach lies in the flexibility it provides to implement almost any kind of strategic behaviour, including feedback loops between the auction market and forward contract markets. However, this freedom also requires that the assumptions embedded in the simulation be more carefully (and empirically) justified.

Some simulation models are closely related to equilibrium models. For example, Day and Bunn (2001) propose a simulation model that constructs optimal supply functions, to analyse the potential for market power in the England and Wales Pool. This approach is similar to the SFE scheme, but it provides a more flexible framework that enables us to consider actual marginal cost data and the asymmetric behaviour of firms. In this simulation model, each generation company assumes that its competitors will keep the same supply functions that they submitted the previous day. Uncertainty about the residual demand curve is due to demand variation throughout the day. The optimisation process to construct nearly optimal supply functions is based on an exhaustive search, rather than on the solution of a formal mathematical programming problem. The authors compare the results of their model for a symmetric case with linear marginal costs to those obtained under the SFE framework, which turns out to be extraordinarily similar. In the next section, we shall explore a subfield within the realm of simulation models that is attracting increased attention for the modelling of electricity markets: agent-based simulation.

Agent-based models of electricity markets

The interactions within an electricity market constitute a repeated game, whereby a process of experimentation and learning changes the behaviour of the firms in the market (Roth and Erev 1995). A computational technique that can reflect these learning processes and model the structure and market clearing mechanism (with a high level of detail) would appear to be necessary. The most promising technique at this point in time is agent-based simulation (Batten, 2000).

Agent-based simulation provides a more flexible framework to explore the influence that the repetitive interaction of participants exerts on the evolution of wholesale electricity markets like the NEM. Static models neglect the fact that agents base their decisions on the historic information accumulated due to the daily operation of market mechanisms. In other words, they have good memories and learn from past experiences (and mistakes) to improve their decision making and adapt to changes in several environments (economic, physical institutional and natural). This suggests that adaptive agent-based simulation techniques can shed light on features of electricity markets that static equilibrium models ignore.

A brief review of earlier agent-based models

Bower and Bunn (2000) present an agent-based simulation model in which generation companies are represented as autonomous adaptive agents that participate in a repetitive daily market and search for strategies that maximise their profit based on the results obtained in the previous session. Each company expresses its strategic decisions by means of the prices at which it offers the output of its plants. Every day, companies are assumed to pursue 2 main objectives: a minimum rate of utilisation for their generation portfolio and a higher profit than that of the previous day. The only information available to each generation company consists of its own profits and the hourly output of its generating units. As usual in these models, the demand side is simply represented by a linear demand curve.

Such a setting allowed the authors to test a number of potential market designs relevant for the changes that have recently occurred in England and Wales wholesale electricity market. In particular, they compared the market outcome that results under the pay-as-bid rule to that obtained when uniform pricing is assumed. Additionally, they evaluated the influence of allowing companies to submit different offers for each hour, instead of keeping them unchanged for the whole day. The conclusion is that daily bidding together with uniform pricing yields the lowest prices, whereas hourly bidding under the pay-as-bid rule leads to the highest prices.

The introduction of NETA in the UK represented a good opportunity to test the usefulness of large-scale agent-based simulation to provide some insights on market design. The agent-based platform enables a detailed description of the market, taking into account discrete supply functions, different marginal costs for each technology, and the interactions between different generators. Bunn and Oliveira (2001) followed that work by developing a simulation platform that represents, with much more detail, the way that market clearing in NETA was designed to function. This platform models the interactions between the Power Exchange and Balancing Mechanism; considers that generators may own different types of technologies; considers an active demand side, including suppliers; and takes into account the learning dynamics underlying these markets as a process by which a player selects the policy to use in the game by interacting with its opponents. In later work, they adapt and extend this simulation platform to analyse if the 2 particular generators in the Competition Commission Inquiry had gained enough market power to operate against the public interest (Bunn and Oliveira 2003).

