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EVOLVING GAME THEORY BASED DECISION MAKING SYSTEMS FOR NETA POWER MARKET MODELLING, ANALYSIS, AND TRADING STRATEGY DEVELOPMENT

A THESIS
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Abstract

The collapse of the Californian electricity trading system in 2001 and other power markets crisis since then have motivated accelerated research in electricity trading strategies and intelligent systems for electricity power markets. The market system of the UK is physically and economically similar to that of California. Power generation companies in the UK are making efforts to develop gaming strategies in their trading systems. Although the electricity trading system in the UK is a deregulated market with the longest history in global energy industry and has become the benchmark of worldwide electricity markets, there are few research results published for analyzing such a trading system involving human intelligence. More crucially, the market power and market manipulation remain unaddressed by either industry or academia so far. Further, current research on modelling market player strategies and behaviours are mostly based on noncooperative assumptions rather than on competitive and also cooperative game theories, which are commonly practiced and cause real problems through market power involving electricity suppliers and customers.

In this thesis, current work carried out on analyzing the strategic behaviours in electricity trading is first reviewed. An intelligent decision-making and support technique, game theory, is often used in the market practice. Game theory is a discipline concerned with how individuals make decisions when they are partly aware of what their action might affect each other and when each individual might take this into account. Deficiencies and limitations of traditional game theory based methods developed for decision-making in electricity trading are also investigated. This research then explores to discover the impact of intelligent systems based trading strategies in the UK power markets. To model these behaviours and the New Electricity Trading Arrangements (NETA) system of the UK, traditional competitive and cooperative game theory strategies are taken into account in the work reported in this thesis. An improved methodology, "trigger price strategy", is introduced to simulate power generation companies' enhanced gaming strategies. Such a modelling problem is, however, intractable and hence an extra-numerical search technique, Evolutionary Computation, is employed to solve the game theory based system modelling problem. An encoded Genetic Algorithm based technique is developed to

search for an effective model for the complex decision-making process and to help decision-makers evaluate their strategies and bidding parameters.

A novel and effective electricity trading simulation model is thus developed, where its design features are close to the NETA. The model scale is as close as possible to NETA. A complex and more realistic two-sided transaction mechanism with demand fully incorporated is incorporated in this model. These are a world first in this research area.

Using the intelligent systems methods and the model developed, market states and consequences of which some generators maintain strategic gaming behaviours are analysed for prediction and decision making. Experimental tests, verification and validation are carried out with various strategies, using different model scales and data published by NETA. Testing and validation show that the modeling and decision making methodologies based on the hybrid game theory and evolutionary algorithm provide an effective tool for analysis and prediction under such a circumstances on the NETA.

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1 Introduction

1.1 Problems Facing Power Markets

Since the 1980's, much effort has been made to restructure the traditional monopolistic electricity industries. Whilst the details differ, the core of this reform involves the introduction of competition among electricity generators and suppliers[1] through the creation of an open electricity market. Ideally, the market structure and management rules in an electricity market are expected to be well designed and it is generally believed that opening the power industry to competition would benefit trading participants and improve economic efficiency. However, the energy crisis in California in the Winter of 2001 and problems in other power markets cross the world have motivated research interests into more understanding of the market.

Before the crisis, the California power systems had been considered a benchmark example to which others made reference, and world-wide developments towards similar competitive electricity markets were in process. However, during the shocking market collapse in California some of the major Californian power generation companies successfully manipulated the market to obtain skyrocket profits [1], the perceptions of the California market has now completely changed. With the truth of the market power applied to this crisis being exposed [2], the "made-up2 shortage of installed capacity or plant availability appears to have been a key driver to the California difficulties. The emergence of market power and collusion among energy

[1] The word 'suppliers' here is used in the sense of retailing electricity to end consumers, which is the convention within the UK industry, as opposed to the physical production of electricity (which is the meaning of the term in many other markets).

companies have been drawing more attention on strategic gaming behaviour and market system on global electricity trading.

Would an energy crisis develop in the UK electricity markets? Would British power generators attempt to carry out market distortions and "price tricks" exploited by Californian generators? What consequence would it have under such circumstances? These questions should be answered through analysis and modelling of the British electricity trading system.

1.2 Gaming Strategies and Market Power on NETA

In March 2001 the New Electricity Trading Arrangements (NETA) were implemented to operate power markets in England and Wales [3]. The trading management mechanisms are still on trial operation and being improved.

The NETA trading systems do not however alter the fact that, there exist loopholes which can be exploited and scope which is left for market power and gaming trading strategies to disrupt trading operations and/or distorts market prices in NETA.

1.3 Aims of This Research

This aims of this research are to model the dynamic and decision making behaviour of the UK electricity trading system under and to discover the impact of gamin trading strategies on the NETA. Since gaming strategies are widely practiced in trading systems for decision-making and decision support, game theory will be used to model such systems. To achieve this goal, Evolutionary Computing, whose search power is beyond pure numerical optimisation, will be used to assist the model building. With the model established, the research will then attempt to address the following objectives.

(1) A market model where the number of trading participants is similar to the real scale of NETA and real data published by NETA will be established to simulate the market operation and trading programs.

(2) The decision making process of how power generators attempt to employ market power and to maintain strategic gaming behaviours to maximize profits on NETA will be analyzed based on the designed model.

(3) The market states and consequence of such actions developed above will then be analysed. The study will also search for possible market equilibrium and optimal trading strategies under such circumstances.

(4) Since there are an amount of non-linear and uncertain variables existing on the decision support and optimisation process, Evolutionary Computing will be introduced to assist the search, learning and optimization problems.

(5) Based on the research achievements, the formation of such a decision making system would also be able to provide an advanced platform for potential electricity trading participants to analyse generators and suppliers' behaviours and to gain experience of the trading environment that they will face under NETA.

1.4 Contributions

- A novel electricity trading system model is developed to reflect the New Electricity Trading Arrangements that administers the power markets in England and Wales. The model scale is as close as possible to NETA and the model is validated against real data published by NETA.

- A more sophisticated and realistic two-sided transaction mechanism has been developed. The demand is fully incorporated in this new model; a fact that so far had not been achieved successfully in this research field.

- A widely used intelligent decision-making support technique, game theory, has been successfully applied to develop the model. The model can take account of actions affecting each participant who may or may not apply traditional competitive and/or cooperative game theory strategies. An improved methodology, "trigger price strategy", is introduced to simulate power generation companies' gaming trading strategies.

- Evolutionary Computing, an intelligent search and global optimisation technique, has been applied to build game theory based models and to solve this type of decision-making problems which has been intractable.

- The methodologies developed are world first in that they employ game theory to model the NETA trading players' behaviours and then employ Genetic Algorithms to search for the game theory model parameters and market equilibrium forecasts; and hence optimal trading strategies. This should help decision-makers evaluate and optimize their strategies and bidding parameters.

1.5 Outline of The Thesis

Chapter 2. The market structure of NETA and current trading strategies adopted in power market are studied. Chapter 2 begins with preliminary information of the NETA trading systems, which covers its basic key building blocks, trading mechanism, and sequential markets. This is followed by the start-of-the-art analysis on the gaming strategies and market power existing in NETA and world-wide power markets. Work carried out in the area of decision making on trading strategies in power market, over the past decade, is then reviewed. Evaluation and comparison are also presented in this chapter.

Chapter 3. The trading strategies published in literatures are studied in Chapter 3. This Chapter is aim to provide the development trend and direction of the decision-making methodologies on trading strategies for power trading, since these results will have important practice implications. The deficiency and limitations of traditional analytical techniques applied to study trading strategies in power markets are also highlighted.

Chapter 4. Chapter 4 demonstrates the trading strategy modelling of development of competition between power generation companies and supply companies through hybrid methods of Game Theory and Genetic Algorithms on NETA. A set of trading strategies, including gaming generation companies', competitive generation companies' and the suppliers', are developed to simulate the market behaviours of players from both of two sides of NETA market. A mix of cooperative and competitive gaming strategies are adopted, which has never been done in both industry and academia. It also attempts to discover the interaction between the market environment and the market player's payoff.

Chapter 5. Based on the trading strategies developed in last Chapter, the NETA trading mechanism is simulated in this Chapter. The objective of this market modelling is to to simulate the dynamic and decision making behaviour of the UK electricity trading system, and to discover the impact of gaming trading strategies on the NETA. The model is based on real case of NETA and published documents. Its designed feature is as close to NETA as possible.

To exercise the model's veracity and efficiency and exercise the modelling's performance, the validation experiments are carried out against real NETA data. All experimental parameters are from actual published data.

Chapter 6. Following modelling of the NETA market, the model is used to analyse the market behaviour of gaming strategies practiced in the power market and to find out possible influence on NETA. Both of cooperative and competitive strategies are adopted and examined in two experiments, which involveg various model scales including a small-scale market, similar to California power market, and a relatively large-scale market where the number of trading participants is similar to the real scale of NETA. The experimental results are compared and evaluated. Discussion is carried out to evaluate the performance the developed model and trading strategies in this marketplace.,

Chapter 7. In order to assess the performance of the proposed NETA market model and the evolving trading strategy, it is evaluated with a comparably similar simulation model, which adopts Genetic Algorithms coupled with various price forecasting techniques to select appropriate bidding strategies for the current market conditions. The major modelling results and market trading outputs are compared and discussed. The difference of these two models with the developed strategies are discovered.

Chapter 8. The final Chapter presents the conclusions drawn form this research and recommends the possible directions for future work.

2. NETA Systems and Current Trading Strategies

2.1 Introduction

In this chapter, the market structure of NETA and current trading strategies adopted in power market are studied. The aim of this chapter is to provide a clear scheme of the NETA market structure and start-of-the-art analysis on the trend and direction of the developments.

2.2 Structure of NETA Market System

Prior to the introduction of NETA, from April 1990 until March 2001 the trading arrangements centered around the electricity Pool which was a traditional centralized mechanism for dispatching generating plant at the day-ahead stage to meet forecast demand, and operated on a marginal pricing basis with all generator dispatched in a particular half-hour being paid the same price. The Pool was criticized that the market was dominated by a small number of generators but the Pool facilitated the exercise of market power at the expense of customers by enabling all generators to receive a uniform price that, in practice, was set by just a few of them.

In order to avoid the unsatisfactory respects of the Pool, the design of NETA was built upon a small number of key building blocks encompassing the need for [4]:

- A two-sided market, with demand fully incorporated;
- Bilateral contracting rather than a centralized market as the heart of the arrangements, to put greater competitive pressure on generators and encourage innovation and customer responsiveness in suppliers;

- (Contractually) firm bids and offers, to enable costs and risks to be reduced and shared efficiently;
- Simple bids and offers, to improve transparency and encourage liquidity; and
- Centralized real time physical balancing and financial settlement arrangements, to allow the system to be balanced and to target appropriately those balancing costs.

The New Electricity Trading Arrangements are designed to be more efficient and provide greater choice for market participants whilst maintaining the operation of a secure and reliable electricity system. The proposals are based on bilateral trading between generators, suppliers, traders and customers, as shown in Figure 1. These bilateral contracts can be traded in [3]:

- Forwards and futures markets (including short-term power exchanges), which evolve in response to the requirements of participants, that will allow contracts for electricity to be struck up to several years ahead;
- Short term power exchanges, where participants have the opportunity to "fine tune" their contract positions in a simple and accessible way;
- A Balancing Mechanism in which NGC, as System Operator, accepts offers and bids for electricity to enable it to balance the system; and
- A Settlement Process (for charging participants whose contracted positions do not match their metered volumes of electricity, for the settlement of accepted

Balancing Mechanism offers and bids, and for recovering the System Operator's costs of balancing the system.

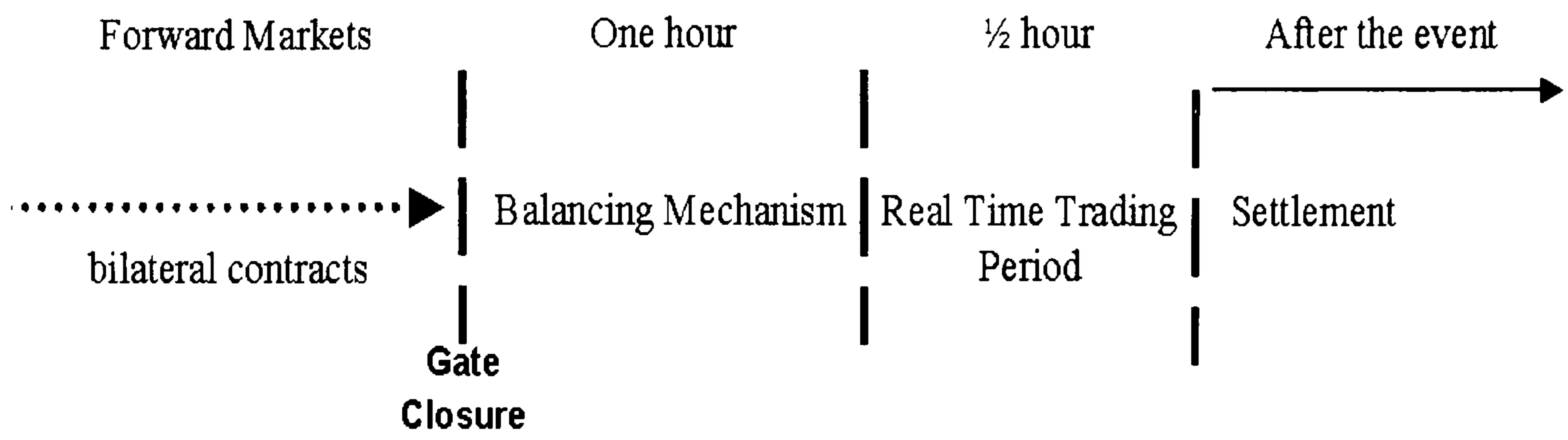

Figure 2.1: Trading stream on NETA

The system operator and power exchanges are central to the functioning of NETA. The physical nature of electricity does not allow a true spot market (instant pricing and delivery) so financial transactions must be scheduled some time in advance of the physical delivery. Power exchanges thus substitute for a true spot market. A variety of financial relationships manifest themselves in electricity market trading. Bilateral contracts may be agreed between generators and suppliers, standardised contracts, futures and forwards, can be traded through power exchanges and half-hourly spot markets provide short-time adjustment of the contractual position of market players close with the time of physical delivery.

As introduced earlier, the NETA market structures are based upon sequential markets, which are investigated as following [3] [5] and [64].

2.2.1 Forward and Futures Markets

The Forward and Futures Markets evolve in response to the requirements of double-side participants. Essentially these are markets for buying and selling large volumes of electricity in advance. Typical trades would be for an annual amount of electricity, or for electricity just for the coming winter or following summer, though they can be for some years ahead. They are termed bilateral physical trades, meaning that two parties (for example, a generator and a supplier) enter into a contract to deliver electricity at an agreed time in the future. These sorts of contracts are used both to manage price risk and speculate against future prices to avoid the risk of having to buy or sell at the last minute through the Balancing Mechanism where prices are very volatile.

2.2.2 Power Exchange

Power exchanges provide the forum for buying and selling power from a few hours ahead to many months ahead. There are a number of power exchanges in existence through which traders can enter bids and offers onto a System Operator, and these can be taken up by other traders with neither party being aware of the other's identity. A power exchange offers trading typically of relatively small quantities of electricity to enable to participants to fine tune their contract positions by buying or selling up to the last possible moment. Contracts, mostly for the very short-term (next day) can be made for specified amounts of electricity at specified times and are binding.

The contract-matching process is performed by System Operator (SO) in UKPX's Clearing House. The single matching round proceeds as following [5]. In each iteration each market participant from two sides respectively submits a set of bids (offers) including prices – responding volumes, i.e., £11.50/MWh – 11.23MW, £16.62/MWh – 18.30MW, . . . £68.42/MWh – 78.70MW, and so on, to the SO. All the offers are sorted out by their prices in ascending order and all the bids are sorted out in descending order. Then the SO matches the prices as below.

(1)The point of the lowest selling price is matched with the point of the highest buying price. If the buying price is higher than the selling, a contract is granted. Then for the seller the amount sold is subtracted from the amount available to sell and for the buyer the amount bought is subtracted from the amount available to buy. Once a buy and a sell order have been matched, the Clearing House becomes the counterparty to both the buyer and the seller who never become aware of each others identity. At all times the Clearing House has a flat position and it does not hold positions for itself.

(2)After that if the lowest selling point still has electricity available for sale, it is matched with the next buying point with second higher bid price.

The above procedures 1 and 2 are repeated until the offer exhausts all its electricity available for sale on this specific point or run out of buyers available to buy his electricity.

The next offer with second lowest selling price is picked and the above procedures 1 and 2 are repeated. The procedure is demonstrated in Figure 2.1. Procedures 1, 2 and 3 are repeated until all offers and bids are matched.

Based on the trading process the PX mean market clearing price (MCP) is defined as:

$$PXP = f(Q_{\mathrm{SPX}}{}^{1},\ldots, Q_{\mathrm{SPX}}{}^{i}, P_{\mathrm{SPX}}{}^{1},\ldots, P_{\mathrm{SPX}}{}^{i}; P_{\mathrm{BPX}}{}^{1},\ldots, P_{\mathrm{BPX}}{}^{j}, Q_{\mathrm{BPX}}{}^{1},\ldots, Q_{\mathrm{BPX}}{}^{j}) \quad (2.1)$$

where i is the number of generators, $i = 1, 2, \ldots n$; j is the number of suppliers, $j = 1, 2, \ldots M$; $Q_{SPX}{}^i$ and $P_{SPX}{}^i$ are the quantity and price generator i wants to sell at PX, $Q_{BPX}{}^j$ and $P_{BPX}{}^i$ are the quantity and price supplier j wants to buy at PX.

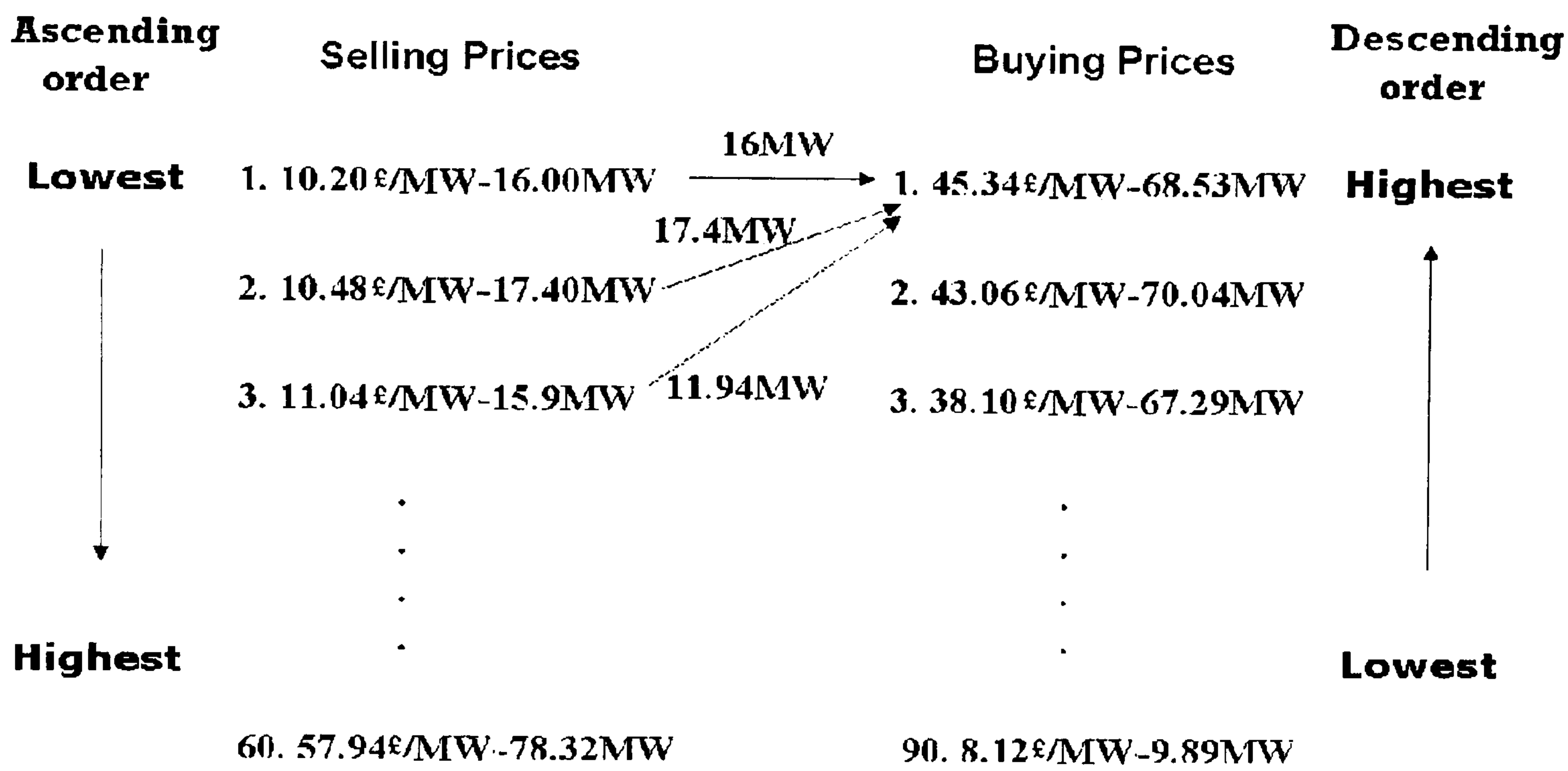

Figure 2.2: Clearing Process on Power Exchange

2.2.3 Balancing Mechanism

The Balancing Mechanism (BM) is a near real time tool operated by NGC to ensure that the supply and demand of electricity exactly matches [17].

Each trading day is divided into 48 half hour periods. One hour before the start of each period trading is effectively 'frozen', this is known as 'gate closure'. Whatever the type of contract struck, for the NETA the 'last possible moment' will occur at the 'gate closure'. This one-hour interval is used to enable the NGC, as the System Operator (SO), to balance the system. In order to enable the NGC to do this, participants will be required to notify:

- Their physical positions (either generation or demand) at gate closure;
- Their expected production in that period;
- Their forecast of customer demand;
- Any flexibility available to NGC (bids and offers)

The NGC will then operate this 'Balancing Mechanism' (BM) by accepting offers of electricity (generation increases and demand reductions) and bids for electricity (generation reductions and demand increases) at very short notice.

2.2.4 Settlement Process

In the Settlement Process generators' metered generation and suppliers' metered demand are compared with the contractual position they notify as the Balancing Mechanism opens together with any accepted Balancing Mechanism trades. The sum total of contracts negotiated in forward and futures bilateral markets and short term PX is added together to arrive at these contract positions. Participants that act both as generators and suppliers will be exposed to separate production and consumption imbalance charges for the two sides of their business.

The difference between the amount of electricity bought and sold under contracts and the actual amount produced and consumed is calculated by the imbalance settlement system. Companies with a mismatch, who either need to buy 'top-up' energy to meet their customers demand, or 'spill' excess energy into the system, are subject to an energy imbalance price.

The price for buying more energy is known as the System Buy Price (SBP), and is a weighted average of accepted Offers and generally higher than the forward market price because it reflects the cost of extra generation at short notice. Conversely, the price for selling excess energy to the system the System Sell Price (SSP), is a weighted average of accepted Bids and generally lower than the forward price, reflecting the relatively low price that generators are prepared to bid to NGC to reduce output at short notice.

If a generator is producing electricity and find at the last minute that it has generated more than it contracted customers demand, the generator will have to sell its excess production at a discounted price. This is the System Sell Price.

However if it finds at the last minute that it has not generated enough electricity to meet customer demand, it will have to buy some more. Not surprisingly the genarator would need to pay a premium because it is buying at the last minute. In fact, with electricity it could pay 10, 100 or even 1000 times as much as the normal price. This is the System Buy Price.

The same goes for suppliers. If a supplier contracts or sells more electricity than they said they would (the demand forecast), they will have to pay a premium for the extra consumption (the System Buy Price). Similarly, if they contract less than the demand forecast, they will have some excess electricity to sell and may not be able to get a very good price for it (the System Sell Price).

This is one of the main principles of trading electricity. If a market participant fails to achieve what it predicted then it is going to cost it to balance the system. The risk of having to buy and sell in this way through the Balancing Mechanism with its very volatile prices emphasises the importance of suppliers working closely with their customers to get the prediction of demand correct.

The spread between the two prices is intended to provide a penalty for being out of balance: The SSP (SBP) is expected to be considerably lower (higher) than forward market price *PXP* [18].

SBP is calculated as [19]:

$$SBP_b = \frac{\sum_{a} \sum^{x} \left(QAO_{xar} * PO_{nar} * TLM_{ar}\right) + BCA_r}{\sum_{a} \sum^{x} \left(QAO_{xar} * TLM_{ar}\right) + BVA_r} \tag{2.2}$$

where

$QAO^x{}_{ar}$ is the Unit a Total Accepted Offer Volume,
$PO^x{}_{ar}$ is the Offer Price for the Offer acceptance x, Unit a and Settlement Period r,
TLM_{ar} is the Transmission Loss Multipliers, set as 1 in this model,
BCA_r is the Buy Price Cost Adjustment,
BVA_r is the Buy Price Volume Adjustment,

SSP is calculated as [19]:

$$SSP_b = \frac{\sum_{a} \sum^{x} \left(QAB_{yar} * PB_{yar} * TLM_{ar}\right) + SCA_r}{\sum_{a} \sum^{x} \left(QAB_{yar} * TLM_{ab}\right) + SVA_r} \tag{2.3}$$

where

$QAB^y{}_{ar}$ is the Unit a Total Accepted Bid Volume,

PB^{y}_{ar} is the Bid Price for the Bid acceptance y, Unit a and Settlement Period r.

TLM_{ar} is The Transmission Loss Multipliers,

SCA_r is the Sell Price Cost Adjustment,

SVA_r is the Sell Price Volume Adjustment.

2.3 Problems Existing in NETA Market

In a perfect electricity market, any power supplier is a price taker. Microeconomic theory holds the optimal trading strategy for a supplier is simply to bid marginal cost. When a generator bids other than marginal cost, in an effort to exploit imperfections in the market to increase profits, this behaviour is called gaming strategic bidding. If the generator can successfully increase its profits by strategic behaviours or by any means other than lowering its costs, it is said to have market power. Theoretically the NETA is not perfectly competitive, and consequently the generation companies would be able to increase profits through gaming trading strategies, specially, through exercising market power on trading in NETA.

Since competition mainly exists at the generation side on NETA, and the transmission and distribution systems remain regulated monopolies [20], the gaming problem in electricity markets is concerned mainly with power generators although demand side gaming is also gaining importance.

Research of the relationship between generators spot market behaviours and their financial trading or hedging contract position on NETA market conclude that a generator in the physical spot market can directly exploit the rigidities of the electricity market to exert a 'dramatic' influence over the physical balancing and financial settlements within NETA. In other words, in the very short term, the market is vulnerable to the exercise of market power by any physical participant whose flexibility (whether in supply or demand) is required, at a particular time, to achieve system balance and to avoid very costly supply failures.

The 'rigidities' of the physical market for electricity, namely highly variable demand and order flows coupled with inelastic supply, also make the financial markets related to electricity vulnerable to potential indirect manipulation strategies being adopted. These strategies could potentially be used by players who have relatively small positions in physical markets.

All these economic interactions between the physical and financial market, and the physical characteristic of only a limited number of generating companies to service a given geographic region described above, which conduct in one can affect trading in the other, make the NETA vulnerable to market power yet, in particular under a critical situation on NETA where the supply exceeds demand, and thereafter the price of electricity on the wholesale market has dropped 40% in the past six years. As a consequence, some major market players are being driven out from the industry [6]. It has been more realistic and practicable that generators tend to maximize profit in using gaming strategies to exploit the loopholes and scopes of NETA.

There has been an amount of effort imposed on analysing the mechanism of gaming strategies and market power and their influences over the electricity trading market. game theory is the most widely used methodology to model market players' strategies [7] [8] [9]. The performance of trading participants who attempt to make coalition in competitive market, particularly the bargaining process and negotiation protocols, are also studied by intelligent-agent systems [10] [11]. Some employ probability distribution to predict market players' behaviours [12].

Research for the practice of gaming trading strategies over the world-wide power market has demonstrated that, the direct exercise of market power by those who control deliverable supply can occur in various ways, such as through changes in the quality of the product supplied, or through artificial increases in price or restrictions in supply, as what happened in California. In addition, the potential may also exist for market power to be exercised indirectly, through gaming the relationship between the physical and financial markets.

The indirect exercise of market power in this way seeks to exploit the relationship between the spot price for the physical electricity and the price of financial contracts over it. Given the relationship between the spot price and the prices of financial contracts, this may provide an opportunity for a firm to profit substantially in a tightly constrained market from movements in either the spot price of the electricity or from the increase in prices of financial contracts. The classic market 'squeeze' or 'corners' are two examples of market manipulation strategies, which could be introduced on NETA by trading participants. Occurrences of manipulation strategies such as corners and squeezes have been detected in power electricity markets as diverse as in worldwide [21].

A market 'squeeze' occurs where an artificial scarcity in deliverable physical supply is created, which raises the price that those who have large contractual obligations to supply are forced to pay to close out of their contracted position in financial markets. Similarly, a 'long' corner occurs where a market participant, who typically has control over a significant amount of deliverable supply, commits other participants to large contractual positions to supply at a future date (through buying large numbers of long futures contracts for example) and then subsequently artificially restricts physical supply for which those who are contracted to supply are forced to pay to close out their position as the delivery date approaches.

In the extreme, for example, consider a situation whereby a generator withdrew all of its available capacity from the NETA market, and the reduced level of available generation results in an upward movement in prices. If attention were confined to the physical market, such an action would clearly not be profitable, since the generator supplies no output. If, however, the generator contracts ahead of time to purchase claims to output, a profit will be obtained from any difference between the spot price (which is raised by capacity withdrawal) and the contract price.

2.4 Review of Decision Making on Trading Strategies

Current research has focused on designing optimal trading strategies in electricity market. Broadly speaking, there are three ways for developing optimal trading strategies on NETA. The first one relays on estimations of the MCP in the next trading period, the second utilizes estimations of bidding behaviour of the rival participants, and the third is game theory based. Besides, market simulation and empirical analysis methods are also used for investigating gaming strategic behaviour [22], but these do not lead to systematic approaches for building gaming strategies.

The first approach is simple in principle. Based on the estimation of the MCP, it is quite straightforward for a power supplier to determine its strategy by simply offering a price a little cheaper than the MCP. However, predicting electricity price in a pool requires analysis that combines demand forecasts with an understanding of participants' bidding and transmission congestion. Since there is very little historical data available in most electricity markets, it is difficult to achieve accurate predication because of the fast-moving reform of the electricity industry. Another problem with this method is an implicit assumption that the bid from one supplier will not influence the MCP. Since the electricity market is basically an oligopoly, this assumption is unlikely to hold for any reasonable length of time. This method has seldom been applied in developing bidding strategies in electricity markets.

Most of the methods published so far are based on estimations of trading strategy on bidding of rival participants in which different techniques, such as probability analysis and fuzzy sets, are utilized for estimation. A description of publications under this group will be given in the next several sections according to their features.

The third approach is the most sophisticated which is to apply some methods or techniques from the game theory. There are many publications available in the area of electricity markets that follow this. There are basically three methods in this catalogue.

The first method is the matrix game based [23] [24] where gaming bidding strategies have to be represented as discrete quantities such as "bidding high", "bidding medium" or "bidding low" to cater for the nature of this game. With discrete bidding strategies, payoff matrices are constructed by enumerating all possible combinations of strategies, and an equilibrium state of the bidding game that corresponds to the optimal bidding strategies for the participants can be obtained. However, in realistic situations, bidding strategies can be continuous and therefore it is not theoretically guaranteed that an equilibrium state does exist for an electricity market. While this method may be suitable for roughly analyzing the strategic behaviours of power suppliers, it is not appropriate as a tool for developing bidding strategies.

The second method follows oligopoly games such as the Stackelberg model and supply function. Basically, these models are more appropriate for analysis of potential market power than constructing trading strategies, although in principle the equilibrium state of these models represents the optimal bidding strategies of the participants. This is because many simplification assumptions have been made in applying these models, and as a result, the equilibrium state may not make sense for building optimal trading strategies.

Coalition gaming is the third and most sophisticated approach employed which is a form of cooperative gaming among the members in subgroups while non-cooperative gaming may still apply among the subgroups. Most coalition strategies studied, which some generators make an agreement including the allocation of production among the members and the policing of the agreement (sometimes and the allocation of organization profits), are based on methods and techniques from cooperative game theory techniques. Most of coalition strategies on electricity markets are on a basis of cooperative game theory. In [14], a classical game theory, Cournot gaming strategy, is adopted to model a coalition among generators. In [11], cooperative gaming is implemented to perform negotiation with potential collusion partners and then suggests market strategies that the generator can adopt.

2.5 Summary

The trading strategies currently used in power trading systems have been reviewed in this chapter. The approaches for building gaming strategies on different forms of markets models will systematically analysed in next chapter. And the advantages and drawbacks of current trading strategy research will also be addressed.

3. Current Research Review

3.1 Introduction

In this chapter, the trading strategies published in the literature are studied. Although these have been attempted by many in both academia and industry, the aim of this chapter is to provide a more comprehensive analysis on the trend and direction of the developments.

The main aim of investigating these objectives is to identify methodologies for analyzing and modelling trading strategies, since these results will have important market implications. In recent years, some research has been done in building optimal trading strategies for competitive/cooperative generators and/or large consumers, and on investigating the associated market power in world wide electricity markets in which the gaming strategies are widely utilized.

3.2 Developed Activity Rules and Market Model

The development of gaming trading strategies on NETA is based on a mechanism in which the power generators, and sometimes large consumers also, are required to offer price and quantity bids to a market operator. The market operator then determines the winning bid and a market clearing price (MCP) using a simple merit order dispatch procedure. The current research in this field is focused on market model and activity rules, especially, auction rules and bidding protocols.

An auction is an economically efficient mechanism to allocate demand to suppliers, and the formation of electricity markets in many countries is based on auctions. Bidding is an issue connecting to the auction.

Many auction methods exist, and can be classified in many ways [25]. Two main categories differ according to whether the auction is static or dynamic. In static auctions, the bidders submit sealed bids, while in dynamic auctions bidders can observe the bids of others and revise their own sequentially. Static auctions can be classified according to discriminating or non-discriminating pricing. In the former bidders are paid their offered prices if they win. In non-discriminating auctions, all winning bidders are paid a uniform price, such as the first losing bid or the last winning bid. In cases of multiple sellers or multiple buyers, the non-discriminating pricing auction is usually employed to encourage the bidders to bid their marginal costs or benefits.

Auctions can also be classified as "open" or "sealed-bid". Open auctions may be classified as English (ascending bid) or Dutch (descending bid). Sealed-bid auctions can be classified into "first price' and "second price' auctions, and both of them are usually referred to as non-discriminating auctions, the only difference is whether the uniform price is set according to the last winning bid or the first losing bid. An auction is called a double one when both the sellers and buyers are required to submit bids.

To our knowledge, almost all operating electricity markets worldwide employ the sealed bid auction with uniform market price.

Another important factor related to trading strategies is auction bidding protocols. Depending on different market designs, the energy bids may include several price components (multipart bid) or a single price component (single-part-bid). In either case, the energy bid include several energy price segments depending on the amount of energy supply (e.g., a separate price for each block of energy from the same unit or a portfolio of units).

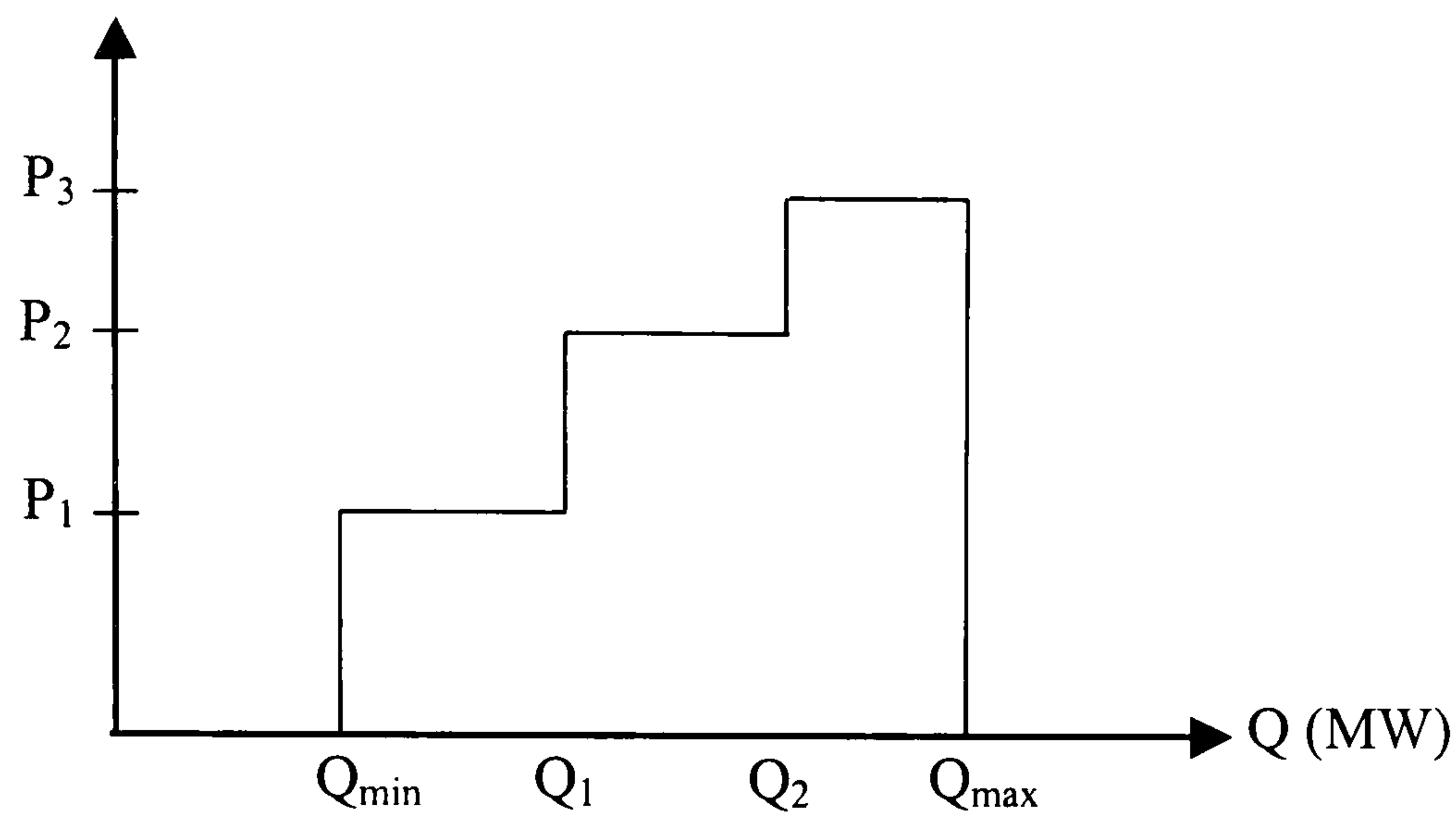

Figure 3.1: Multipart bid curves of generators

Various auction bidding protocols bring significantly different concerns while developing trading strategies. The research on design and performance of development trading strategies on different bidding models in electricity markets are discussed below.

3.2.1 Strategies on Multipart Bidding

A multipart bid, sometimes called a complex bid, may include separate prices for ramps, start-up costs, shut-down costs, no-load operation, and energy. This kind of bid can reflect the cost structure and technical constraints of generation units. The market clearing procedure must be based on an optimization algorithm that determines the winning bids and wholesale prices taking into account not only the bid prices, but also technical constraints and related economic information.

This approach leads to a centralization of the unit commitment decisions at the market operator's level and does not make market power involved: bidders are required to send all the relevant information and the market operator makes optimal decisions. This approach can guarantee the technical feasibility of the resulting schedule.

The unit commitment problem is non-convex, and there does not exist a method that can guarantee to converge to the global optimal solution for large scale systems. This approach has been widely because a local optimal solution may not produce equitable dispatches for all participants.

A well-known example of the multipart bid is the Pool of England-Wales electricity market, in which a combined bid of many items had been required for the next 48 half-hours before the NETA was introduced.

The trading strategic problem for competitive power suppliers was addressed for the first time in [26]. A conceptual optimal bidding model and a dynamic programming based approach was developed for this market in which each supplier is required to bid a constant price for each block of generation. System demand variations, unit commitment costs, and commercial considerations such as profit or economic utility maximization and expectations of competitor behaviour were considered in the model. In [27], an analytical formulation for building the optimal gaming strategy in this type electricity market was developed under a very stringent assumption that the market clearing price is independent of the bid of any supplier, or in other word, the market is perfectly competitive. Under this assumption the MCP can be accurately known before the auction takes place. This assumption seems not reasonable for the electricity market, which is more akin to oligopoly than a perfectly competitive market. While this method contains elegant theoretical development, it provides little insight into the formulation of the optimal bidding problem under nonperfect competitive conditions.

3.2.2 Strategies on Single-Part Bidding

In this scheme, generators' strategy is only based on independent prices for each hour, and a simple market clearing process based on the intersection of supply and demand bid curves is used to determine the winning bids and schedules for each hour. This approach is intrinsically decentralized: the market operator does not make unit commitment decisions. Hence, suppliers need to internalize all involved costs and physical constraints in preparing their bids since this bidding structure does not explicitly account for recovery of these costs.

This approach does not guarantee feasibility. Therefore, whenever a generation unit presents significant technical constraints, this approach typically requires a mechanism to eventually introduce modification in the schedule, such as a short term balancing market, which is incentive for market participants to adopt strategic bidding.

The single-part bid has been implemented in several electricity markets such as California, Australia and Norway/Sweden. A variation of the simple bid approach is employed in Spain, in which certain complex conditions were allowed for but were not used in the bid sorting itself. Most of the publications discussed next aim at developing bidding strategies for this kind of markets.

In [28], a simple suboptimal strategic bidding strategy was proposed for the situation when two buyers (utilities) are competing for a single block of energy, and the competitor's cost function are modeled with probability density functions. This method cannot be extended to the general case with multiple suppliers and/or multiple buyers. In [29], a dynamic model of strategic bidding for the situation with three power suppliers was proposed by utilizing the historical and current market clearing prices. This model is heuristic in principle, and is not applicable to the general case with more than three suppliers. In [30], a linear supply function model was presented to investigate strategic bidding behaviour, and to illustrate some of the ways market power can be exercised. A similar linear supply function model was employed in [31] to build optimal trading strategies for competitive suppliers, and the rival suppliers' bidding behaviours are represented as discrete probability distributions. Moreover, a payment rule named 'multiple-commodity second price auction' is compared with the popular uniform price rule, and it is shown by simulation results that the suppliers have a larger incentive to bid at marginal costs if the former rule rather than the latter one is utilized. In [12], the bidding problem over a planned horizon is represented as a multiple stage probabilistic decision-making problem, and a discrete-state and discrete-time type Markov Decision Process (MDP) was applied to calculate a supplier's bidding decisions, in which a competitor is modeled by its discrete bidding options associated with a corresponding probability. In [32], the authors argue that since the electricity market is relatively new and there is not sufficient data, it may not be realistic to calculate some probabilities such as the probability of rivals' bidding option and heuristic methods may be an alternative. A probabilistic/fuzzy heuristic inference system based on observable evidences and the subjective probabilities is then proposed as a tool for this purpose. In [33], a trading bidding strategy for suppliers in the uniform price clearing auction is developed by estimating the probability of winning below and on the margin, and a simple bidding model is then obtained under some simplified assumptions. The result indicates that suppliers have incentive to mark up their bids above their costs. In [34], intelligent trading agents, such as genetic algorithm, genetic programming and finite state automata, are utilized for developing adaptive and evolutionary bidding strategies.

Up to now, research work on strategic bidding has been concerned with one-period auctions, only little has been done on multiple-period auction [35] [36] [37]. In [35], this problem was described as a two-level optimization procedure. At the top level a centralized economic dispatch is employed to determine the market clearing price, the production and demand levels of all generators and consumers, and at the lower level a self-unit commitment based on a parametric dynamic programming with an embedded variable bidding parameter is used by each supplier to determine a profitable bid. An implicit assumption is that each supplier has complete information about rivals so that a centralized economic dispatch can be used to design the bidding strategy, and certainly this assumption is not reasonable. In [36], a Lagrangian relaxation based method is presented for daily bidding and self-scheduling decision from the viewpoint of a utility which can bid part of its energy to the market and self-schedule the rest, as is the case in New England. Bids are represented as quadratic functions of power supply levels, and the parameters in rivals' bids are assumed to be available as discrete distributions. In [37], a systematic approach is presented for developing bidding strategies for power suppliers participating in the California-type day-ahead energy market. In this market, a series of 24 auctions are conducted simultaneously and separately, one for each hour. A supplier first builds optimal bidding strategies for each of the 24 hours, if the unit cannot be dispatched in some hours, a self unit commitment algorithm is then employed to account for operating constraints and startup and shutdown costs to develop an overall bidding strategy in the day-ahead market.

Since a uniform price over the whole network cannot provide economic signals for the suppliers and consumers, much research work on nodal pricing has been carried out which is the most complicated but accurate pricing method derived from the marginal cost theory. This method determines prices for power at each bus of the system, accounting for all costs and transmission constraints. The nodal prices are typically calculated as dual variables or LaGrange multipliers of an optimal power flow (OPF) calculation. A major advantage of this method is that the right operational pricing signals are revealed. Although there is not a fully operative example of nodal pricing in the industry, some research work has been done to address the potential strategic behaviours of power suppliers by intentionally causing congestion and exploiting arbitrage opportunities of nodal price differences [25].

3.2.3 Strategy on Iterative Bidding

In [38], an iterative bidding scheme is suggested in which generators and consumers are permitted to modify their bids, according to several rules, to make sure that their costs are appropriately allocated and their technical constraints respected. This method may have heavy computational burden and could pose practical problems. Ref. [39] first argues that a single bid may not be the best mechanism to ensure the market is driven to an efficient operating condition, and then presents an asynchronous iterative strategic scheme in which a feedback mechanism is introduced such that upon receiving generation levels following the first-round of market clearing, suppliers are allowed to modify their bids once more if they so desire. The optimal trading bidding problem is addressed based on this bidding scheme, and a radial basis function neural network has been employed for this purpose. Ref. [35] also addressed the bidding strategy problem under a suggested iterative bidding scheme in which the auction proceeds iteratively and closes when a physical feasible dispatch and a stable market clearing price is obtained.

3.2.4 Demand Side Strategies

In some electricity markets such as NETA, California, New Zealand and Spain, demand side bidding is permitted for large consumers to react to electricity pricing. In this case the maximization of social welfare approach should be employed for bid clearing, and the minimum price approach employed in those markets only with supply side bidding is no longer fair to the sellers. This is because in this case both the sellers and buyers are bidders, and the buyers are no longer passive. If the demand side bidding is not permitted, the minimum price approach should be employed because in this case the buyers are passive and their benefits should be protected by regulations.

Up to now, research work on trading strategies is concentrated on the supply side, quite little attention has been imposed on demand side. In [40], the potential impacts of the demanding side trading strategies on market prices are analyzed and several somewhat negative remarks on the effects of the demand side bidding are made. In [41], a two-level optimization procedure for building trading strategies was presented in which market participants try to maximize their profits under some constraints. An independent system operator (ISO) determines their dispatches and market price utilizing a transparent optimal power flow (OPF) program with an objective of maximizing social welfare. It is assumed that each participant has an estimated value for the bid from each of the other participants. In [42], the optimal trading strategies of generators and large consumers are addressed simultaneously utilizing linear bidding functions, and the behaviours of rival competitors are represented as continuous probability distributions. A Monte Carlo based method is developed to find the optimal bidding strategies and the associated market power is evaluated. It is shown that the market power can be mitigated through introduction of the demand side bidding.

3.2.5 Trading Strategies in Ancillary Service Market

Similar to energy markets, it has been recognized that most of the generation based ancillary services such as spinning reserves and AGC provision can be procured through auction based competitive markets. In some electricity markets such as NETA and Spain, some ancillary services markets such as AGC provision have been in operation for a period.

Serious strategic behaviour by power suppliers has been observed at the initial operation stages of the NETA ancillary services markets. It has been noted in [43] that these markets did not operate in a manner consistent with workable competition and prices do not fluctuate in a manner that reflects changes in the underlying marginal costs of supplying these products. These markets have exhibited extreme price volatility, even during periods when demand was unchanged for long periods of time. The conditions are not yet in place to rely on these markets to set efficient, cost-reflective prices. Prices for lower quality services such as replacement reserve routinely exceed the prices for higher quality services such as regulation. Often ancillary services capacity prices exceed the energy market price for the same hour. For example, on July 9, 1998 the prices in the replacement reserve market was as high as $9999/MW in Californian ancillary services markets. Since then a price cap was introduced to limit this strategic bidding behaviour.

Some of the main factors that lead to these problems are structural deficiencies, irrational procurement method for ancillary services, and perverse incentives created by reliability must-run contracts. A rational buyer algorithms [44] has been utilized for ancillary services procurement since August 18, 1999 as a partial solution to these problems.