Researchers at Argonne National Laboratory in Chicago have developed the Electricity Market Complex Adaptive System (EMCAS) model (North et al. 2002; Veselka et al. 2002). Like the above-mentioned simulation models developed at the London Business School, the EMCAS model is an electronic laboratory that probes the possible effects of market rules by simulating the strategic behaviour of participants. EMCAS agents learn from their previous experiences and modify their behaviour based on the success or failure of their previous strategies. Genetic algorithms are used to drive the adaptive learning of some agents, and pool, bilateral contract and ancillary services markets are included. The EMCAS model is arguably the most sophisticated agent-based electricity model to date, embodying more development hours than other simulation models of its type.

At Iowa State University, Leigh Tesfatsion and her colleagues have examined market power experimentally in an agent-based computational wholesale electricity market operating under different concentration and capacity conditions (Nicolaisen et al. 2001). Pricing is determined by a double auction with discriminatory midpoint pricing. Buyers and sellers use a modified Roth-Erev individual reinforcement learning algorithm to determine their price and quantity offers in each auction round. High market efficiency is generally attained, but the aggregate measures used are too crude to reflect the opportunities for exercising market power that buyers and sellers face. Their results suggest that the precise form of learning behaviour assumed may be largely irrelevant in a double auction system.

Taylor et al. (2003) developed an agent-based model to simulate the complexity of the large-scale Victorian gas market in south-eastern Australia. The model can be used to elicit possible emergent behaviour that could not be elicited otherwise under an uncertain future of deregulation and restructuring. Like an electricity market, the complexity in the gas market derives from the uncertain effects of a multiplicity of possible participant interactions in numerous segments, such as production, storage, transmission, distribution, retailing, service differentiation, wholesale trading, power generation and risk management. The agent-oriented programming platform devised for this work has the potential to overcome the limitations of traditional approaches (discussed earlier) when attempting to operate in changing environments. A similar platform has been adopted for our National Electricity Market Simulator.

Agent behaviour in Australia's national electricity market

Among the 90 registered participants in the NEM, most fall into categories based on the role they perform in the market. [3] These categories are generators,

[3] Some participants play more than a single role in the NEM and therefore belong to more than one category.

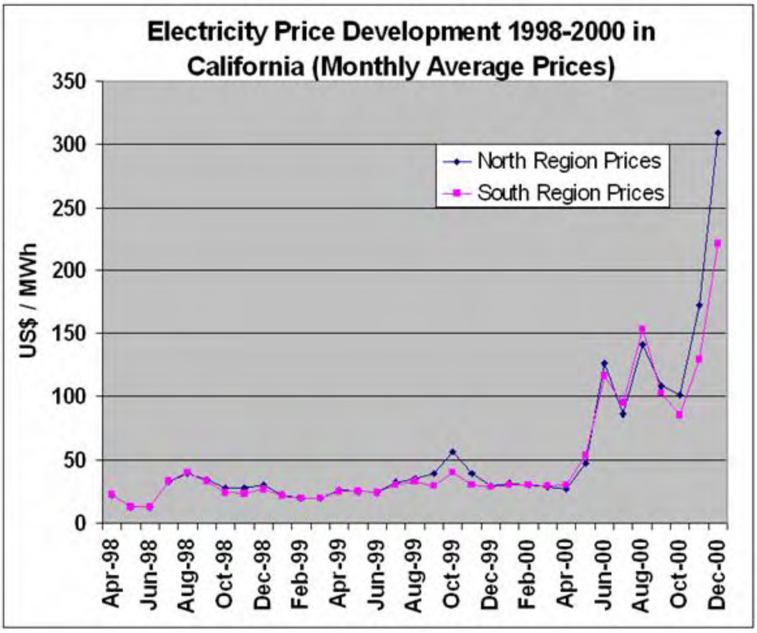
Transmission Network Service Providers (TNSPs), distribution network service providers (DNSPs), market network service providers (MNSPs), customers (retailers and end-users), and traders. NEMMCO, key regulators (such as NECA and the Australian Competition and Consumer Commission), and a number of other organisations (like the Council of Australian Governments and the Australian Greenhouse Office) are among the additional actors. For convenience, in the remainder of this chapter we shall refer to all of these relatively autonomous actors as *agents*.