3.3 Discussions

Current research results have gain significant insights into overall aspects of most existing power market trading systems in the world, especially the mode of the California power market. Most linear and static strategy development problems have been successfully solve out by these research efforts. Besides, solely using either of competitive game strategy or cooperative game strategy has been able to the traditional game theory

While a lot of work has been done, quite limited attention has been paid to the NETA market research. [13] analyses the economic dispatch for the NETA balancing mechanism. A load management technology is developed in [14]. [15] presents risk assessment on local demand forecast uncertainty. The wind generation trading in NETA short-term energy markets is carried out in [16]. There exists a lack of attempt to model this trading market mechanism in current research. Furthermore the other major work that has so far not been undertaken by academia and industry is to study the possibility and consequence of gaming behaviours and market power on NETA.

Furthermore, the effort on studying trading strategic behaviours is to find suitable solutions to solve the problems that have happened and would happen in power industries. However current strategies research is inadequate in some aspects described as below.

(1) Game theory has been widely utilized analyzing market power and market participants' gaming behaviours. However there are deficiencies existing. For example, Nash Equilibrium, which is the most adopted Game theory to simulate participants' strategies, assumes that the rules of the game, the strategies available to the players, and the payoffs are common knowledge, which does not reflect the real cases in power markets. Also, some research model which employ Cournot game theory to stimulate oligopoly game, only involves two firms deciding how much to produce without knowing the output decision of the other, turns into a simplified duopoly game that are not applicable to the general cases with more than two or three trading participants. More crucially, all published research contributions have only solely used either noncooperative or cooperative game theory to model and develop market player's gaming strategies. It is not capable of analyzing the gaming behaviours practiced in power market, because market players have been using mix of both to manipulate the market prices to maximize their profits, especially the cooperative game, which is getting more practical to study the real problems caused

be market power and coalition game practiced by electricity suppliers in global electricity market.

(2) Although a vast amount of contributions has been done by academia, there are a few published research results of analysis on NETA, which is one of blueprint deregulated electricity trading arrangements in the world. Principally, the research on modelling this market structure and trading strategies are still in their infancy. For instance, the process of how power generators attempt to employ market power and to maintain strategic gaming behaviours to maximize profits has never been addressed. And the possibility of forming cooperation agreement among generation companies and consequence of such actions were unknown for industry. This problem has become acute since the prices of global energy products have been soaring.

(3) Many real world problems generally do not have accurate measurement of its variables. Many published electricity bidding strategies are represented as discrete quantities at which in realistic situations, bidding strategies can be continuous. Some models are calculus-based that require derivatives information to find out equilibrium; it is easy to be trapped on local peaks.

Considering the problems and lack of current research stated above, it is necessary and important to go further of developing more practical and complete game theory strategies and analysing the influence of gaming strategies on NETA market. Further, the extra-numerical search technique should also be taken into account to solve the search, learning and optimization problems.

4 Development of Game Theory Based Trading Strategy and Decision Making Systems

4.1 Introduction

Based on the analysis of the previous chapters, the main purpose of this chapter is to demonstrate the trading strategy modelling of development of competition between power generation companies and supply companies through hybrid methods of Game Theory and Genetic Algorithms on NETA. A set of trading strategies are developed to simulate market players' behaviors and to discover the interaction between the market environment and the market player's payoff. The essential feature of the stretegy design and development is based on the market structure of NETA [3], [5], [17], [18], [19] and [58].

4.2 Generator Cooperative Trading Strategy Modelling

4.2.1 Introduction

The fundamental fact on NETA is that high level of over-capacity exsits in the market, the wholesale prices have been gradually falling down and some major British generation companies, like British Energy, were forced to edge of bankcuptcy. The central object behind these generators' strategic trading is to manipulate the market prices through reaching coalition among main generators under NETA, in order to transform the marketplace into a profitable situation, idealy given oligopoly in some markets of NETA for some periods. Along with this challenge, electricity suppliers are forced to adjust their trading methodology keeping their profits.

Such action in which major market players bind together to control market and manipulate the market prices has been applied to other kinds of commodity markets. For instance, since 2003, OPEC producers have increased their output 10 percent to make up for a rise in global oil demand, however the oil price has still been pushing up over the last two years. It is believed that it is unlikely that either lifting the group's quota or indicating that it is ready to produce more oil will bring much new supply to the market, because the bottleneck in energy supplies comes from the inability of refiners to process enough oil to meet demand, not from a shortage of crude oil. Analysis results [59] present that some major oil companies, like Royal DutchShell, Chevron, have been making up constraint on the downstream of this industry – to withhold their refining capacity to cause the shortfall in energy markets.

Coalition is a form of cooperative gaming strategy among the members in subgroups while non-cooperative gaming may still apply among the subgroups. It is simply a subset of N that is allowed to make a binding agreement. As pointed out by Heap [60], "In the N-person case, ... if a coalition is to form and remain for some time, the different members of the coalition must reach some sort of equilibrium or stability. It is this idea of stability that must be analyzed in any meaningful theory." In this model, the equilibrium (or stability) in a coalition is defined as follows: each and every member's profit in a coalition is greater than the profit it can obtain from a non-cooperative game among all of the producers. This means that the individual profits of the n producers in a completely non-cooperative game must be calculated first. The individual profits from any non-cooperative game between or among the coalition subgroups are then calculated and compared with the profits obtained from the complete non-cooperative game. If no individual profit falls short in the latter case, the equilibriums within the subgroups can be achieved on condition that an equilibrium is also achieved among the subgroups. Note that the case of complete collusion (all producers act together as a monopolist) is assumed infeasible and is excluded from our analysis. This is why n is set to be no less than 3; the case with $N = 2$ has only one coalition that is also collusion.

The coalition formation is a process of forming a profitable partnership among some main generators. The objective of these generation companies is to artificially restricts physical power supply volumes during some specific periods, i.e. in Christmas or Easter, then lead the whole marketplace to an oligopoly situation then subsequently make the market prices driven up.

It is assumed that participants form a coalition either by being the founder or by joining one at a time with a coalition that already exists. There are some uncertainties involved with this strategy that need be solved by the partnership members:

(1) As the NETA consists of two separate markets, i.e. PX and BM, how do cooperative strategy players arrange output volumes between these two markets and make the most profits through this strategy?

(2) For each generator, how much are the optimal volume of withheld output capacity and selling prices?

(3) How do coalition agreement members keep cooperative generators loyally carrying out the agreement?

(4) Is it likely that there exists equilibrium that collusive generators can make best profits meanwhile the markets trading can be kept in balance, e.g., may not lead to endless competition or collapse?

Currently in studying the gaming trading strategy used in electricity trading, cooperative gaming strategy has hardly been intruduced to model market participants' behaviours because of the extensice application of traditional game theories, Nash and Cournot game theories, which are applicable to noncoperative strategy. The problems in real power market call for more practical solutions. Furthermore present research examples examined by academia have never been involved with the constraint among binding agreement members, which may be the most difficult and intereting point that collusive energy firms are concerned about.

4.2.2 Strategy Combination of Generator Gaming Strategies

Based on the introduction outlined in Chapter 2, the imbalance penalties in BM are much higher than market clearing prices in wholesale market PX where most of power volumes are traded. As effect of maintaining this stragety at which gaming generators make the supply/demand unbalanced on this market, power suppliers are expected to be driven to BM and purchase the shortfall with imbalance charges.

The cooperative power generators' strategy combination can be described by a small number of paths together with rules stating when to switch from one paht to another. The first path, is followed at the beginning and continues to be followed until a deviation from it occurs. In this model, the initial step to implement this gaming strategy is that a certain number of collusive generators withhold a portion of their available capacities to change the PX market into an oligopoly situation. Withholding can be physical (bid only a portion of one's capacity) or economic (bid a portion at a very high price). Theoretically which type of withholding a generator should choose depends on the market structure. In NETA circumstance, all markets (forwards and futures markets, short-term Power Exchange and BM) are continuous and interchangeable. Therefore both of physical and economic withholding is employed to make the maximal profit by gaming generators. The details are described as below.

The basic content of this cooperative strategy is presented below:

(1) Each member of the agreement withholds a portion of its total capacity, as variable X, expressed as a percentage of its total generation capacity. The range of X is assumed to be from 10% to 25%. Then the remaining volume $Q_{smax}{}^{i} \cdot (1\text{-}X)$, is traded into the PX, where $Q_{smax}{}^{i}$ is generator i's maximal generation capacity.

(2) After the suppliers are driven to BM and have to submit bids for getting extra supply with paying SBP, the gaming generators need to provide offers to BM to meet the shortfall demand and determine how much volume should be taken from the withheld volume $Q_{smax}{}^{i} \cdot X$ to trade in BM. Given the part taken from $Q_{smax}{}^{i} \cdot X$ is Y, expressed as a percentage from 0-100%.

(3) The last part of the cooperative strategies is to optimise the trading on forward markets. Because the state of suppliers is no longer superior when the market is under an oligopolistic condition, generators can improve their selling curves to drive up the market prices as high as the suppliers could accept under PX.

Each generator is characterized by a set of portfolio parameters:

(1) Self-electricity generation parameters. Each agreement participant first derives its local information, for example, the maximal generation capacity $Q_{smax}{}^{i}$, marginal cost $P_{mc}{}^{i}$, and so on, then determines the profit when acting alone. This profit is called the player's self-value. This set of such local information depends on the player's environment.

Once each participant has the requested information from all other participants in the environment, the local calculation phase begins. Here, each participant calculates the strategic variables and parameters.

(2) Strategic variables: X being generator i's portion parameter on PX, $P_{SPX}{}^{i}$ being the price that generator i wants to sell on PX, $Q_{SPX}{}^{i}$ being the quantity that generator i wants to sell on PX, portfolio instrument l expressed as a percentage of its total generation capacity, BM Offer price $P_{O}{}^{i}$ and $Q_{SBM}{}^{i}$ being the quantity generator i wants to sell at BM. Their relationship is formulated as:

$$Q_{smax}{}^{i} \cdot l = Q_{SPX}{}^{i} + Q_{SBM}{}^{i} \tag{4.1}$$

(3) Collusion parameters: P_{TR}, T, Q_{comp} and Q_{coop}.

There are two types of remaining paths being used by cooperative generators in the game. One follows a strategy called "opportunistic collusion" whereby generators withhold capacity from the market only when they perceive an "opportunity" to raise profits by doing so exists. Opportunistic collusion might result in a generator setting aside a portion of their capacity and deciding for each hour whether or not to offer that capacity to the market depending on expectations of raising profits. This is different from the other type, suggesting that generators should "always" withhold a portion in anticipation of an agreement. The second kind is named "loyal cooperator".

For making the agreement more efficient, a more extreme management-enforcement is utilized to constrain the agreement members. In this application, a well-known technique of cooperative game strategy, "trigger price strategies" [61], which was created and used to constrain "Coffee Cartel" that dominated 80 percent of global coffee market share in

1970s, is employed to enhance this agreement by "loyal cooperator". In a trigger price strategy, "loyal cooperators" make inferences about any members in this agreement from the observation of market price P_{PX}. If market price remains above some critical value – the trigger value – then these generators will infer no cheating on the collusive agreement and will maintain a cooperative output level. If the price falls below the trigger, then some punishment must be imposed on the cheater(s).

Trigger price strategies depend on four parameters, P_{TR}, T, Q_{comp} and Q_{coop}, where P_{TR} is the trigger price, T is the number of time periods the punishment will last, Q_{comp} is the competitive output, given 100% generation volume $Q_{\mathrm{smax}}{}^{i}$ in this model, and Q_{coop} is the cooperative output given $Q_{\mathrm{smax}}{}^{i}$. (1-X).

Th trigger price strategy works as follows:

Each trading round is designatedas either cooperative or competitive. In a competitive round, a menber of the "loyal cooperator" produces an output level Q_{comp}, where $Q_{\mathrm{comp}}=Q_{\mathrm{smax}}{}^{i}$, and in a cooperative round, it produces an output level Q_{coop}. In initial rounds, both of the "opportunistic generator" and "loyal cooperator" cooperate. After that, the "loyal cooperators" continue to cooperate as long as there is evidence that the other member of the agreement is cooperating. However the "opportunistic generator" will decide for each round whether or not to cooperate depending on expectations of raising profits by doing so. With the trigger price strategy, the evidence that the other member is cheating consists of a "suspiciously low" market price, P_{TR}. So if the market price, P_{PX}, fell below the trigger price, P_{TR}, the next $T-1$ years are competitive and year $t+T$ is again cooperative.

The trigger price strategy described above is less extreme than traditional grim strategy. Unlike grim strategy, the punishment is of limited rounds. After a fixed period of time has elapsed, the players begin cooperating again instead of the punishment lasting forever.

4.3 Generator Noncooperative Strategy Modelling

The generators who do not join the collusion independently sell their individual output volume on the NETA markets. The relationship among these individual market participants and those gaming generators is completely non-cooperative. There are two situations existing that these non-cooperative generators need to face. Firstly, according to the initial situation on NETA that there is high level of over-capacity exsitting in the market, the state of such generators is inferior to suppliers because the latter have enough choices to select generators with low selling prices to make contracts, and hence all suppliers' demand is theoretically satisfied. The contracted prices, as forward markets prices, could be as low as what generators could accept. Consequently, generators can only sell out parts of their total volumes at P_{PX} level. Secondly, because some major generators are using gaming strategies in manipulating the trading, the market circumstance might be driven to oligopoly situation. The non-cooperative generators would adjust their strategies.

4.4 Suppliers Combined Strategy

As introduced earlier, the dual cash out prices of BM are intended to discourage market participants from being out of balance because the penalty for contracting at less than actual demand can be extremely high. The main concens of the suppliers focus on two main issues: demand prediction capabilities and contract cover (how much of there expected demand they want to buy in the PX). The first is beyond the covery of this research. Therefore the study here is to discover how suppliers respond to NETA imbalance prices by over-contracting to reduce exposure to SBP [58]. The cost of over-contracting can be viewed as an insurance premium that reduces exposure to the potentially high risks of being short.

Each supplier's objective is to optimize its contract position, as well as trading prices, to minimize the cost of contracting in order to maximize total daily profits. The strategy of each supplier *j*, is characterized as following [62]:

$$C_L = \sum_{r}^{48} -PXP^r \cdot Q_D{}^r \tag{4.2}$$

where C_{mr} is the marginal revenue of supplier *j*, *r* is the settlement period number, *PXP* is the PX clearing price and $Q_D{}^j$ is the actual demand at settlement period *r*:

$$C_S = \sum_{r}^{48} (PXP^r \cdot Q_C{}^r - \text{Max}[0, Q_C{}^r - Q_D{}^r] \cdot SSP^r + \text{Max}[0, Q_D{}^r - Q_C{}^r] \cdot SBP^r) \tag{4.3}$$

where C_{con} is the contracted revenue of supplier *j*, $Q_C{}^j$ is the contracted volume at settlement period *r* on PX.

A percentage premium for supplier's strategy can be defined as $(C_S / C_L) \cdot 100$; the lower the premium the more efficient the strategy.

4.5 Strategy Development

In order to find out the best solutions, both sides of the trading need to constantly improve and optimize their adopted strategies through varied tools during the trading procedure.

On the selling side of this marketplace, cooperative generators have many strategic parameters, i.e., $P_{SPX}{}^{i}$, $Q_{SPX}{}^{i}$, l, X, PO^{i}, $Q_{SBM}{}^{i}$, which need to be optimaized. Whereas non-

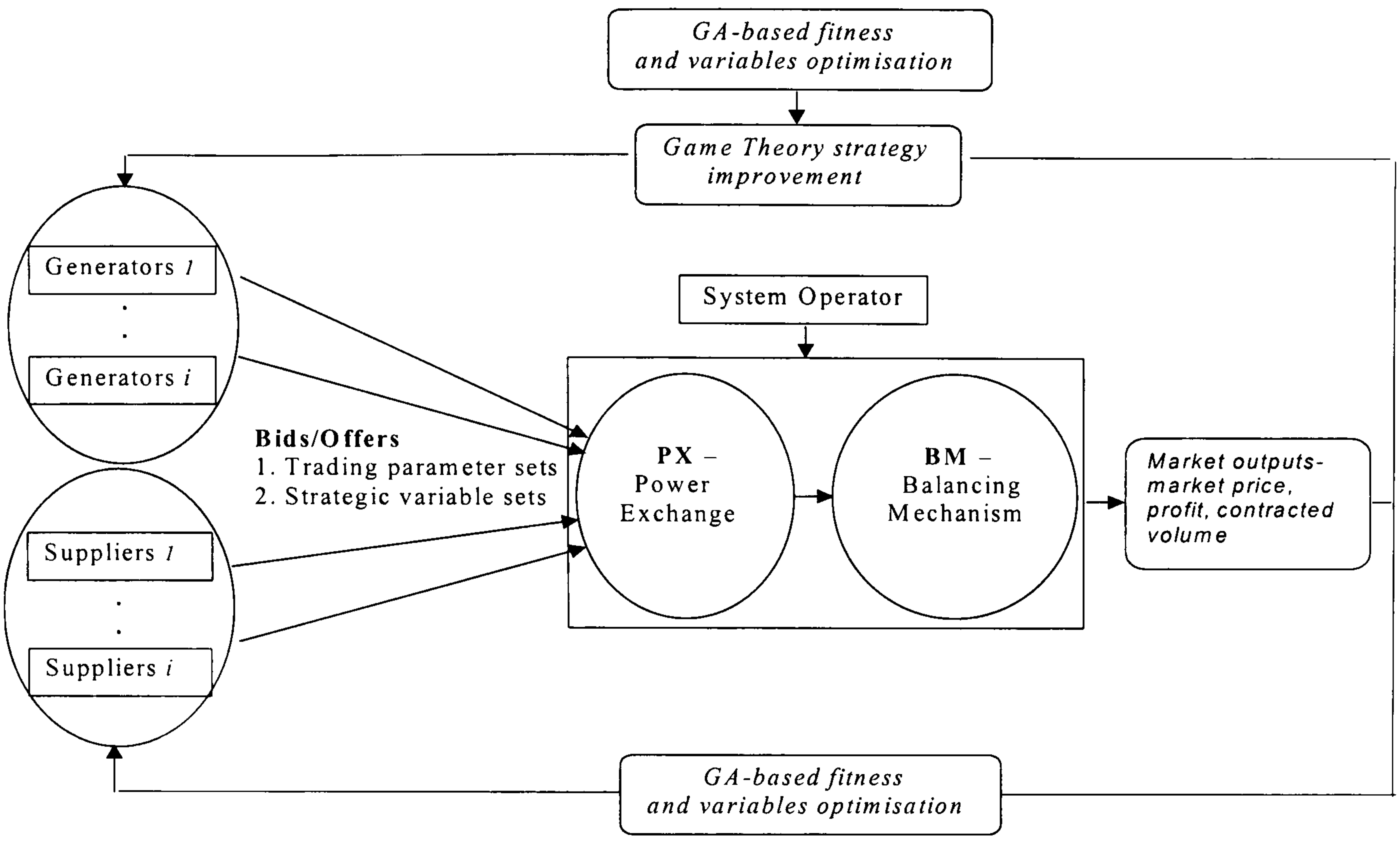

Figure 4.1: Block diagram of model structure

cooperative generators face a dilemma: on one hand, they need to offer selling prices higher than individual marginal cost $P_{mc}{}^{i}$ to cover the production cost; on the other hand, they have to make their selling prices appropriately low to win contracts. On the other side of this competition, supply companies also face the evaluation and optimization problems expressed in equations (4.2) and (4.3).

The major task here is to model generators and suppliers as decision-making participants. Many performancec and problems in the power market trading strategy developement do not have accurate measurement of their varibles. Pure maths is not enought here. Many incommensurable and competing objectives require to met before any solution is considered adequate. By the nature of Genetic algorithms, it can handle this inaccuracy more effectively than any other classical search algorithms and solve these optimization

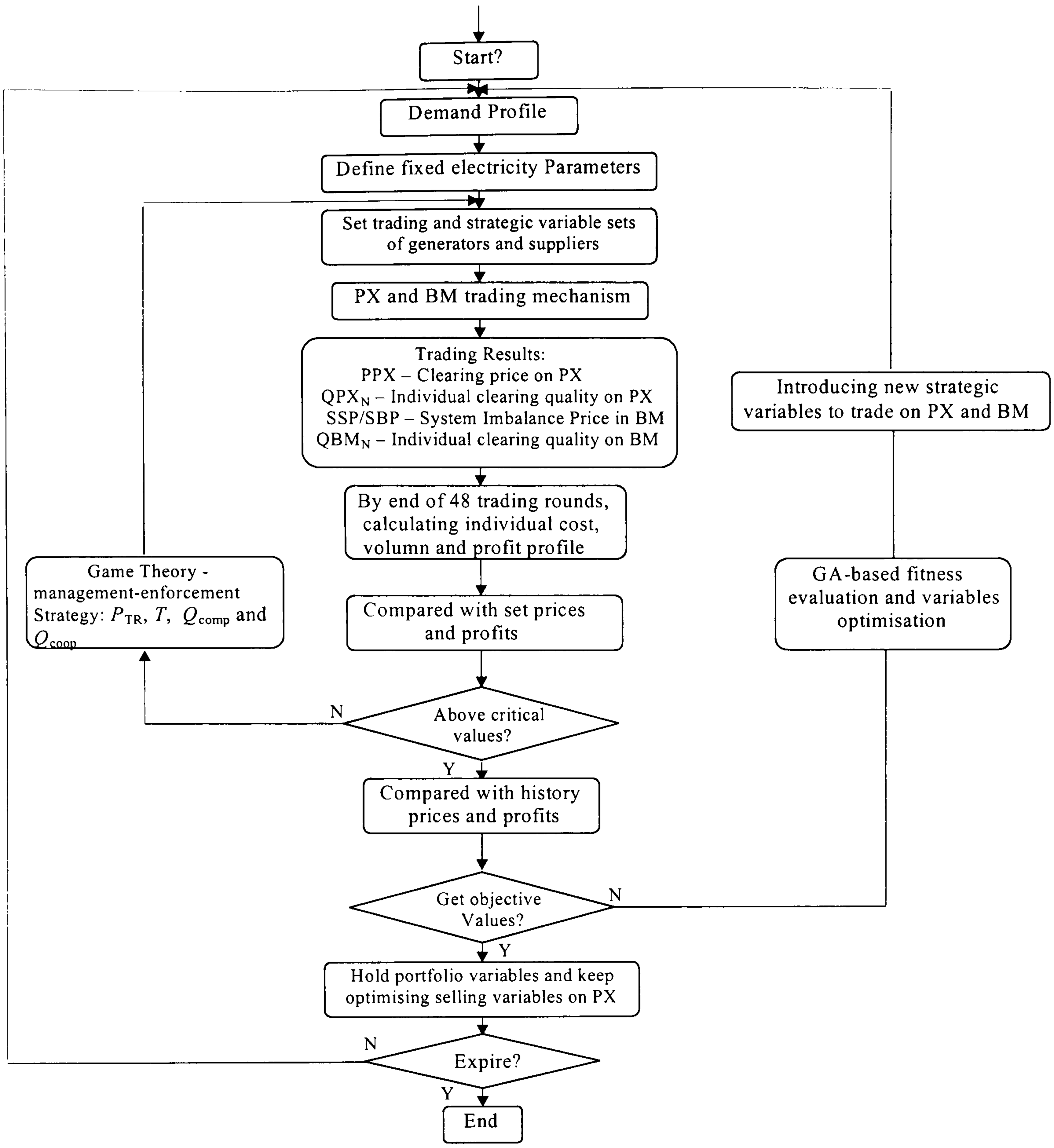

Figure 4.2: Flowchart of "loyal generators" gaming strategy

problems. Strategic variables and parameters of market players are mapped into GA chromosomes. Each auction round represents a generation. The GA population is divided into sellers and buyers. Information is exchanged solely within each type of trader. There is no information exchange between buyers and sellers other than the amount of profit they make. The fitness of each trader is proportional to the profit made in the auction round and is recalculated every round. Once a population of individuals with assigned fitness values arises, the next step is to preferentially select a subset of individuals that should survive into the next generation. These genetic operators introduced in Chapter 3 are performed on the populations.

Tournament selection is employed in this research. This is based on grouped competition. Here a population is divided into subgroups or members with the best fitness among the subgroups get selected. The subgroups could be any size, it is set as three in this model. The tournament is repeatedly held in which N individuals are selected from the current population and the fittest individual is copied into the intermediate population (this may be with or without replacement). The uniform crossover method is employed in this research, in which offspring individuals are created from a ramdomly genereted uniform bit mask.

An elitism scheme is also implemented. The elitism shceme retains the top performing individuals form each population, copies them to the new population. The rest fo the population is filled with individuals generated by the crossover and mutation as described above. The percentage of top performing individuals to be retained is set at the beginning of the auction run. The elite is not mutated.

Given gaming generators are concerned about the expected payoff in the long run rather than the pay-off in a particular round of auction, the average of 6 generations (6 trading rounds) fitness is utilized as one fitness.

5. Model Simulation and Validation Experiments

5.1 NETA Trading Mechanism Modelling

The NETA trading mechanism is simulated in this Chapter. The motivation behind developing this market model is to to model the dynamic and decision making behaviour of the UK electricity trading system, and to discover the impact of gaming trading strategies on the NETA. Although extensive effort has been made to simulate power trading mechanisms with their performance and player's strategies, the traditional modelling techniques, which solely apply noncooperative game theory and/or traditional optimization methodologies, have been not able to conduct the study on existence of gaming strategies and market power practiced in global electricity markets. It is understood that traditional mathematical methods are not suitable to demonstrate the decision-making procedure, especially search the optimal solutions. Therefore Evolutionary Algorithms is introduced to help building this morel. Not only can it generally provide the trade-off for each individual problem, also be capable of evaluating and determining the final suitable solution. The fundamental structure of the market modelling is based on market structure of NETA and developed from published documents of Office of Gas and Electricity Markets [3], [5], [17], [18], [19] and [58].

5.1.1 The Broad Objectives

Three broad objectives are set for the modelling activities:

- To gain insights into aspects of the new trading arrangements;
- To search for possibility and impact of market manipulation on the UK power market given Britain's generation companies make effort to attempt market power and gaming strategies;

- To provide a platform which potential participants can use to gain experience of the trading environment that they will face under NETA.

The first and second objectives are achieved by conducting a series of experiments using the simulation model that has been developed. The third could be achieved by encouraging the industry to participate in those experiments and then making the model generally available.

5.1.2 The Approach to Modelling

To capture all the markets expected to operate under the new trading arrangements and explore all their interactions within one model would be a considerable task and would result in a model of substantial complexity, both in its construction and its operation. This would lead to significant risks, including that:

- The development and operation of the model would be prohibitively time consuming;
- The results of any run of the model would be hard to interpret, as so many factors would need to be taken into account; and
- The model would be too complex for meaningful insights to be obtained from its use by potential participants.

The research therefore focuses its modelling efforts on the specific parts of the New Electricity Trading Arrangements proposals most likely to generate results of interest. A range of modelling approaches has been considered. The principal interest is not only to investigate what level of prices might be obtained, but also to explore how different incentives might influence participants' behaviour. It was therefore decided to commission an experimental simulation model, as this is fit best the need to assess behaviour by market participants.

5.1.3 The NETA Model

Since the interest is in the incentives to trade in the various markets that together make up the new trading arrangements, the modelling effort can not focus solely on the those elements that are being procured by the program, namely the Balancing Mechanism (BM) and the Imbalance Settlement Mechanism (ISM).

At the same time, as noted above, it cannot capture all the markets in their entirety. It is therefore decided to focus on trading in a Power Exchange (PX), with the assumption that prior trading has taken place on the forwards and futures markets, and assess the impact of the Balancing Mechanism and the ISM in terms of what trades take place in the PX, and what are left to those mechanisms. In doing this, the implicit assumption is that the PX trades are a proxy for trades in all the markets that might operate in advance of gate closure, including those with longer-term activities than the day ahead usually assumed for the PX.

It is accepted that this is only one of a number of approaches that could have been used and that other models could also provide insights into the operation of the markets under the NETA proposals.

5.1.4 Outline of the Model

The model simulates trading in a PX. A number of players trade in real time, each playing the role of a market participant and working from information on prior trades, production or consumption costs, capacity limits and potential prices, to develop trading bids and offers. The model simulates the operation of a PX and matches beneficial trades and then allows unmatched positions to be offered into the Balancing Mechanism; any open positions that are not closed out by the acceptance of offers or bids became subject to Imbalance Settlement. The overall results of trading are then analyzed and passed back to participants to allow them to amend their behaviour in future runs in the light of experience.

The trading model with these set of parameters introduced in Chapter 4 is experimented and then profits from the participants with complete non-cooperative strategy and coalition members are then calculated and compared in next chapters. A set of validation and experiments are carried out based on different system parameters on which the model scale is limited. The estimates used are consistent with those used in published studies on the NETA electricity market, i.e. actual demand profiles, generation and supply system parameters. There are five sorts of power generation concerned in this model, including gas turbine, oil, coal, combined cycle gas turbine (CCGT) and nuclear plants.

Because the flexibility of each kind of generation plant is different and it results in different market performance, it is reasonable to introduce the flexibility (maximal numbers of startups within one day) of each type of plants in the UK:

(1) Gas turbine and oil generation plants were classified as having three daily cycles.

(2) Midmerit technologies were classified with one and two cycles, which include CCGT and coal.

(3) Finally, the base-load plants (running in a nonstop regime) are the nuclear stations, which need to run continuously and specify zero cycle.

This is a reasonable way of incorporating some consideration of dynamic plant constraints. We define the parameter cycles for each type of plant (see above). Thus, base-load plants with high startups or inflexible technology need to run continuously and specify zero or just one cycle. Flexible plant with low startup cost can have a higher number of cycles. The availability of installed capacity is specified by individual generator's self-parameter.

Plants owned by each generator are specified at the generating set level. Plants of the same type are assumed to have similar operating generation cost (marginal costs, fixed costs including startup costs, and no-load costs). This model does not take into account the fixed cost. Thus, each agent has an objective for the position of each plant in the load duration curve (we identify for each plant the maximum number of cycles per day that it can operate).

We impose some lower bounds of rationality through operational rules.

1) Portfolio Management: a plant with higher or equal number of cycles will never undercut the offers of another plant with equal or less number of cycles.
2) Noninterruption: plants that have to run continuously or plants with one cycle may run without profit in certain hours of the day.
3) Peak Premia: Peak plant never offer prices below marginal cost.

The estimated marginal generation costs for each plant ranged from £9/MWh to £88/MWh. The base-load generation plants, i.e. nuclear, combined cycle gas turbine (CCGT), and some large coal plants, are operated in lower marginal costs. The gas turbines and oil plants are associated with higher marginal costs. Generation plants on the same type are assumed to have similar marginal costs. The estimates used are consistent with those used in other published studies on the UK generation market, as well as with known data on plant efficiencies and fuel costs. The estimated marginal generation costs P_{mc}^{i} for each generator and assumed maximal generation capacity, Q_{smax}^{i}, of each generator of each generation type are presented in Table 5.1:

Table 5.1 Generators' system self-parameters

Type of generation plants	**Nuclear**	**Combined cycle Gas turbine (CCGT)**	**Large coal**	**Gas turbines**	**Oil**
Marginal generation cost (£/MWH)	24.50	9.72	33.23	66.95	87.91

For suppliers, their individual self-parameters are assumed as identical and the estimated marginal revenues C_{mr}^{j} for each supplier is set as 71£/MWH.

Once this is completed, the generators' profits and suppliers' revenues are calculated, so that each seller and buyer will respectively get their fitness on each round. The operating cost function of each generator, usually is represented as the following form;

$$C_i(Q_i) = a_i + b_i Q_i + c_i Q_i^2 \qquad i = 1, 2, \ldots n \qquad (5.1)$$

$$Q_i^{min} \leq Q_i \leq Q_i^{max}$$

where

$C_i(Q_i)$ operating costs of entity i with generation;

Q_i^{min}, Q_i^{max} minimum and maximum generation output of entity I;

a_i, b_i, c_i constants.

The profit PG of generation entity i at time t will be;

$$PF_{i,t} = PXP_t \, Q_{i,t}^{allocated} - C_i \, Q_{i,t}^{allocated} \qquad (5.2)$$

where

PXP_t market clearing price (MCP) at time t,

$Q_{i,t}^{allocated}$ allocated generation volume of entity i.

The profit PS of supplying entity j at time t will be;

$$PS_{j,t} = C_{mr}^{j}\, Q_{j,t}^{allocated} - PXP_t\, Q_{j,t}^{allocated} \quad (5.3)$$

where

C_{mr}^{j} marginal revenue of entity j with supplying;

PXP_t market clearing price (MCP) at time t,

$Q_{j,t}^{allocated}$ allocated supply volume of entity j.

5.1.5 Running the Model

A run of the model proceeded as follows.

- Forwards contracts arising from any vertical integration and the customer base are represented by an 'opening position' provided to each participant before a model run begins.

- The PX opens for trading and participants post offers and bids as introduced earlier.

- There are 48 trading rounds running each day. The market both clears any mutually acceptable offers and bids (in other words an offer at or lower than a bid) and allowed participants to accept an extant offer or bid. The clearing procedure is based on the methodology introduced in Chapter 4. The Market Clearing Prices (MCP) will be used as one of benchmarks to asses the different trading strategies. Until the end of trading, participants were allowed to post new offers and bids and to remove unaccepted extant offers and bids.

- Once the relevant trading period was closed, participants submit FPNs for generation to the system operator and, if they so choose, Balancing Mechanism bids.
- The model's system operator(SO) then optimizes and balances the system at a single turn, accepting offers and bids necessary to do this and allowing for any random perturbations in demand or generation failures introduced by the model operator. System and participant imbalances were then calculated.
- Imbalance prices and payments are calculated. Participants who are out of balance are charged or paid at energy imbalance prices.
- Results are collated and participants are informed how they have performed.
- Participants' strategies and strategic parameters adopted in previous trading round are evaluated and new parameters are searched out by optimization tool for next round.

In the experiments conducted by the program, the model is run with up to a number of players representing a variety of industry participants. A supervisor, acted as both market and system operator, takes overall charge of each run.

The model provided the following types of output:

- Traded prices in the PX;
- Balancing Mechanism trades prices;
- Imbalance Settlement prices and volumes;
- Distribution of profits between participants.

- Costs of generation;
- Short run profitability for each participant.

5.1.6 Simplification

Before evolving the strategy, some features of this model are described as following:

- Trading participants include *m* electricity generators (sellers), as some generation companies that sell energy in the market, *n* power suppliers (buyers), as energy service companies, i.e. power transmission companies that buy electricity to serve end-users, and the System Operator (SO) who operates the markets;
- Bilateral bidding mechanism is adopted following the fact on NETA;
- Collusive generators are concerned about the expected payoff in the long run rather than the pay-off in a particular round of trading;
- System Operator broadcasts 2-14 day-ahead demand forecast and provides real time information and offers made and accepted, as the same case on NETA;
- The total amount of bidding generations is enough to provide the market demand (i.e., $\Sigma_i\, Q_{i,t}^{bid} \geq L_{t,}$ where $Q_{i,t}^{bid}$ denotes the bidding generation of entity *i*, and L_t denotes total system demand at time *t*);
- The bidding generation of each player is less than the total system demand in a specific spot market (i.e., $Q_{i,t}^{bid} < L_{t,}$).

The model makes several simplifications. These include the following:

- All trades contain price and quantity only. Other contract forms, such as caps, collars and load following were excluded;

- Plant technical constraints, such as ramping, are not modeled or included in the Balancing Mechanism calculations;

- Transmission constraints and loss are not modeled or included in the Balancing Mechanism calculations;

- Offers and bids to the Balancing Mechanism were made once only;

- The Balancing Mechanism is treated as a 'one-shot' market and the real time effects of emerging Balancing Mechanism acceptances is not modeled.

5.1.7 Scenarios in the Experiments

The experiments look at two types of scenarios:

- Validation test is carried out in the first set of experiments. The scenario is run with an approximation of the market structure likely to be in place in around October 2004. All these experiments are based on the average winter daily demand profile in October published by NETA, shown earlier in Figure 4.3 in this Chapter. On the validation test, all market players only employ non-cooperative strategy to conflict on this marketplace at which no gaming behaviour is attempted. The relationship among each generator is completely competitive, following the general reality on NETA.

  The feasibility and efficiency of this model and analysis technique are tested in this examination. The experimental results will present if the sequences of strategic actions designed for the model is capable of producing similar outputs from the real market, in the absence of disturbance.

- Application experiments are made in Chapter 6. Cooperative gaming strategies will be covered on the second and third tests based on different model scales.

Because the modelling exercise employs only a certain number of players, some simplifications to the full complexity of the anticipated structure have to be made introduced previously. As well as the two main scenarios, sensitivities are run either with shocks, such as a generator failure or a change in fuel prices, or with a changed industry structure, especially greater vertical integration.

5.2 Setup of Validation Experiments

In order to evaluate performance of this research technique, the model is examined in this section. The modelling results are compared with real data of NETA to identify its efficiency and against unseen data.

The model is organized into running 4 weeks in October 2004, given 20 trading days totally. Therefore each week has 5 trading days. On each trading day the market mechanism runs 48 iterations according to the reality of NETA market, correspondingly they are represented by 48 generations in GA algorithms.

Each trading day starts with the System Operator (SO) publishing one-day demand forecast, then the market participants buying (selling) electricity in the Power Exchange (PX). In the PX, the suppliers try to buy, at a price as low as possible, the amount of electricity needed to fulfill their contract covering objectives. Oppositely, the generators will try to sell at a price as high as possible. On each single trading round in PX market, each market participant from two sides respectively submits a set of bids (offers) including prices – responding volumes, i.e., £11.50/MW – 11.23MW, £16.62/MW – 18.30MW, . . . £68.42/MW – 78.70MW, and so on, to the SO. The overall matching procedure follows the market running process introduced in section 2.2.2 in Chapter 2.

At gate closure, each participant will know exactly how much it has sold or bought and provides the SO with its final physical notifications (FPNs).

Then the trading in the Balancing Mechanism (BM) begins. The System Operator total demand forecasts are common knowledge in the industry, period by period (and it is assumed for these experiments that the forecasts are accurate). Nevertheless, each one of the suppliers will have some uncertainty predicting its own demand. Thus, using their FPN's and its demand forecast, the SO calculates the total system surplus or shortfall for each. Given this total system position, the SO will accept either spillage or top-up in the BM. The trades in the BM are done between the SO and each one of the generators and suppliers offering (bidding) the spillage (top-up) into the BM.

After all trading in the BM has occurred and the SO has bought or sold whatever energy is needed to balance the system, the SO will compare the contract positions (quantities contracted), plus whatever is bought or sold in the BM with the actual position (quantities generated or consumed) for each one of the suppliers and generators (plant by plant) to calculate the imbalances, then the imbalance prices and volumes of each generator and supplier are calculated. If the SO accepts spillage, the will be defined as the weighted average of the offers accepted in the BM. Otherwise, if the SO accepts top-up, the SSP will be defined as the weighted-average of the bids accepted in the BM. Thus, if a trading participant is long (short) when the system is short (long), there will be no imbalance price defined for its case. We adopted a rule that the SO has indicated it may have to use if there are insufficient bids (offers), which is to take the average of past SBP (SSP) values for that particular hour for the SBP (SSP) not defined. The formulations of calculating SBP and SSP were presented in Chapter 2.

It should be noted that a supplier without load management will not be influencing the net position of the system and so its bids in the BM are only to cover its own uncertainty to avoid the imbalance charges. The bids (offers) of these players will only be accepted if there is an arbitrage opportunity.

The objective of the power generators in this experiment is to search for optimal bidding points to sell power at prices as high as possible in PX market, and no cooperative strategy is adopted in the validation experiment. Whereas, the objective of the suppliers is to buy power at prices as low as possible. However, on the other hand, since the imbalance penalties in imbalance settlement system are much different from market clearing prices in wholesale market PX where most of power volumes are traded, the risk of having to buy and sell in this way through the Balancing Mechanism with its very volatile prices emphasises the importance of market participants' trading strategies. A lot of efforts with introducing traditional mathematical methods have not been able to solve this kind of challenges with many uncertainties and incommensurable objectives. Evolutionary Computation, which was not so far effectively employed in this field, plays a vital role to lead the search process and solve the optimization problem.

By the nature of Genetic Algorithms, the trading strategies parameters are evaluated and determined by GA. In the task each seller runs its own GA. Each participant's portfolio parameters are mapped into a GA's chromosomes. The trading procedure and searching process are described in Figure 5.1:

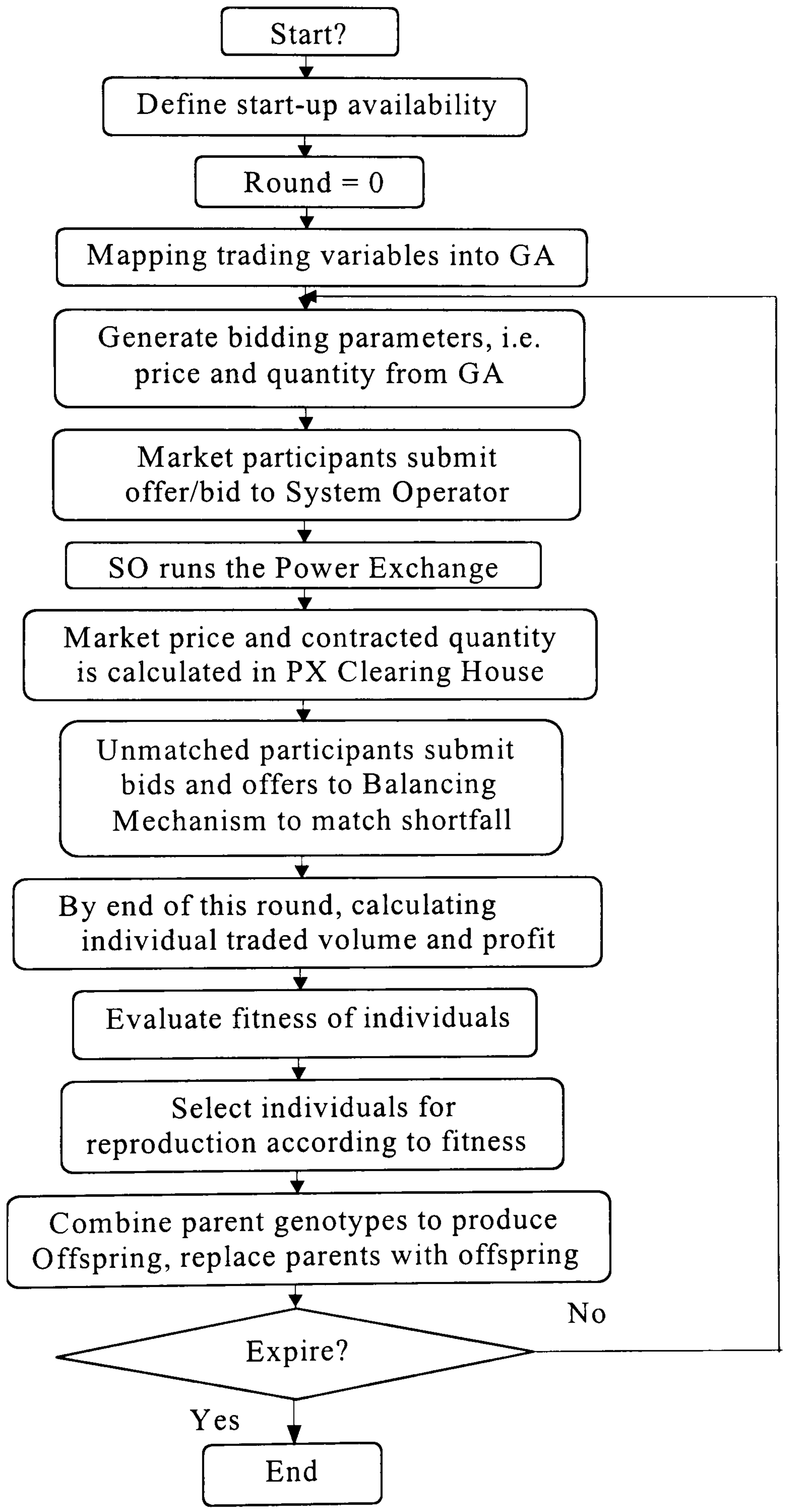

Figure 5.1: Flowchart of generators strategy algorithms

5.3 Validation Experiments and Experimental Results

To exercise the model's veracity and efficiency, the validation experiments are carried out against standard daily demand profile in October 2004, published by NETA and shown in Figure 5.2. The experimental model runs for 4 trading weeks continuously, given 20 trading days, at which there are 5 working days per week and 48 trading iterations within one day. As introduced in chapter 4, there are five sorts of power generation type investigated in this model, including gas turbine, oil, coal, combined cycle gas turbine (CCGT) and nuclear power generators. The number of generators, m, is assumed to 15, given 3 generators each generation type, and suppliers', n, is assumed to 10 in this experiment. The generators of the same type are assumed to have similar marginal costs and generation capacity. The estimated marginal generation costs $P_{mc}^{\ i}$ for each generator and assumed maximal generation capacity, $Q_{smax}^{\ i}$, of each generator on each generation type are presented in Table 5.1 below. The total available generation capacity is set as 66.7GW. Oppositely, the maximal market demand is 50GW, which is same as the market scale of the NETA. Hence the average maximal demand, $Q_{dmax}^{\ i}$, of each supplier is 5000MW. The ratio of maximal market demand to total available generation capacity is therefore 0.75, following the real situation in NETA.

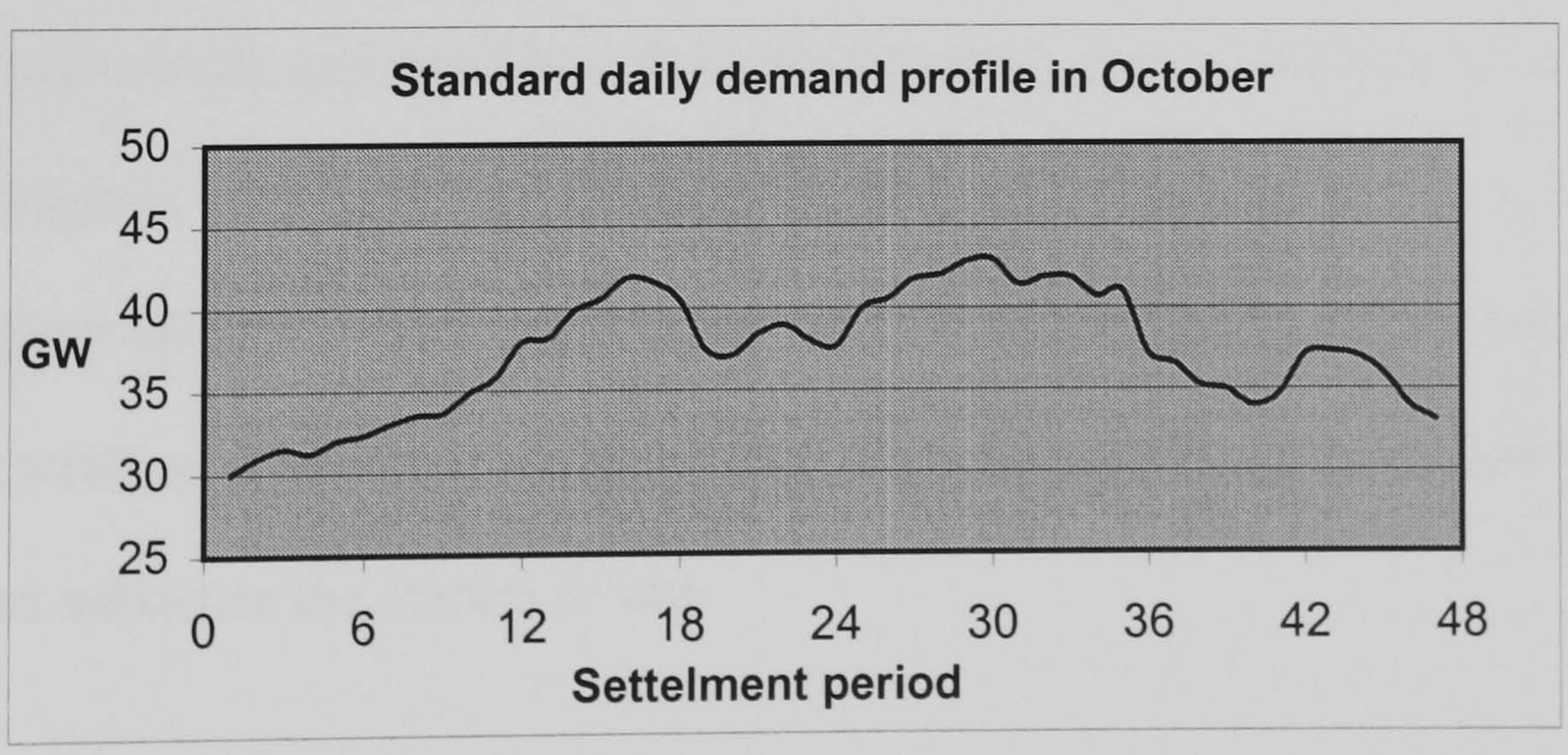

Figure 5.2: Standard daily demand profile in October 2004 [63]

Table 5.2 Generators' system self-parameters

Type of generation plants	Nuclear	Combined cycle Gas turbine (CCGT)	Large Coal	Gas Turbines	Oil
Marginal generation cost (£/MWH)	24.50	9.72	33.23	66.95	87.91
Maximal generation capacity (MW)	4450	4450	4450	4450	4450

5.3.1 Modelling Results

In order to validate the model's performance, three major model outputs, the wholesale market clearing price *PXP*, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP*, are presented and evaluated with NETA data below.