Agents are intelligent and adaptive, meaning that they make operational and strategic decisions on the basis of the information available to them and the market's rules, and they modify their own strategies on the basis of new information that comes their way. In many decision situations, however, some agents can do no better than exhibit purposive but contingent behaviour. Although they have specific goals of their own (for example, to maximise profits, market share, utilisation factors, etc.), their ability to attain these goals is largely beyond their own control. Furthermore, earlier research on the NEM has shown that demand side participants have very little ability to influence outcomes compared with those on the supply side.

In an adaptive market such as the NEM, no single agent can control what *all* the other agents are doing. Many of the collective outcomes are not obvious, because simple summation to linear aggregates is impossible. The outcomes are governed by and dependent on a system of nonlinear interactions between individual agents and the market environment, i.e., between agents and groups of other agents or between agents and the whole market. In such limited-information situations, some agents can and do exert more influence than others. Groups of agents may benefit from informal partnerships or tacit collusion. Bidding and rebidding is unlikely to be competitive under these circumstances, since individual agents or coalitions may find it more profitable to search for opportunities to exert market power.

In electricity markets, we often find examples of locally interacting agents producing unexpected, large-scale outcomes. Problems experienced by the Californian electricity market provide a vivid illustration. During the summer of 2000, wholesale electricity prices in California were nearly 500 per cent higher than they were during the same months in 1998 or 1999 (see Figure 11.4). This explosion of prices was not only unexpected but sustained. Unlike previous price spikes observed in the US wholesale markets, the California experience proved to be more than a transient phenomenon of a few days' duration. It persisted until roughly mid-June 2001. Increases in gas prices and consumer demand, reduced availability of power imports, and higher prices for emissions permits are known to have contributed to price rises. But these market fundamentals are insufficient to explain the extraordinary gap between realised prices and competitive benchmark prices. Evidence of capacity withholding by suppliers (generators or traders) has been found, and this, together with other factors, is thought to have led to such remarkable price increases and market manipulations during 2000/2001.

Figure 11.4. Electricity prices in California, 1998-2000



Source: California Electricity Wholesale Price Review, 2001

Although some observers have argued that the NEM spot market is more robust to gaming than its Californian equivalent, the NEM is still vulnerable to market power.[4] For example, generator companies can profit more than customers by exploiting the bidding rules set by the National Electricity Code Administrator (NECA). Because no single body has control over market outcomes, agents exploiting anomalies can reap rich rewards. The rest of the market suffers accordingly. Recent spot prices have been observed to fluctuate from a low of around \$5/MWh to a high of \$10,000/MWh. Some of this volatility is caused by the weather, industrial action or diurnal/seasonal peaks and troughs in demand, but a significant proportion is not. Rather, it is an intrinsic by-product of the way the trading system and its rules operate.

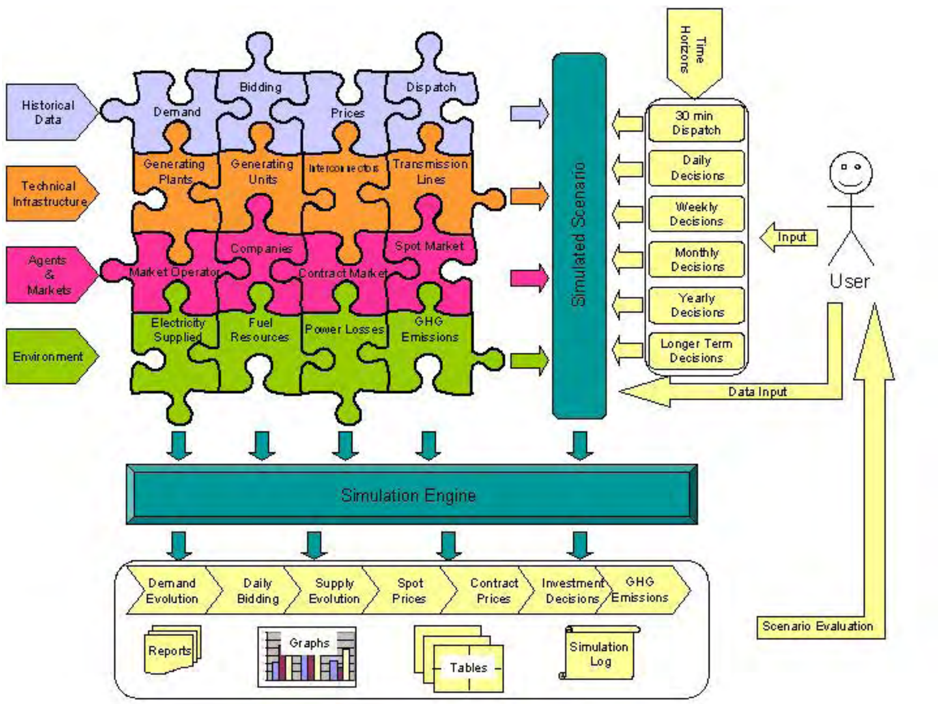
[4] See Outhred (2000), pp.19-20.