5.3.1.1 Traded Market Clearing Prices in Power Exchange

In order to have a better view of how the model works and the evolution of market participants strategies, the model's running process, given 20 days, are divided into four consecutive stages, given the first week, the second week, the third week and the fourth week. These three trading results, including PX market clearing price *PXP*, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP*, in each trading week, are separately represented by three typical mean daily trading results. Consequently for each of the three model outputs, there are 4 sets of experimental results corresponding to the four trading weeks, and one set consists of 48 experimental outputs which are coming from 48 trading iterations in which the market player take part within one trading day. These trading results are demonstrated week by week to discover how the market players learn through GA and how their behaviours influence the market results.

As introduced previously, the PX trades are a proxy for trades in all the markets that might operate in advance of gate closure, including those with longer-term activities. The market clearing price in PX, *PXP*, calculated by equation (2.1), which is the fundamental output and evaluation parameter of this model, is presented following.

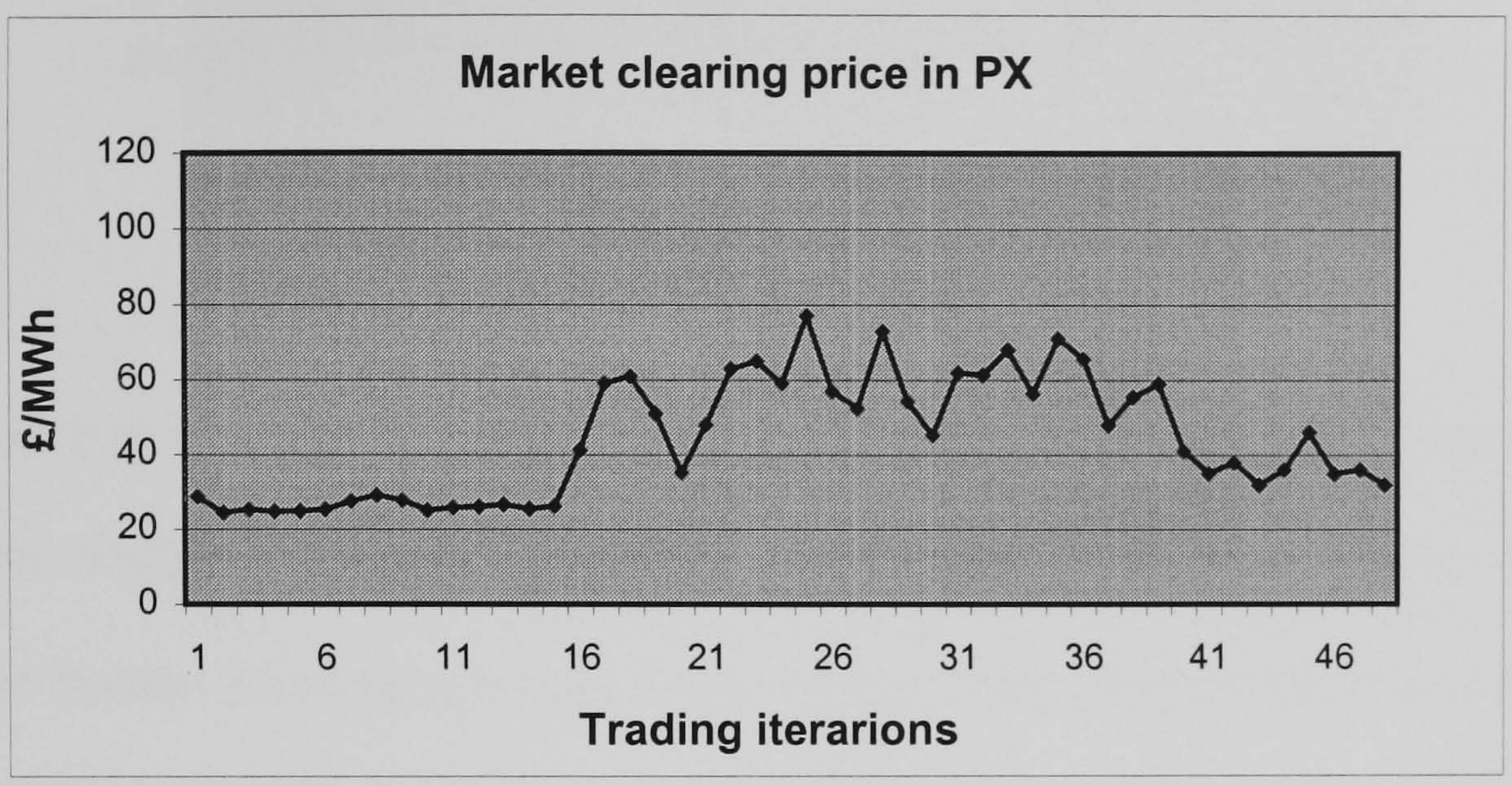

Figure 5.3: Mean daily market clearing price in PX in the first trading week

As one of the most important system outputs and model performance references, the market clearing price in Power Exchange, *PXP*, in each of the four weeks, is represented by a set of mean daily market clearing price. The *PXP* in the first week is aggregated into a mean daily PX clearing prices and is demonstrated in Figure 5.3. This price value curve is consisted of 48 *PXP* values. We can see that in the initial stage there are a large number of price spikes rising up, and the *PXP* is waving around a high level after the first peak demand period starts at 7:00am to 8:00am, ranging from £37/MWh to £88/MWh.

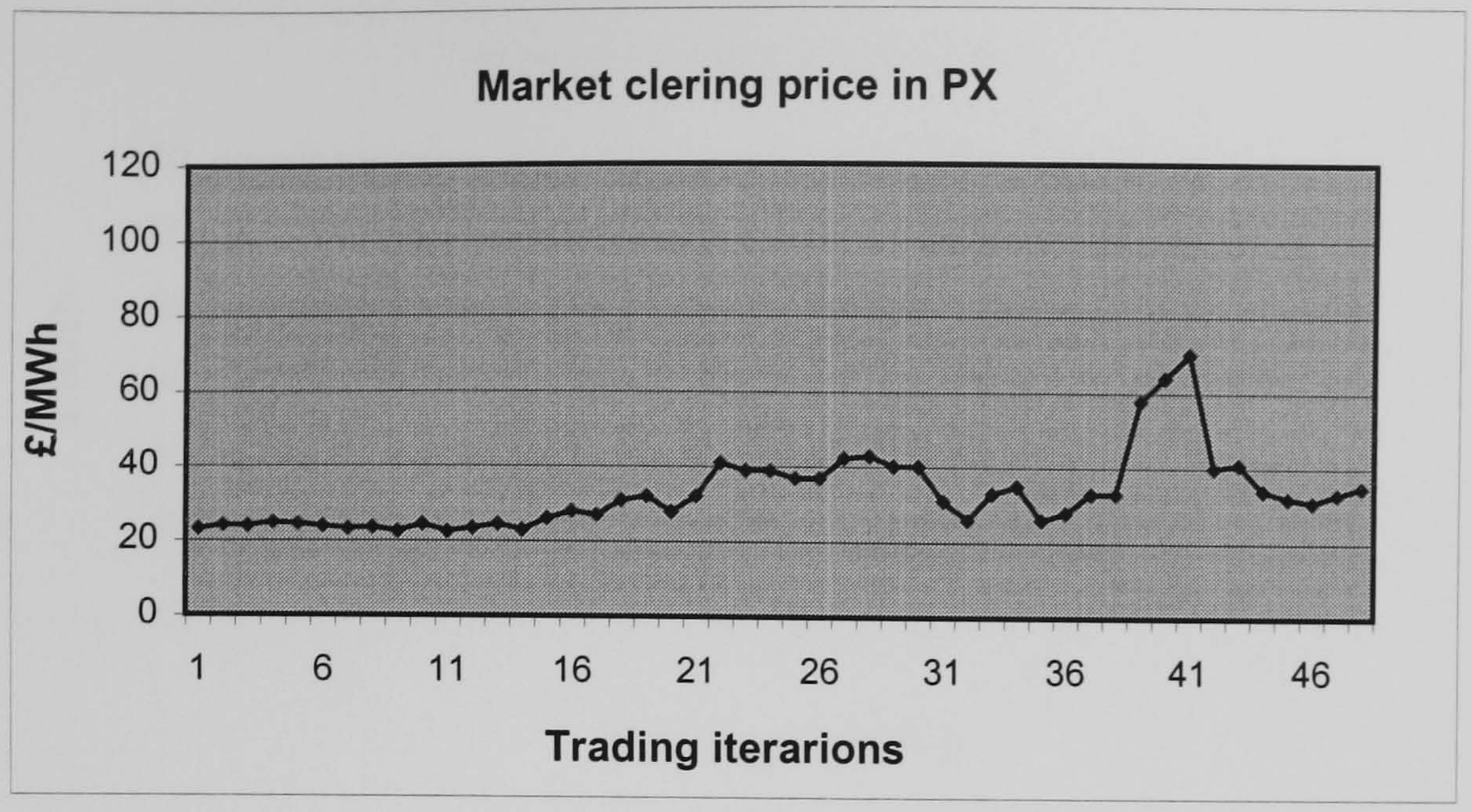

Figure 5.4: Mean daily market clearing price in PX in the second trading week

Since the trading runs over 4 periods continuously, there are 4 sets of Power Exchange market clearing prices as experimental results. Figure 5.4 shows the mean daily *PXP* in the second week.

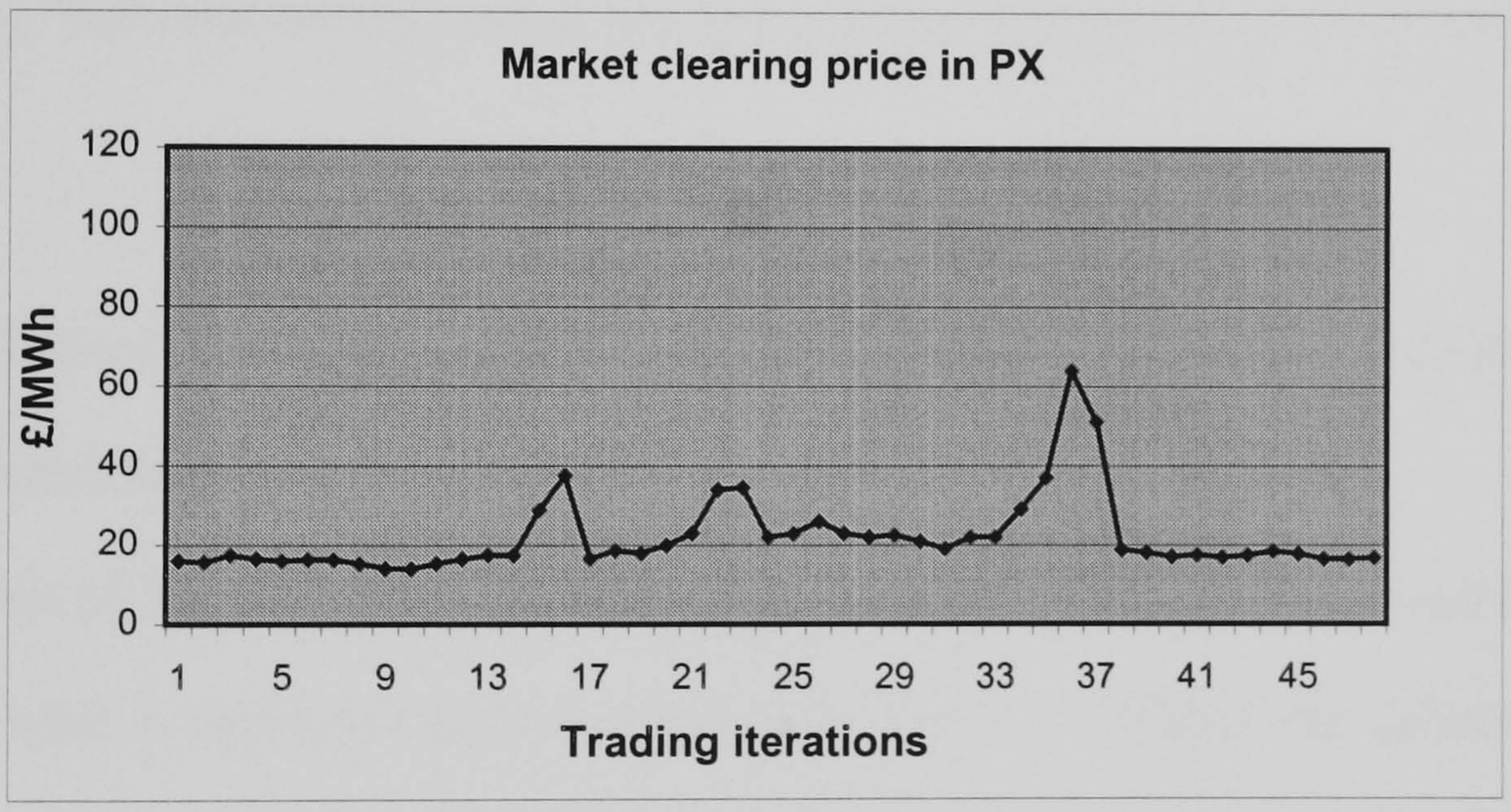

Figure 5.5: Mean daily market clearing price in PX in the third trading week

Figure 5.5 shows the development of mean daily *PXP* in the third week. Figure 5.4 and Figure 5.5 show two clear trends exhibited on these two weeks. First, the PXP is going down along with the model's running and strategies evolution. Second, the price spikes have less appearance.

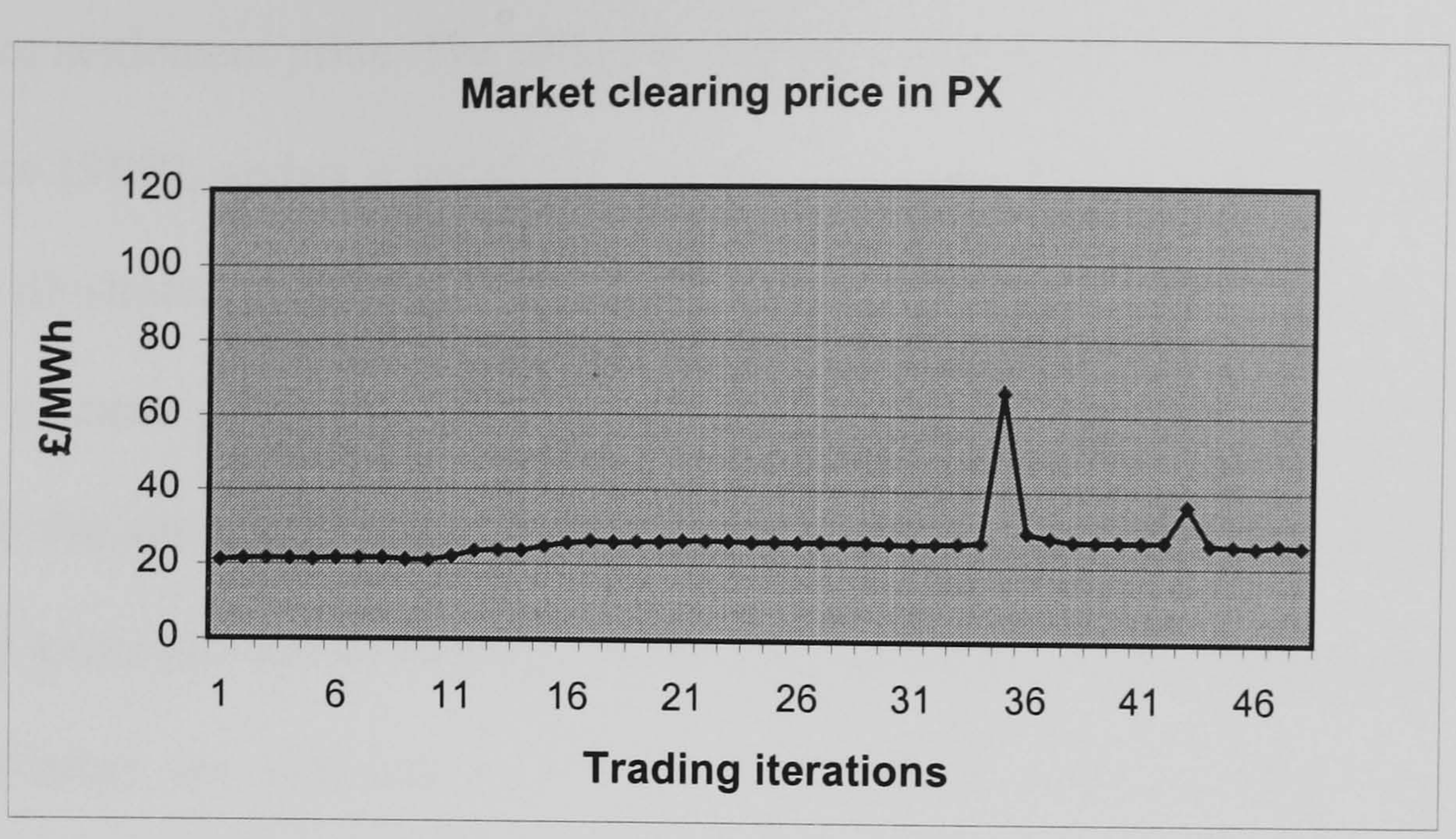

Figure 5.6: Mean daily market clearing price in PX in the forth trading week

Figure 5.6 illustrates mean daily *PXP* from the last trading week. An observation is evident that the *PXP* remains stable in most of the trading periods. There are only two price spikes rising in peak demand periods, 17:00pm to 18:00pm and 21:00pm to 22:00pm. The detailed discussion for these results will be taken in the end of this chapter.

5.3.1.2 Traded Prices in Imbalance Settlement System – System Sell Price and System Sell Price

This is one of the main principles of trading electricity. If a market participant fails to achieve what it predicted then it is going to cost it to balance the system. In the imbalance settlement process, the generators' metered generation and suppliers' metered demand are compared with the contractual positions they notify. The sum total of contracts negotiated in PX is added together to arrive at these contract positions. Participants that act both as generators and suppliers will be exposed to separate production and consumption imbalance charges for the two sides of their business. The difference between the amount of electricity bought and sold under contracts and the actual amount produced and consumed is calculated by the imbalance settlement price. The price for buying more energy is known as the System Buy Price (SBP), and is a weighted average of accepted Offers and calculated by a function illustrated in chapter 2. Generally it is higher than the *PXP* because it reflects the cost of extra generation at short notice. Conversely, the price for selling excess energy to the system the System Sell Price (SSP), is a weighted average of accepted Bids and generally lower than the forward price, reflecting the relatively low price that generators are prepared to bid to SO to reduce output at short notice. It is calculated by the other function introduced in chapter 2. The same goes for suppliers.

Figure 5.7, Figure 5.8, Figure 5.9 and Figure 5.10 reveal the effect of market participants' strategies on the imbalance settlement process in terms of showing the other two important reference parameters, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP*. Since the market model's trading process is divided into four consecutive weeks, for each of these two imbalanced settlement prices, there are four sets of mean daily prices corresponding to the four trading weeks, separately. There are 48 price values in each set representing 48 trading iteration results from each typical trading day.

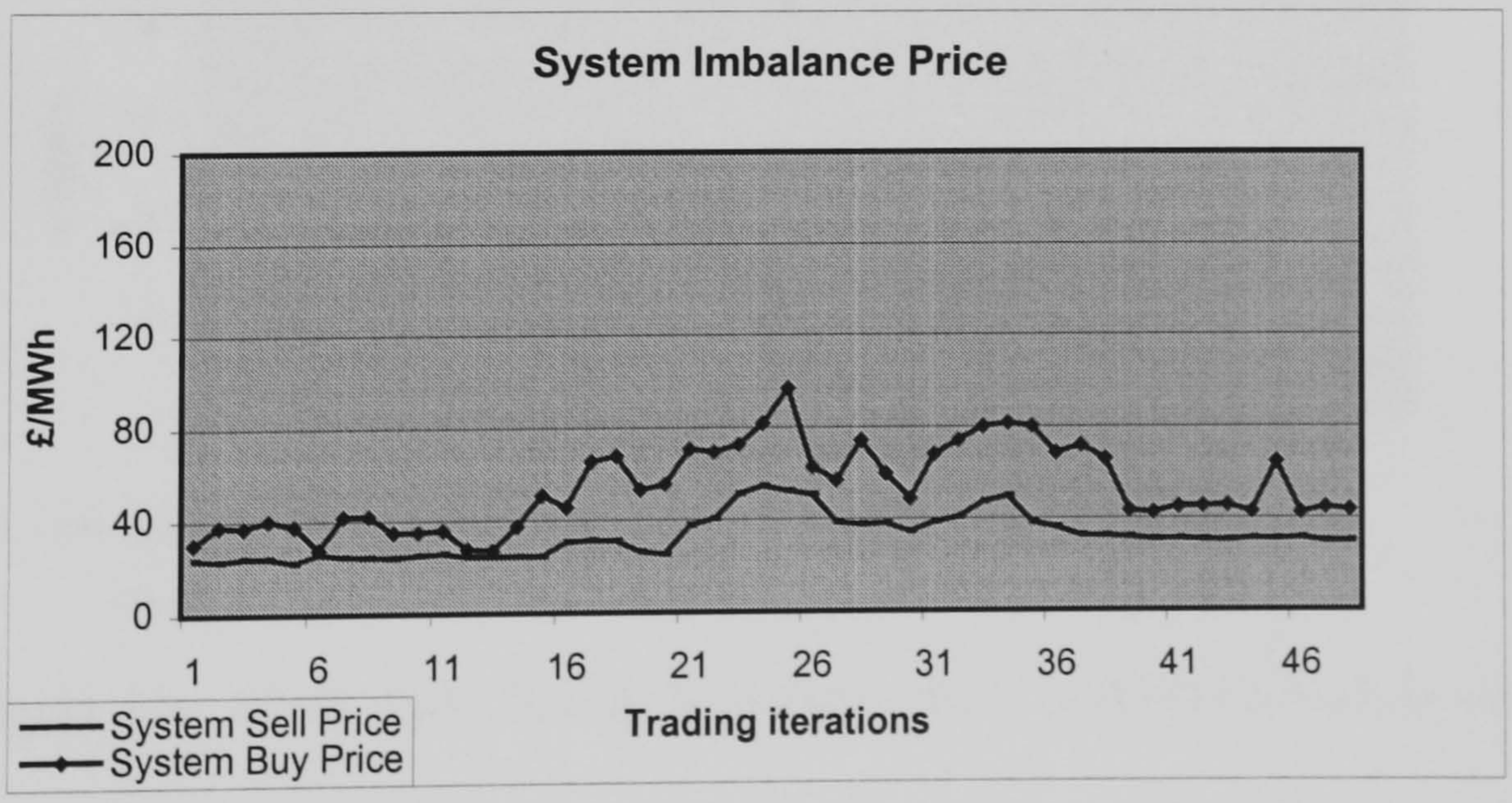

Figure 5.7: Mean daily System Imbalance Price in the first trading week

Figure 5.7 demonstrates the mean daily price curves of the imbalanced settlement prices *SBP* and *SSP* in the beginning week.

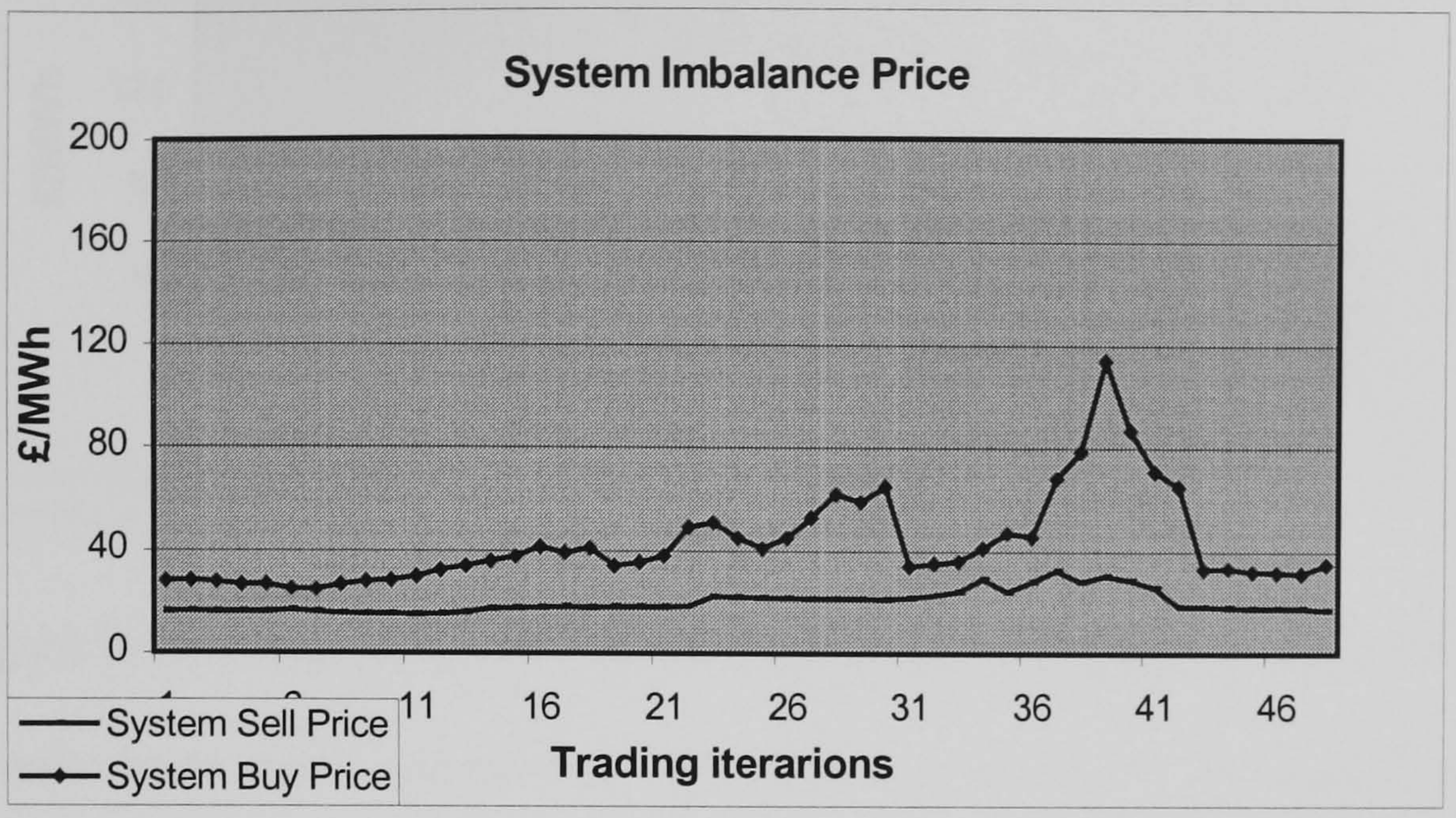

Figure 5.8: Mean daily System Imbalance Price in the second trading week

The mean daily price imbalance settlement prices curves in the second week are presented in Figure 5.8 above. Based on the figures shown here and in previous section, when *PXP* curves has price spike arising, so does the System Buy Price during the same trading period, and the *SBP* is considerably higher than the price in PX market.

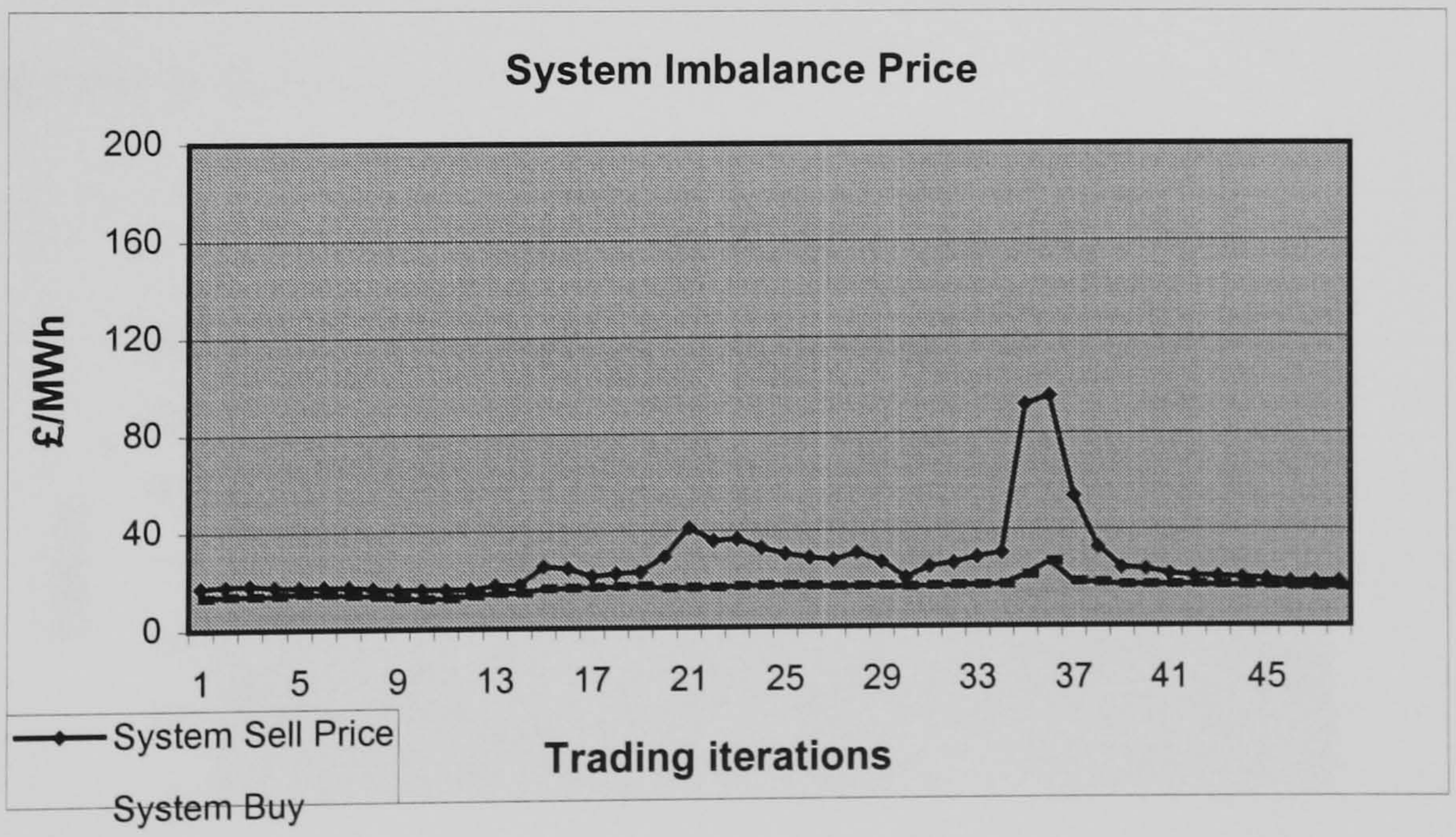

Figure 5.9: Mean daily System Imbalance Price in the third trading week

Figure 5.9 shows the development of mean daily imbalanced settlement prices in the third week.

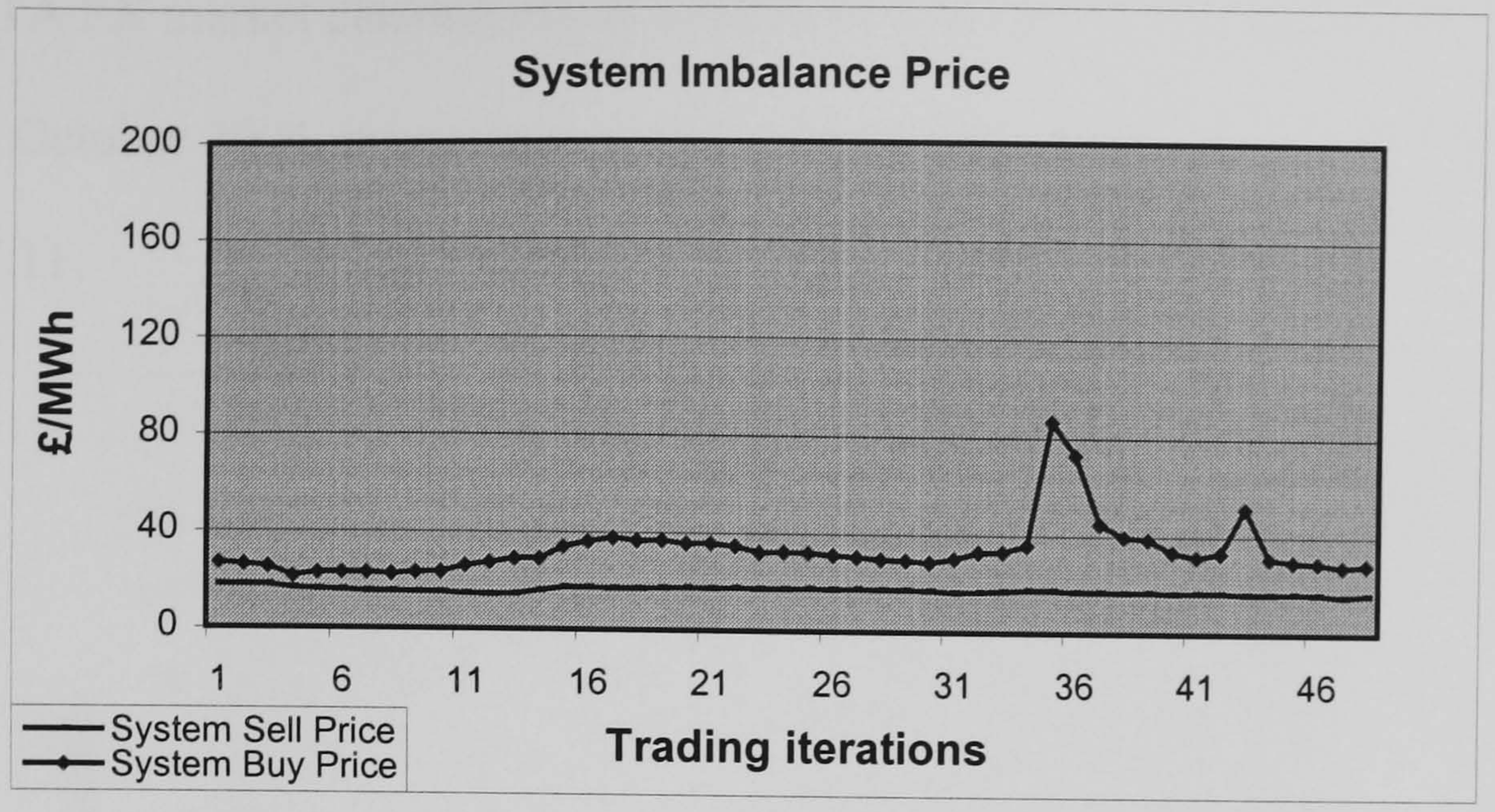

Figure 5.10: Mean daily System Imbalance Price in the forth trading week

The model's mean daily imbalanced settlement prices in the last trading week are introduced in Figure 5.10. Next, we shall proceed to investigate the results efficiency against real NETA data.

5.3.2 Discussion of Modelling Error

To asses the accuracy of the market model, the NETA market outcome data corresponding to the standard daily demand profile in October 2004 which is shown in Figure 5.2, are presented as benchmark data in Figure 5.11 to Figure 5.18. Then the modelling error is measured next.

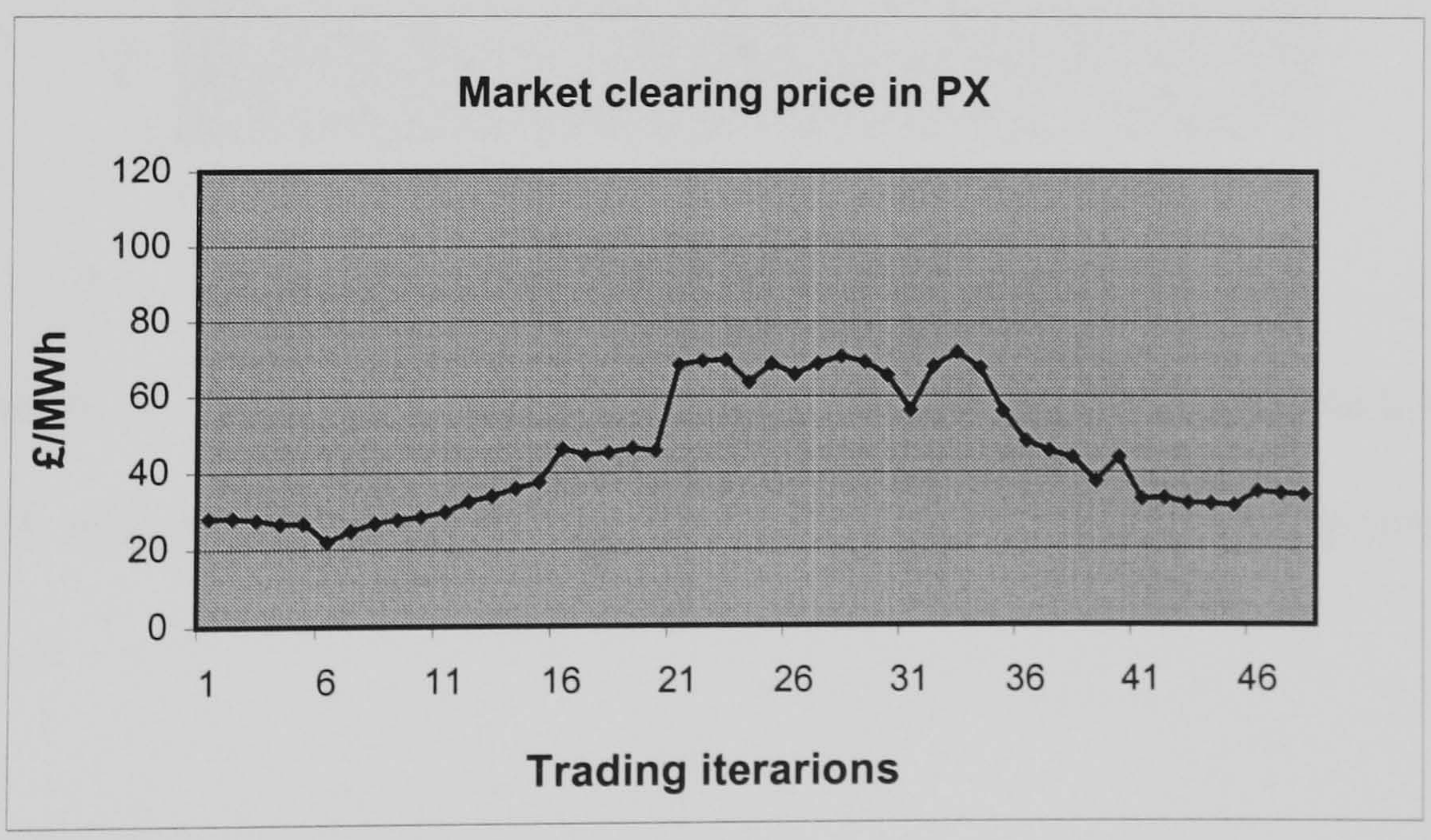

Figure 5.11: Mean market clearing price on NATE in the first trading week

The NETA PX market clearing prices which are from the trading happened in the first week in October 2004, is aggregated into a single daily price curve and illustrated in Figure 5.11.

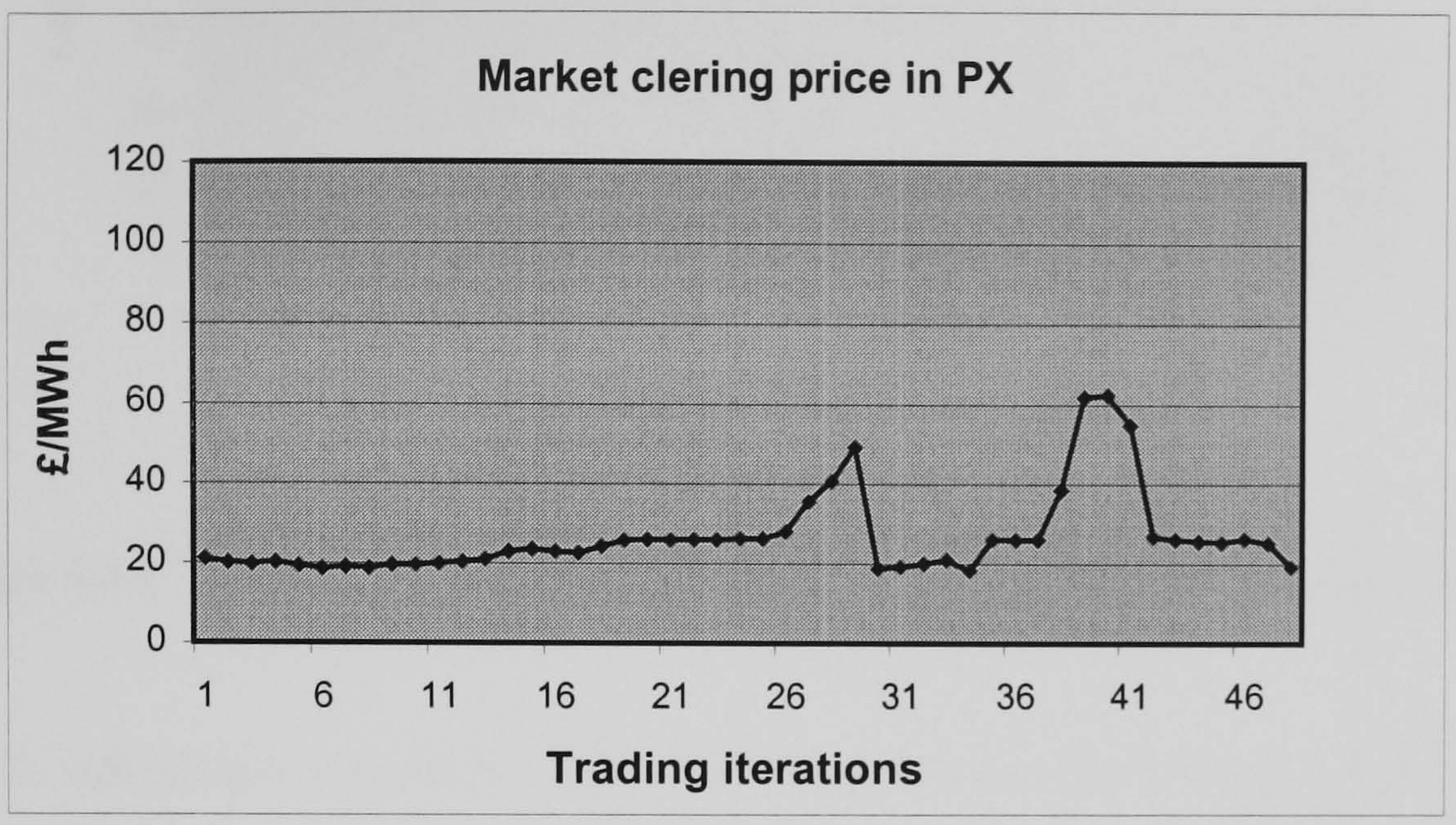

Figure 5.12: Mean market clearing price on NATE in the second trading week

The NETA mean daily prices in the second week in October 2004 is demonstrated in Figure 5.12.

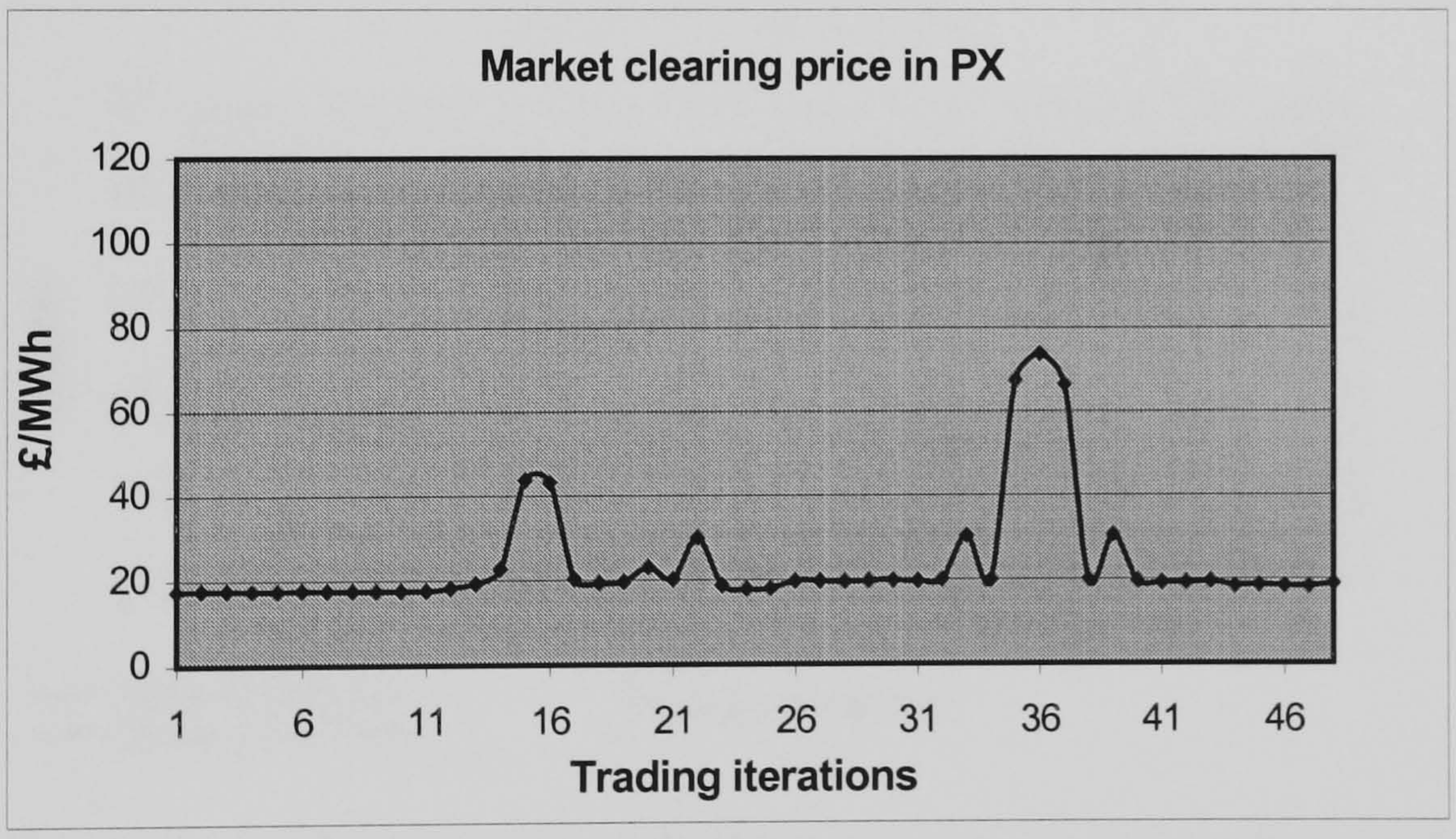

Figure 5.13: Mean market clearing price on NATE in the third trading week

The NETA mean daily prices in the third week in October 2004 is shown below in Figure 5.13.