NEMSIM: the National Electricity Market simulator

NEMSIM is an agent-based simulation model that represents Australia's NEM as an evolving system of complex interactions between human behaviour in markets, technical infrastructures and the natural environment. This simulator is the first of its kind in Australia. Users of NEMSIM will be able to explore various evolutionary pathways of the NEM under different assumptions about trading and investment opportunities, institutional changes and technological futures—including alternative learning patterns as participants grow and change. The simulated outcomes will help the user to identify futures that are eco-efficient, for example, maximising profits in a carbon-constrained future. Questions about sustainable development, market stability, infrastructure security, price volatility and greenhouse gas emissions could be explored with the help of the simulation system.

An overview of NEMSIM is shown in Figure 11.5. The NEMSIM project is part of CSIRO's Energy Transformed Flagship research program, which aims to provide innovative solutions for Australia's pressing energy needs. Motivation for the project is the Flagship's mission to develop low emission energy systems and technologies. Electricity generation is a substantial source of greenhouse gas emissions contributing 35 per cent of Australia's total emissions.

Figure 11.5. An overview of NEMSIM



Learning from experience

The development of NEMSIM is facilitated by 6 years of historical market data on demand, pricing and power dispatch for the NEM. Being a dynamic, repetitive and information-rich system, the NEM offers a huge amount of data. NEMSIM uses this data to extract representative patterns of regional demand (on a daily, weekly and seasonal basis), regional prices, supply and demand growth, etc. The historical database includes an extensive time series of bidding data, an essential source of information about market participants and their trading strategies. In NEMSIM, silicon agents (for example, representing generator firms, network service providers, retail companies, a market operator, etc.) buy and sell electricity in a simulated trading environment. Agents have different goals. As well as maximising profits, some may wish to increase market share, diversify generation sources or work more closely with end-users. Short-term strategies (for example, bidding tactics in the NEM) are affected by medium-term strategies (for example, hedged positions in the OTC markets). In turn, both are affected by investment decisions and other changes over the longer term. NEMSIM treats agents as being uniquely intelligent, making operational and strategic decisions using the individual information available to them. Also, they are adaptive, learning to modify their behaviour in order better to realise their goals. Learning algorithms can allow agents to *look back* (learn from their historical performance), *look sideways* (learn from other participants' strategies) and *look ahead* (take future plans and forecasts into account).

In an adaptive market such as the NEM, no single agent has control over what all the other agents are doing. Because of the way the market is structured, however, the marginal bidder can exert more influence on market outcomes. The overall outcome is not always obvious, because it depends on many factors. The aim of NEMSIM is to provide a platform where a population of simulated agents interact, constrained only by realistic rules and the physical grid system. Agents' individual and collective behaviours co-evolve from the bottom up, producing both expected and unexpected emergent outcomes at the system level.