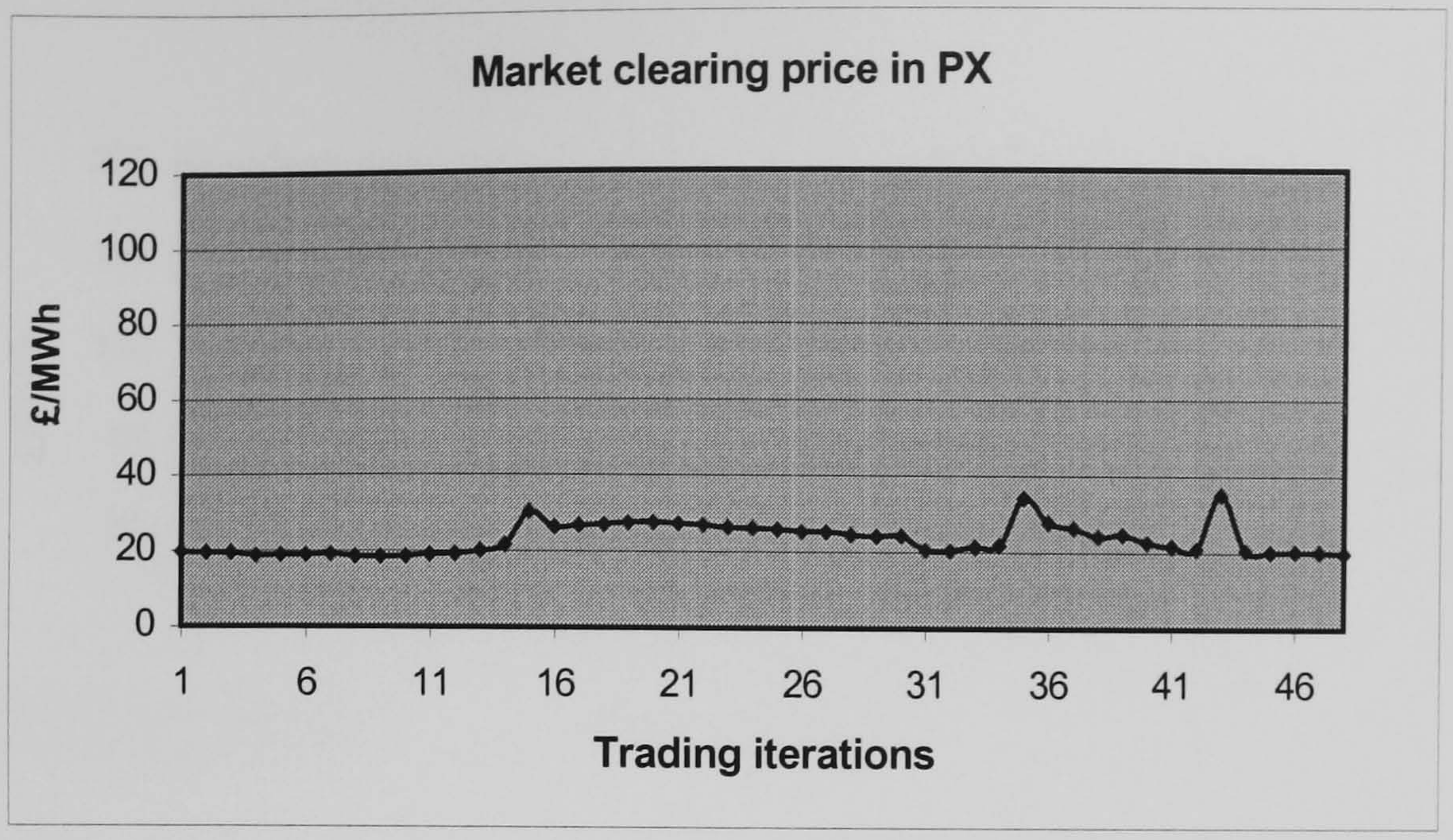

Figure 5.14: Mean market clearing price on NATE in the forth trading week

The NETA imbalance settlement prices which are from the trading happened in the first week in October 2004, is aggregated into a single daily price curve and illustrated in Figure 5.15.

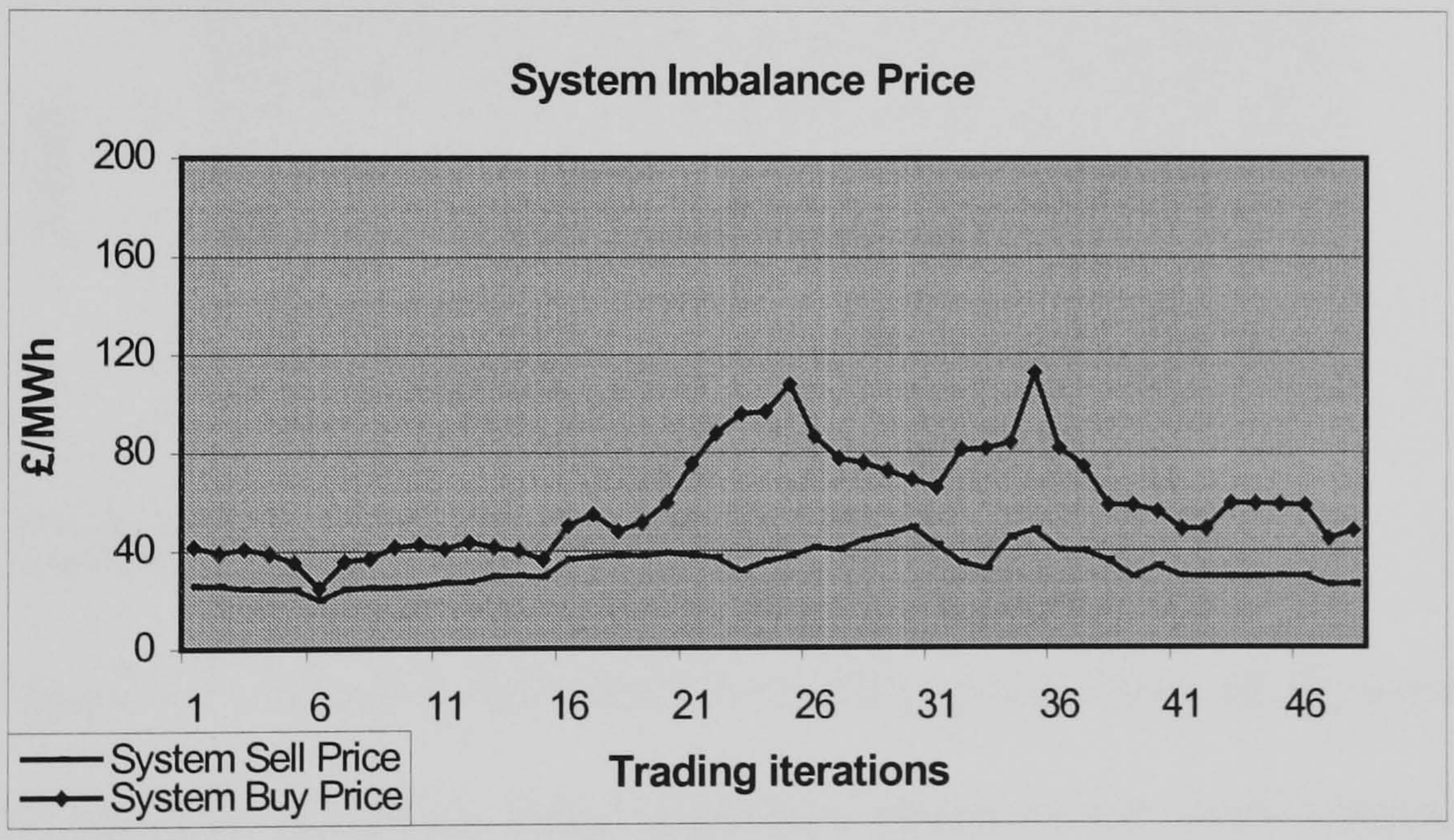

Figure 5.15: Mean System Imbalance Price in the first trading week

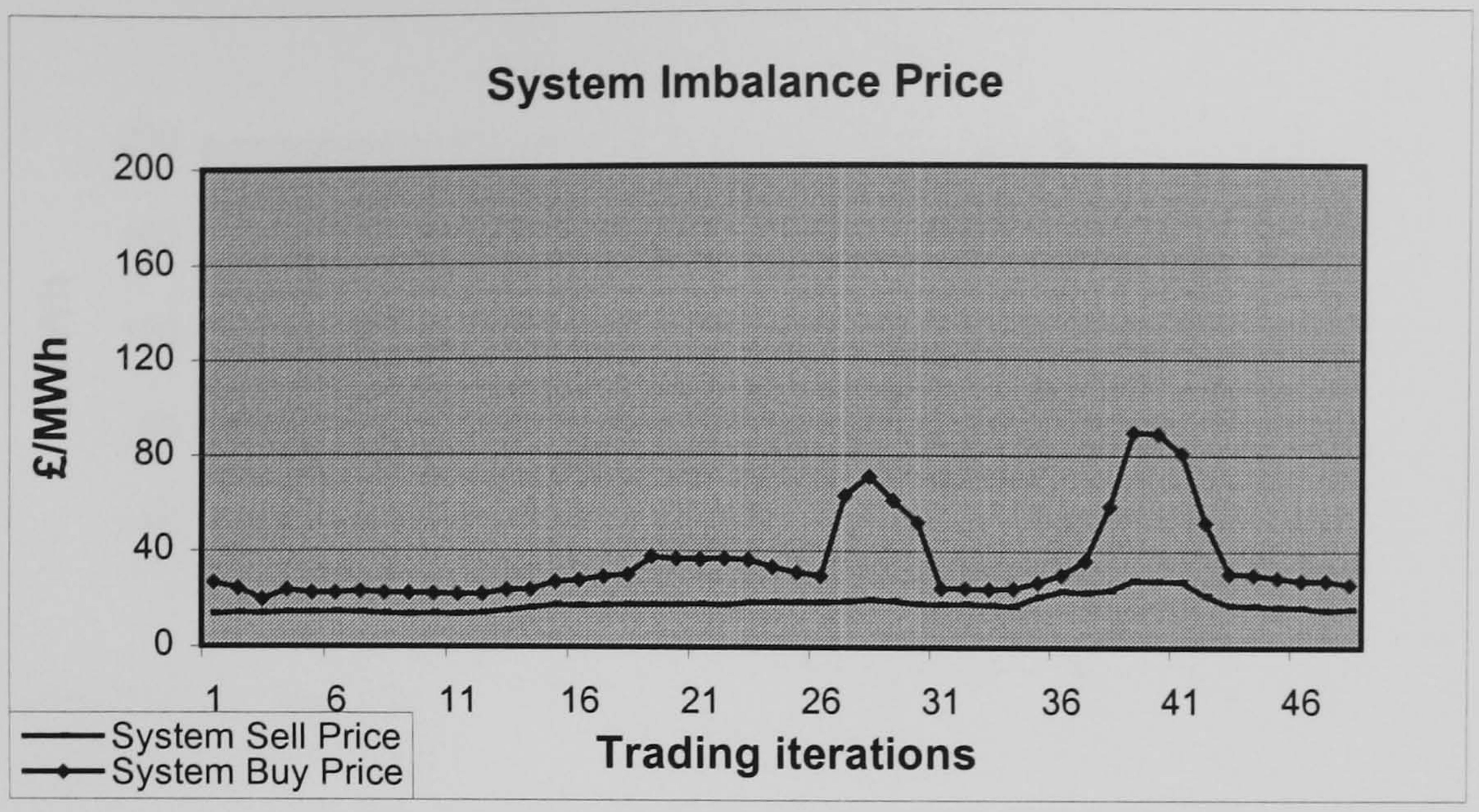

Figure 5.16: Mean System Imbalance Price in the second trading week

The NETA mean daily imbalance prices in the second week in October 2004 is illustrated in Figure 5.16.

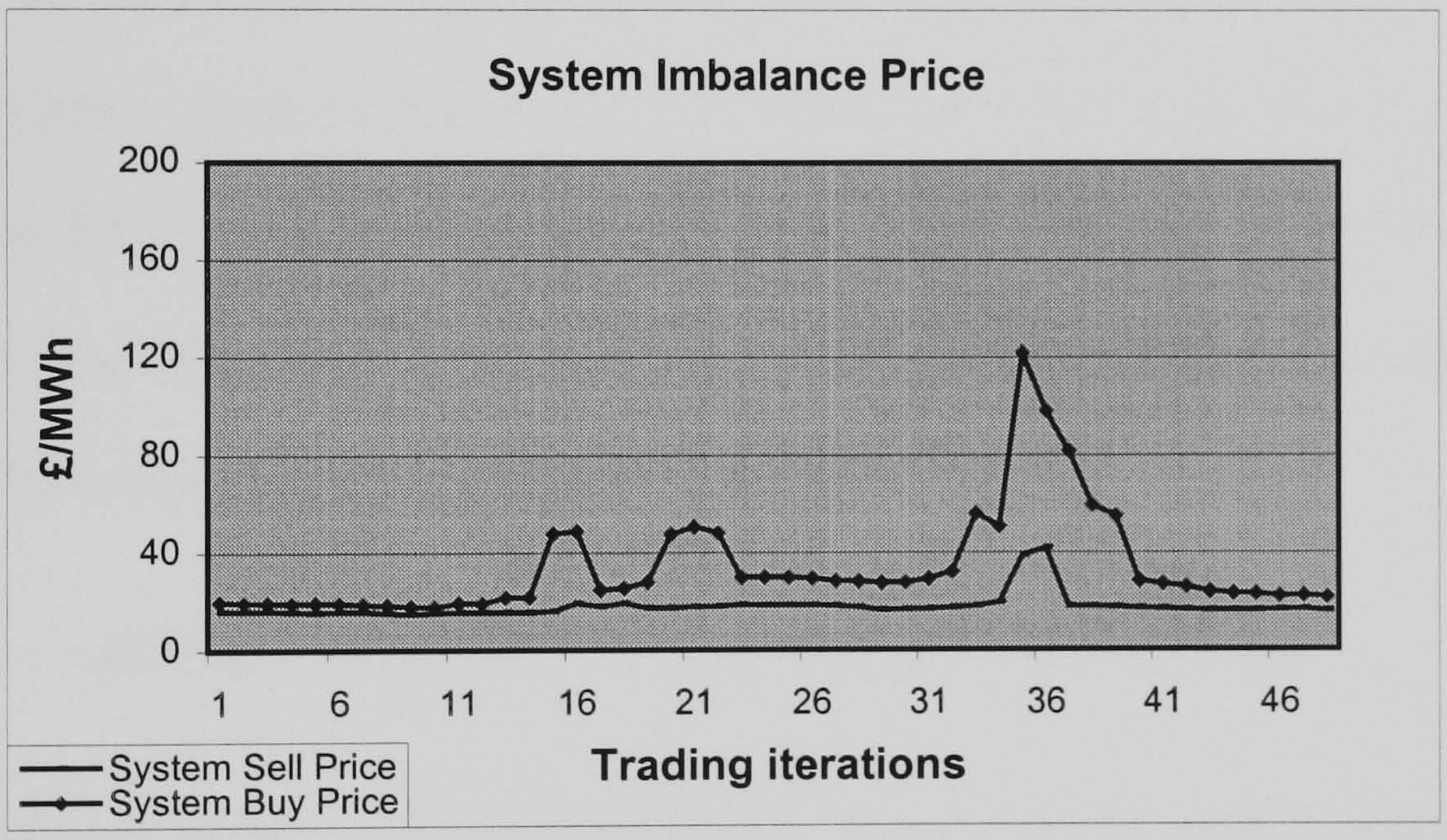

Figure 5.17: Mean System Imbalance Price in the third trading week

Figure 5.17 presents the mean daily imbalance prices in the third week in October 2004.

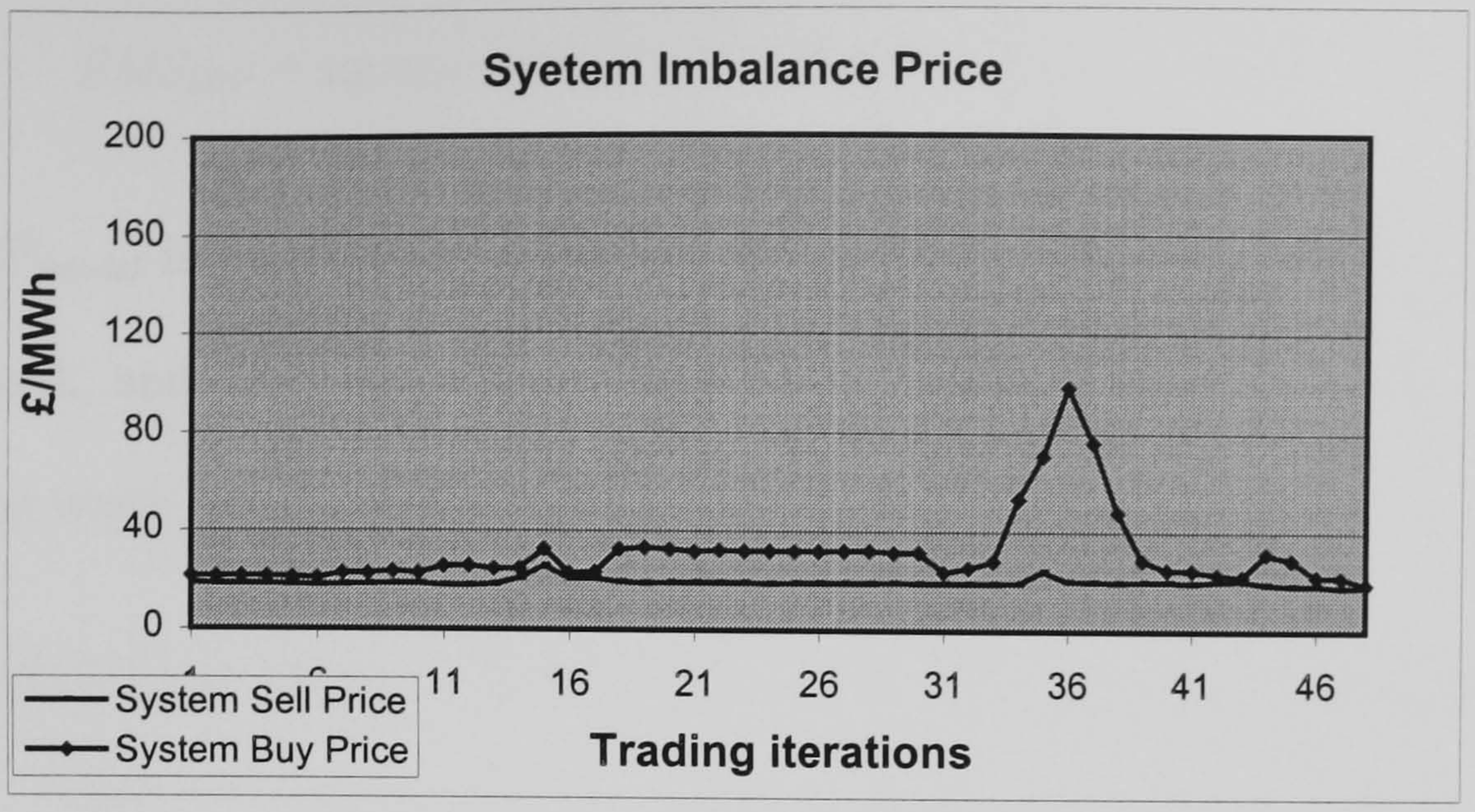

Figure 5.18: Mean System Imbalance Price in the forth trading week

The imbalance system result from the last week is shown above in Figure 5.18.

Next, all the experimental results, including market clearing price *PXP*, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP* are measured against the NETA market results presented in Figure 5.11 to Figure 5.18 above, to assess the modelling. The modelling error is discovered by RMS (root-mean-square) error which is introduced following.

$$RMS_{PXP} = \text{square-root of} \left(\sum_{i=1}^{n=48} (PXP_{imodel} - PXP_{ineta})^2 / 48 \right) \quad (5.5)$$

where PXP_{imodel} is the model estimated *PXP* value at the *i*th trading iteration in one trading week, and PXP_{ineta} is true *PXP* value on NETA at the *i*th trading iteration in one trading week.

$$RMS_{SSP} = \text{square-root of} \left(\sum_{i=1}^{n=48} (SSP_{imodel} - SSP_{ineta})^2 / 48 \right) \quad (5.6)$$

where SSP_{imodel} is the model estimated *SSP* value at the *i*th trading iteration in one trading week, and SSP_{ineta} is true *SSP* value on NETA at the *i*th trading iteration in one trading week.

$$RMS_{SBP} = \text{square-root of} \left(\sum_{i=1}^{n=48} (SBP_{imodel} - SBP_{ineta})^2 / 48 \right) \tag{5.7}$$

where SBP_{imodel} is the model estimated *SSP* value at the *i*th trading iteration in one trading week, and SBP_{ineta} is true *SBP* value on NETA at the *i*th trading iteration in one trading week.

Table 5.3 shows the results of modelling error during the overall trading process.

Table 5.3 Modelling error performance during 4 trading weeks

Trading Period	1st Trading Week	2nd Trading Week	3rd Trading Week	4th Trading Week
RMS_{PXP}	9.30	8.55	6.98	5.65
RMS_{SSP}	7.19	3.09	3.70	2.86
RMS_{SBP}	12.02	11.12	11.80	9.47

Based on the experimental results and the modelling errors demonstrated above, the evolvement trend of major modelling results, market clearing price, *PXP*, system imbalance prices, *SSP* and *SBP*, are considerably similar to the NETA market outcomes. The proposed model appears to be capable of running the trading mechanism well in the way of which NETA is doing.

5.4 Discussion

A validation experiment against unused real NETA data has been finished, and the modelling performance has been exercised.

An example of how the market participants learns and how they improve their strategy can be observed from Figure 5.2 to Figure 5.9 and Table 5.2, in terms of displaying the development progress of main model outputs, including mean daily prices in the PX and in the Imbalance Settlement Process (*PXP*, *SBP*, and *SSP*) during the large number of trading iterations of the baseline experiment. For detailed analysis, according to the results shown above, in the initial stages the prices in the wholesale PX market, *PXP*, and in balancing mechanism and imbalance settlement, *SSP* and *SBP*, are very volatile. Occasionally, high priced bids and offers have been taken at very short notice. The volumes of accepted bids and offers in the balancing mechanism have sometimes been very small. *SSP* for spilling have been low with sometimes extreme high *SBP* for shortfalls. It appears that the spread between the SSP and SBP reduces in later weeks. It is not unreasonable because the market participants, especially the players on demand side, are learning to respond to the mechanism and improve their trading strategies. The relationship between supply and demand gets loose and it is likely to lead further convergence of *SSP* and *SBP* prices.

There are also price spikes on wholesale market price *PXP* happened in later stage. These price spikes emerge when the demand is on peak periods, 9:00am to 11:00am, 14:00am to 16:00am, and 20:00pm to 22:00pm. For most industries, standard economic theory suggests that, under perfect competition, where no individual supplier has market power, the bids offered by each supplier should equal their marginal production costs. Under this scenario, price spikes should only occur when demand exceeds supply. However, in virtually all electric power markets, price spikes giving profits much in excess of marginal costs have been observed, even when sufficient supply is available.

Note that market prices do emerge to create a wide spread between SBP and SSP and that PX clearing price is centrally located between them. This is what the advocates of NETA hoped would occur in that out-of-balance players would regret they had not traded forward at PX. The level of prices that have emerged around £80MWh for winter days is rather high because in this experiment, as will be seen below, market participants learn to create price spikes at the three peak periods. Notice that the SBP is much more volatile than the PX market clearing price or the SSP, also the emergence of daily price cycles (with high prices at the peaks) as participants learn from experience.

The prices in all cases come out below existing NETA real prices. There seem to be at least two reasons for this:

1. The experiments lasts for a maximum of twenty days. This gives less opportunities for participants to observe the behaviour of others and subsequently adjust offers accordingly. In real life, participants literally have years to achieve this;
2. and one of the modelling assumptions is that the PX trades are a proxy for trades in all the markets, including those with longer-term activities than the day ahead usually assumed for the PX. The model assumes a higher degree of trade concentration than is currently the reality.

The study in this chapter has certified that the model designed here is well capable of operating over simulating the market mechanism and players' trading behaviours. In general, the type of trading system envisaged by this model is able to respond efficiently to changing supply and demand conditions. The response of prices to demand variations through the days is close to actual, and there is no evidence from the experiments that there would be any problems in the system responding to supply and demand shocks.

It is clear that the proposed technique for search, learning and optimisation of best strategies is efficient. The next chapter will use the model to discuss the development of gaming strategies on NETA.

6. Strategy Development and Prediction Experiments

6.1 Gaming Behaviours

Following successful modelling of the NETA market, the model can then be used to analyse the market behaviour of gaming strategies practiced in the power market and to find out possible influence on NETA. The cooperative strategy is adopted and examined in this model, which is based on two different scales. The experiment results are discussed and compared with the results of the first set of experiments, which represents the actual market performance in this marketplace.

Based on what has been discussed previously, it is revealed that generators have an incentive to withhold capacity from the market. That is, under certain conditions, enough generation companies cooperatively withholding capacity can drive the market into an oligopoly situation.

Nevertheless the relationship among the collusive members is not stiff. There are two types of gaming generators. The first is the classical "tacit collusion" that occurs in static repeated withholding output capacity, where the object is for all players to learn that they can always make excess profits if they withhold amount of capacity from the market. This kind is referred to "loyal cooperators", suggesting that these generators should "always" withhold a portion in anticipation of an agreement. The second type asserts, however, that it is not always profitable to withhold capacity from the market, since the opportunity for raising profits does not always exist due to internalities and externalities, such as collaborative generators breaking the agreement, the demand bid, imbalance prices, etc. In other words, the payoff in the payoff matrix change with the internalities and externalities, making it necessary to recognize when the "opportunity" to drive up profits exists. We refer this phenomenon to "opportunistic tacit collusion" to distinguish it from the classical "tacit collusion". These generators follow an "opportunistic collusion" strategy whereby generators withhold capacity from the market only when they perceive an "opportunity" to raise profits by doing so exists. Opportunistic collusion might result in a generator setting aside a portion of their capacity and deciding for each trading round whether or not to offer that capacity to the market depending on expectations of raising profits. Once this is learned suppliers "tacitly collude" to sustain high market prices.