NEMSIM environments

Simulated agent life in NEMSIM unfolds in three *environments*: firstly, a *trading environment*, in which transactions can occur in interlinked spot and forward contract markets; secondly, a *physical grid* of sites, generation units, lines and interconnectors across which electricity flows, and; thirdly, a *natural environment*, which provides energy resources and accumulates greenhouse gas emissions. Each environment is separate from the agents, on which the agents operate and with which they interact.

The physical environment of transmission and distribution infrastructure imposes several constraints on electricity market operations. For example, the quantity of power sold from one region to another is constrained by the transmission capacity between the 2 regions. NEMSIM represents the diversity of objects and attributes associated with generation and transmission infrastructure in a simplified form. Some key objects (with corresponding attributes in parentheses) are: generating plants (location, unit composition), generating units (maximum capacity, generation technology, ramp rates, efficiency and emission factors) and interconnectors (transmission technology, adjacent regions, losses).

NEMSIM as a greenhouse gas emissions calculator

The effects of anthropogenic and natural Greenhouse Gas (GHG) emissions on the absorption of terrestrial radiation and global warming have been extensively studied in the last 2 decades. It is scientifically proven that changes in the concentrations of GHG can alter the balance of energy transfers between the atmosphere, land, oceans and space and that the increase concentrations of GHG will increase energy absorption by Earth, producing global warming. With a share of approximately 55 per cent, carbon dioxide (CO_2) is the main component of GHG emissions. During the last 150 years, atmospheric CO_2 has increased from about 280 parts per million by volume (ppmv) to about 372 ppmv (US Environmental Protection Agency 2004). Without intervention, it will exceed 550 ppmv by the end of this century.

There have been many efforts to mitigate and/or reduce GHG emissions, including international initiatives such as the Climate Convention and the Kyoto Protocol. However, the total anthropogenic GHG emissions are projected to continue to grow despite current initiatives, with one of the main causes being increasing demand for electricity generation.

Electricity generation is a substantial source of greenhouse gas emissions. According to the Australian Greenhouse Office (2004) it contributed 182 Mt of carbon dioxide equivalent emissions (Mt CO_2-e) in 2002, or 33 per cent of net national emissions (550 Mt CO_2-e) in Australia. The net emissions are calculated across all sectors under the accounting provisions of Kyoto Protocol for Australia.

One method of calculating the potential GHG emissions due to the future electricity generation in Australia is given in (Graham et al. 2003). This study aims to evaluate the impact of future development options of the electricity market in terms of GHG emissions and costs. It is based on a portfolio simulation framework and CSIRO's Electricity Market Model (Graham and Williams 2003) that is similar to the bottom-up type of dynamic optimisation models such as MARKAL.[5] In this chapter, 5 GHG targets (business as usual, 2 moderate and 2 extreme emissions targets) were studied in conjunction with seven key data assumptions (for example, more abundant gas available, CO_2 capture and sequestration feasible/infeasible, high/low demand growth).

NEMSIM, as an agent-based simulation tool of the NEM, is capable of calculating the GHG emissions associated with electricity generation of a given simulation scenario. The method is also bottom-up type aggregation. The advantages of NEMSIM are that its simulation framework allows quite precise modelling of the emissions up to the level of each generating unit, accommodating a variety of changes in the operational, technological, company, market and regulatory values and parameters. We believe that the main advantage in this sense is the agent-based framework that allows slow changes to accumulate over long periods and sudden changes to be introduced due to the emerging events based on the decision making and interactions of the participating agents.

Calculating the GHG emissions due to electricity generation is implemented in NEMSIM on a fossil fuel consumption basis using fuel (generation technology) specific emission factors. A set of generation technologies are modelled, for example, conventional black coal (pulverised fuel), conventional brown coal (pulverised fuel), and natural gas simple cycle. The set of generation technologies is specified in an XML input file and one example is given in Table 11.1. The XML input file format allows changes to generation technologies and their parameters to be done easily. The main attributes of each generation technology are the emission GHG factor (*f*) and the net energy efficiency (*e*), how much of the embodied energy of the fossil fuel is transformed into electricity energy.

Table 11.1. XML fragment with Generation Technologies description

```
<GenerationTechnologies>
  <GenerationTechnology id="BLACK_PF" name="Conventional black coal PF"
    emissionFactor="89.92" netEfficiency="0.376"/>
  <GenerationTechnology id="BROWN_PF" name="Conventional brown coal PF"
    emissionFactor="93.53" netEfficiency="0.28"/>
  <GenerationTechnology id="NG_SC" name="Natural Gas Simple Cycle"
    emissionFactor="51.59" netEfficiency="0.38"/>
  <GenerationTechnology id="NG_CC" name="Natural Gas Combined Cycle"
    emissionFactor="51.59" netEfficiency="0.534"/>
  <GenerationTechnology id="HYDRO" name="Hydro"
```

[5] MARKAL, developed by the International Energy Agency over a period of more than 20 years, is a generic model aiming to represent evolution of a specific energy system over a period of up to 50 years at the national, state or regional level.

```
        emissionFactor="0" netEfficiency="1"/>
    <GenerationTechnology id="WIND" name="Wind"
        emissionFactor="0" netEfficiency="1"/>
</GenerationTechnologies>
```

Each generating unit is assigned one of the defined generation technologies. The net energy efficiency can also be defined for a selected generating unit (in that case it overrides the same attributes of the assigned generation technology) to allow flexibility in long term, when due to the different reasons the efficiency may change. GHG emissions for a given simulation period or simulation scenario are estimated by using the following formula:

$$q = \frac{3.6\, g\, f}{10^3\, e}$$

where: q is the amount of CO_2 equivalent emissions expressed in t;

g is the amount of the electricity generation expressed in MWh;

f is the emission factor for a given generation technology expressed in kt CO_2-e/PJ;

e is the net energy efficiency of the generation technology/generating unit (dimensionless);

and 3.6 10^{-3} is a conversion factor from kt/PJ to t/MWh.

The direct values of emission factors are used, which means that emissions that are associated with extraction and production of the fossil fuels used are not considered. This approach allows easier comparison between different plants, companies and regions, however, its accuracy is inferior as it does not include indirect emissions that are usually several per cent from direct and they show moderate variability by region, company and technology.

Some examples of NEMSIM output windows (in tabular and graph form) for GHG emissions are shown in Figure 11.6. They display company data and the values are illustrative only. A regional summary of GHG emissions is shown in Figure 11.7. Again the numbers are only illustrative. Other options for output windows and reports for GHG emissions are available within NEMSIM.

Figure 11.6. NEMSIM GHG emissions example windows for a generator plant: tabular form (top); graphical form (bottom)

GeneratorPlant Bayswater - CO2 tonnes

Show Format

Interval	BW01 (tonnes)	BW02 (tonnes)	BW03 (tonnes)	BW04 (tonnes)
Mon 26 Apr: 0430	210.93	210.93	210.93	210.93
Mon 26 Apr: 0500	210.93	210.93	210.93	210.93
Mon 26 Apr: 0530	210.93	210.93	210.93	210.93
Mon 26 Apr: 0600	210.93	210.93	210.93	210.93
Mon 26 Apr: 0630	198.02	198.02	210.93	210.93
Mon 26 Apr: 0700	210.93	210.93	210.93	210.93
Mon 26 Apr: 0730	198.02	198.02	198.02	210.93
Mon 26 Apr: 0800	210.93	210.93	210.93	210.93
Mon 26 Apr: 0830	210.93	210.93	210.93	210.93
Mon 26 Apr: 0900	198.02	198.02	198.02	210.93
Mon 26 Apr: 0930	210.93	210.93	210.93	210.93
Mon 26 Apr: 1000	198.02	198.02	198.02	210.93
Mon 26 Apr: 1030	210.93	210.93	210.93	210.93
Mon 26 Apr: 1100	198.02	198.02	198.02	198.02
Mon 26 Apr: 1130	198.02	198.02	198.02	198.02
Mon 26 Apr: 1200	198.02	198.02	198.02	198.02
Mon 26 Apr: 1230	198.02	198.02	198.02	198.02
Mon 26 Apr: 1300	198.02	198.02	198.02	198.02

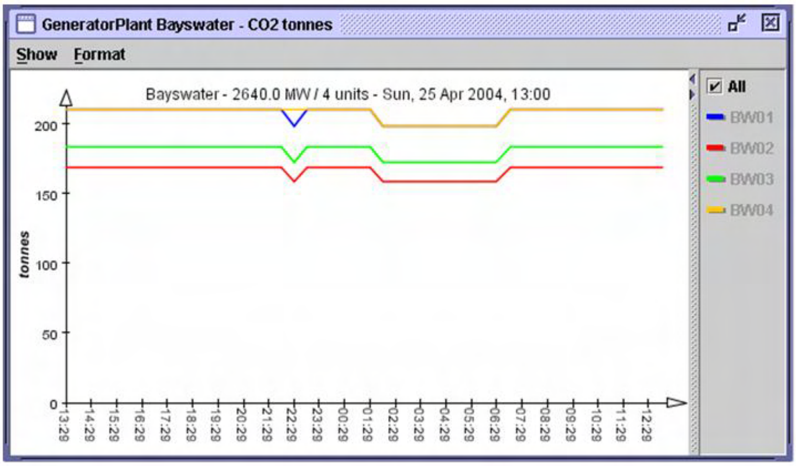


Figure 11.7. NEMSIM regional summary window for GHG emissions

Region Summary - CO_2 Emissions tonnes

Show

Time	New South Wales	Queensland	Snowy	South Australia	Tasmania	Victoria
Sun 25 Apr: 1730	5365.13	4546.14	0.0	902.17	0.0	4054.66
Sun 25 Apr: 1800	5365.13	4534.05	0.0	893.62	0.0	4385.35
Sun 25 Apr: 1830	6075.4	5303.93	0.0	867.84	0.0	4716.05
Sun 25 Apr: 1900	6075.4	5098.78	0.0	915.1	0.0	4716.05
Sun 25 Apr: 1930	6075.4	5009.61	0.0	959.85	0.0	4716.05
Sun 25 Apr: 2000	5838.64	4407.6	0.0	964.35	0.0	4716.05
Sun 25 Apr: 2030	5838.64	4569.81	0.0	949.56	0.0	4716.05
Sun 25 Apr: 2100	5838.64	4350.17	0.0	977.92	0.0	4716.05
Sun 25 Apr: 2130	6075.4	5455.05	0.0	949.2	0.0	4716.05
Sun 25 Apr: 2200	7700.98	3707.74	0.0	1210.59	0.0	4054.66
Sun 25 Apr: 2230	6803.78	3707.74	0.0	1330.8	0.0	3721.03
Sun 25 Apr: 2300	7117.16	3707.74	0.0	1328.76	0.0	3625.42
Sun 25 Apr: 2330	6797.49	3707.74	0.0	1328.01	0.0	3553.27
Mon 26 Apr: 0000	7557.34	4197.5	0.0	1330.91	0.0	3481.11
Mon 26 Apr: 0030	6490.4	3707.74	0.0	1317.54	0.0	3517.19
Mon 26 Apr: 0100	7269.58	3707.74	0.0	1200.74	0.0	3711.25
Mon 26 Apr: 0130	7355.75	3707.74	0.0	1331.51	0.0	3481.11
Mon 26 Apr: 0200	6785.4	3707.74	0.0	1200.21	0.0	3707.83

Simulated outcomes

The purpose of NEMSIM is not to predict the future, but to generate and explore the various alternative futures that could develop under different conditions. NEMSIM generates various *What if?* scenarios under different input definitions. The simulator can also be used to show the possible evolutionary trajectories of a given scenario under given conditions. For example, the introduction of more distributed generation into the marketplace involves a transition from the current paradigm of the centrally-dispatched electricity grid to new, more decentralised ones. This may involve new markets, new brokers, new technology and new grid structures. NEMSIM is a generative tool that can identify the transition states needed to reach specific final states such as these.

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