For the "opportunistic collusive" generators, it is difficult to judge an "opportunity" to get more profits by estimating possible profit with cooperative strategy. Because in a certain market environment where a wide number of market participants are trading interactively, there are uncertainties and it is unlikely to precisely predict all participants' future moves and trading consequence. Nevertheless, the market clearing price in PX, *PXP*, and individual generators' capacity used in both of PX and BM, are introduced as the reference for the "opportunistic collusive" generators to decide whether or not to join the coalition agreement and withhold capacity from the market.

6.2 Experimental Setup for Analysis

The market clearing prices in PX is divided into three periods:

1) A low price period, where the prices tend to be close to individual generator's specific marginal costs;
2) An average price period, where the prices are at least 75% above the marginal costs;
3) A high price period, where the prices rise to at least 20 times the marginal cost.

The generators' used capacity is also divided into three stages:

1) A low demand period, below 75% of individual generator's particular available capacity;
2) An average demand period, between 75% and 85% of available capacity;
3) A high demand period, above 85% of available capacity.

We assume if, and only if, that the market clearing prices, PXP, is in either of average price period or high price period of a "opportunistic collusive" generator, and its used capacity is in low demand period, this "opportunistic collusive" generator will quit coalition agreement and trade independently in market. If either of these two conditions is unsatisfied, it will rejoin the collusive group.

The base-load plants (running in a non-stop regime), say the nuclear stations, are specified as "the "loyal cooperator", because they need to run continuously and specify zero start-up cycle so that they are not able to respond flexibly to real time trading in the BM. The gas turbine power plants and oil generation plants are defined as "opportunistic collusive" generators as they own the highest flexibility which means their generation features allow them to start up a numbers of times within one day. CCGT and coal power plants are assumed only adopt non-cooperative strategy and trade independently in power market.

Besides, as we assume, this gaming behaviour can take place independently of transmission constraints, or insufficient supply, and is only enhanced by those factors.

6.3 Small-Scale Model Experiment and Verification

In order to gain a better view of the effects of gaming trading strategies on NETA, the first application experiment is carried out based on a small scale model. The total available generation capacity is assumed as 33.3GW in this experiment, half size of the model experimented in last chapter. The number of generators, *m*, is assumed to 5, and suppliers', *n*, is assumed to 4 in this experiment. The total demand is set as 25 GW, therefore the individual maximal demand, Q_{dmax}^{i}, of each supplier is set as 6250MW. These experiments are based on the standard daily demand profile in November 2004, published by NETA and shown in Figure 6.1.

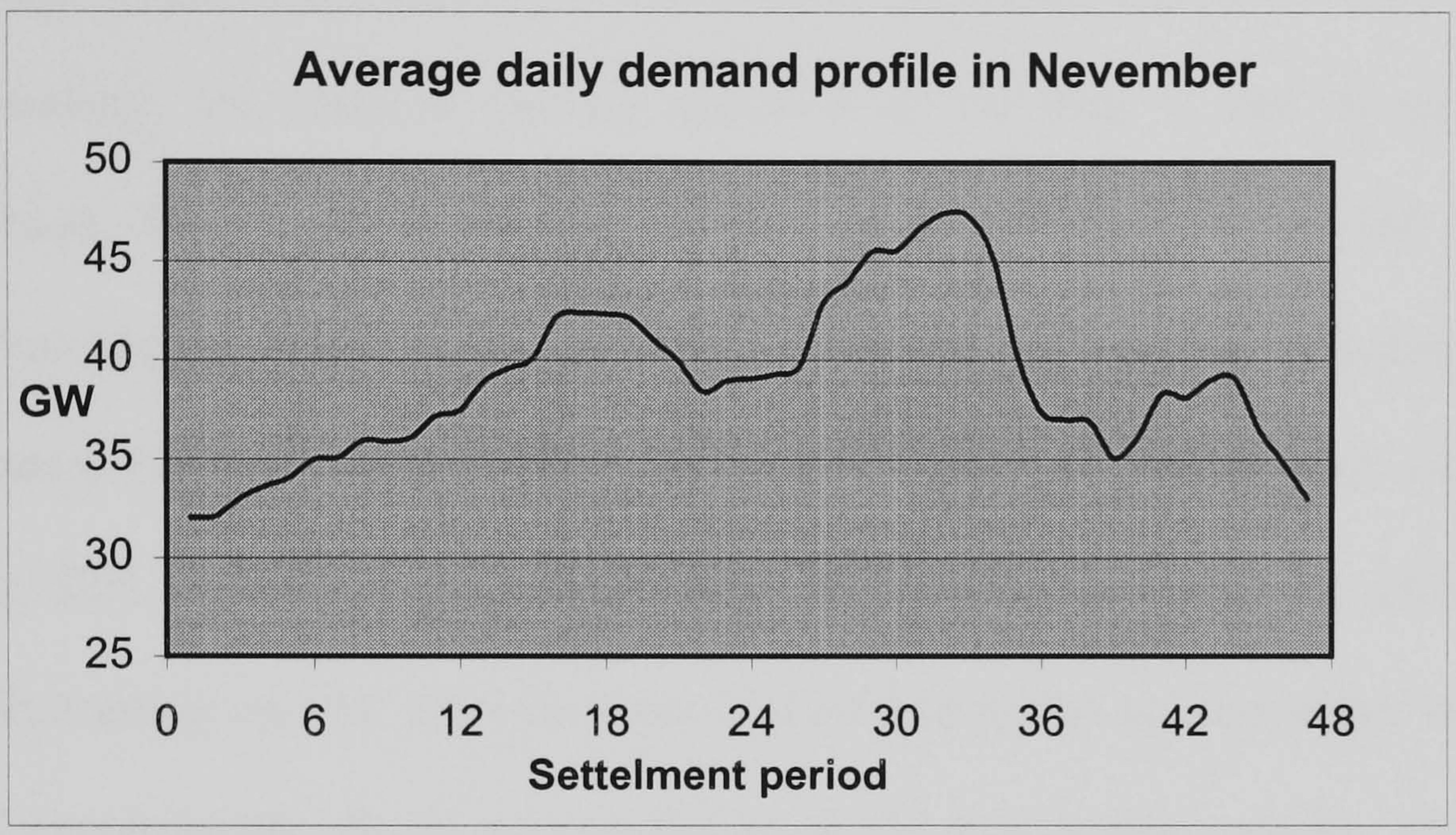

Figure 6.1: Standard daily demand profile in November [63]

There are still five sorts of power generation concerned considered in this model, including gas turbine, oil, coal, combined cycle gas turbine (CCGT) and nuclear plants. The generators of the same type are assumed to have similar marginal costs and generation capacity. Their generation system self-parameter is demonstrated in Table 6-1.

Table 6.1 Generators' system self-parameters

Type of generation plants	**Nuclear**	**Combined cycle Gas turbine (CCGT)**	**Large coal**	**Gas turbines**	**Oil**
Marginal generation cost (£/MWH)	24.50	9.72	33.23	66.95	87.91
Maximal generation capacity (MW)	6600	6600	6600	6600	6600

6.3.1 Market Results

In order to assess the performance of market players' different strategies, three major model outputs, the wholesale market clearing price *PXP*, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP*, are presented and evaluated below.

6.3.1.1 Traded Market Clearing Prices in Power Exchange

For gaining insights into aspects of the model and observing the evolution of the trading strategy, the analysis method imposed on the data in last chapter is also adopted here. The model's running process, given 20 days, is divided into four consecutive stages, week by week. These three trading results, including market clearing price *PXP*, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP*, in each trading week, are respectively represented by three typical mean daily trading results. Then for each of the three model outputs, there are overall 4 sets of experimental results corresponding to the four trading weeks, and one set includes 48 model experimental outputs. These trading results are shown week by week to observe how the market players improve their strategies and how their behaviours influence the market outcomes.

The PX runs as a proxy for trades in all the markets. As the crucial system output and model performance assessment reference, the market clearing price in Power Exchange, *PXP*, in each of the four weeks, is represented by a set of mean daily market price. Each daily *PXP* curve has 48 *PXP* values coming from the 48 trading iterations within each typical trading day. Figure 6.2 demonstrates the mean daily Power Exchange market prices in the first week.

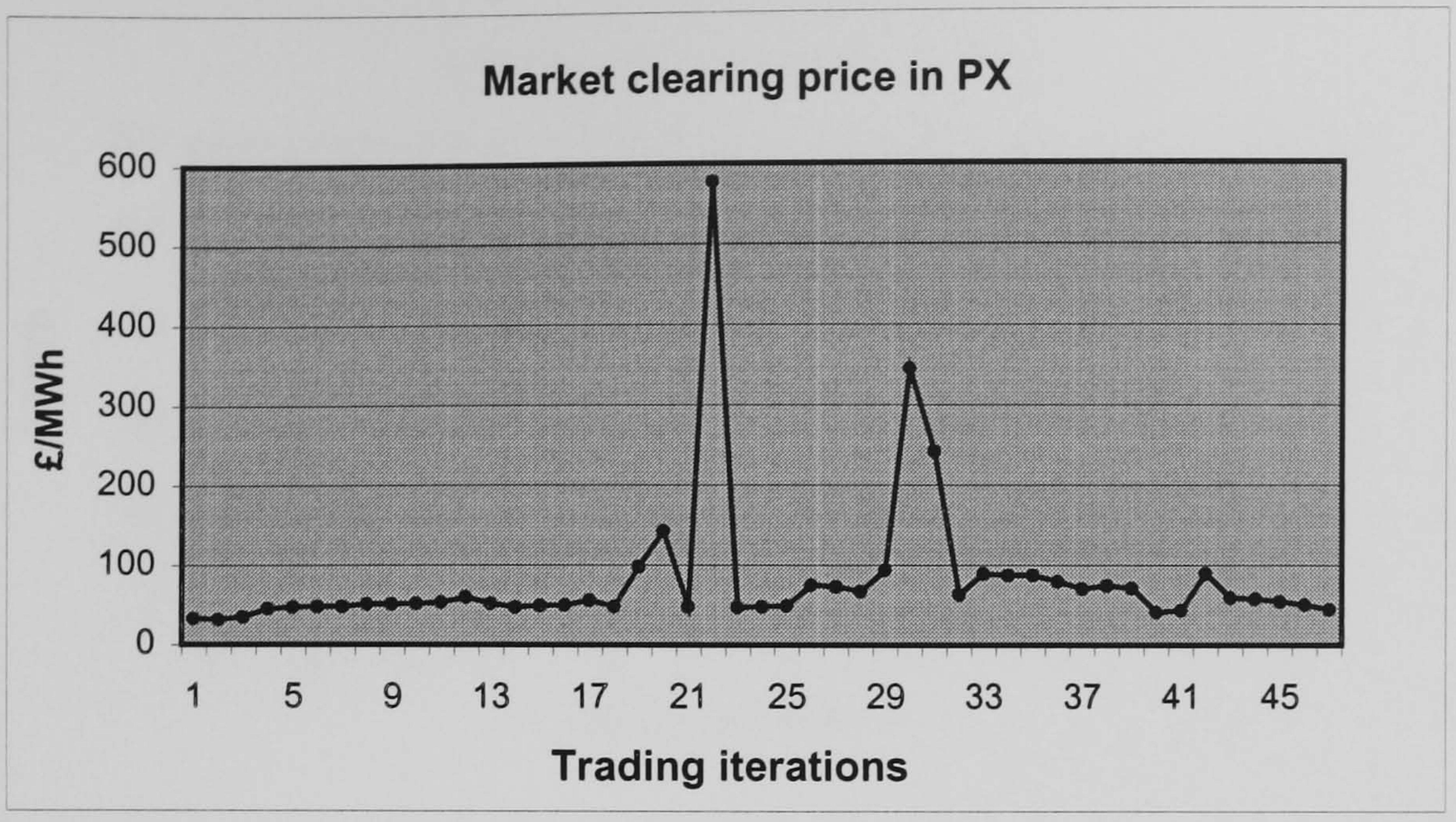

Figure 6.2: Mean daily market clearing price in PX in the first trading week

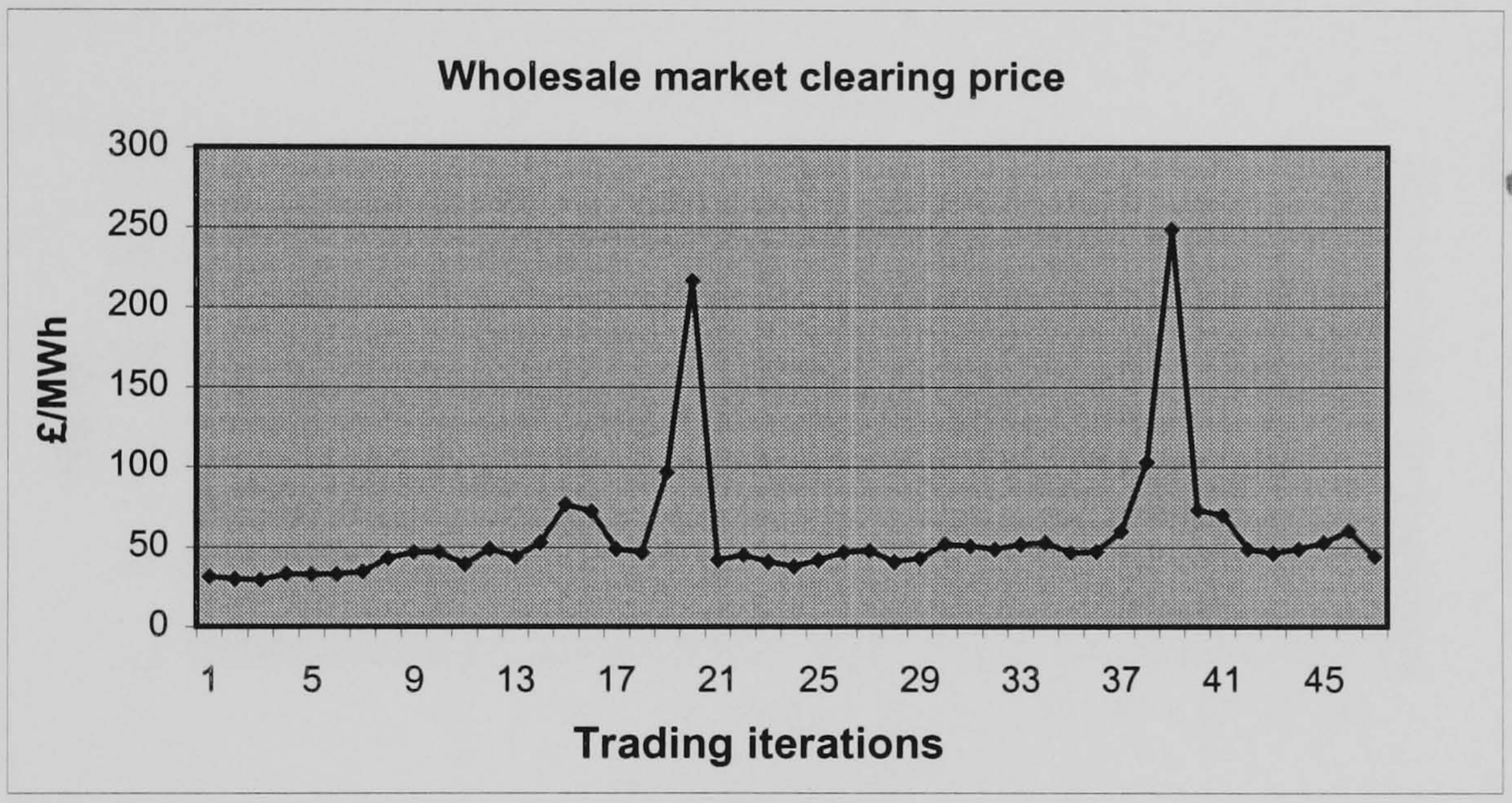

Figure 6.3: Mean daily market clearing price in PX in the second trading week

According Figure 6.2 and Figure 6.3 above, there are a number of extremely sharp price spikes emerged in demand peak periods during the first two weeks. It is interesting that in the rest of trading times the PXP remains on similar level to the experimental data in last experiment in Chapter 5, where no cooperative strategy is introduced.

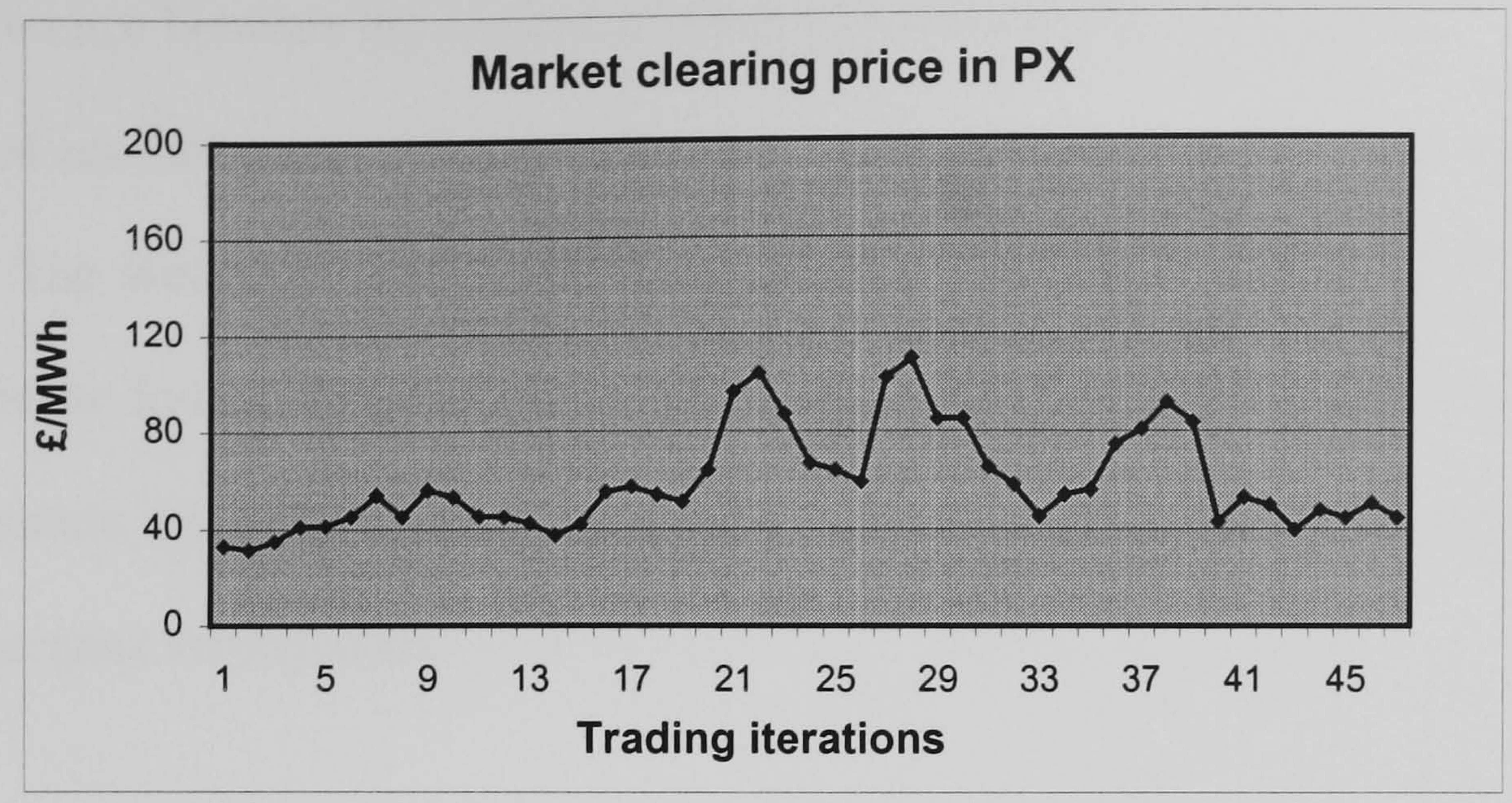

Figure 6.4: Mean daily market clearing price in PX in the third trading week

Figure 6.4 shows the development of mean daily *PXP* in the third week.

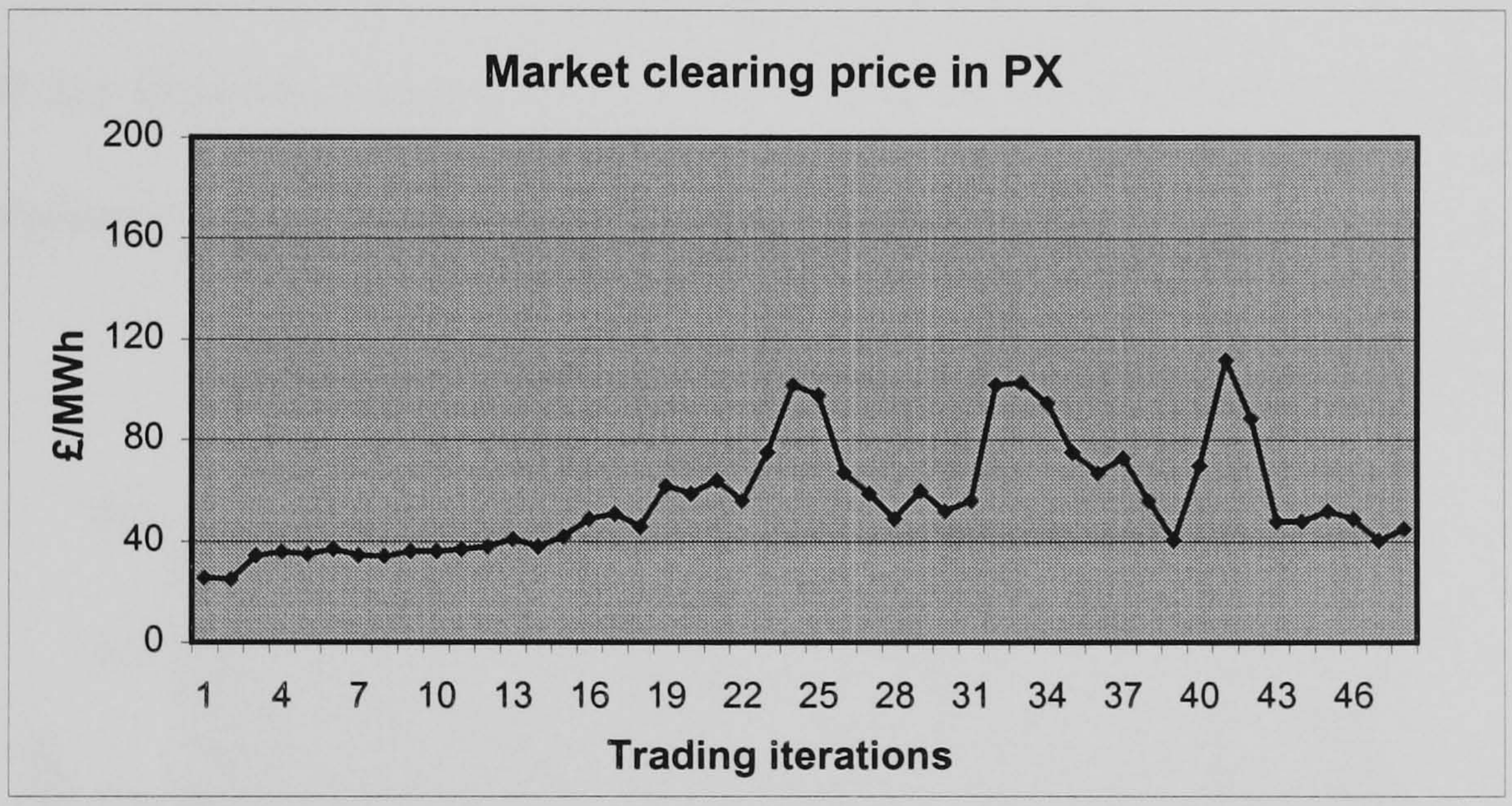

Figure 6.5: Mean daily market clearing price in PX in the forth trading week

The market's mean daily Power Exchange clearing prices from the last trading week are presented in Figure 6.5. We can see that the degree of price spikes has dropped down along with the model's running and strategies evolution.

6.3.1.2 Traded Prices in Imbalance Settlement System – System Sell Price and System Buy Price

In the Imbalance Settlement Process, the generators' metered generation and suppliers' metered demand are compared with the contractual position they notify.

The difference between the amount of electricity bought and sold under contracts and the actual amount produced and consumed is calculated by the imbalance settlement system. The weighted average of accepted Offers price for buying more energy is known as the System Buy Price (SBP). Conversely, the price for selling excess energy to the system the System Sell Price (SSP), is a weighted average of accepted Bids.. The same goes for suppliers.

Figure 6.6 to Figure 6.9 reveal the impact of market participants' strategies, especially the gaming strategy, on the Imbalance Settlement Process. The other two fundamental system outputs, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP* are illustrated below. Figure 6.6 demonstrates the mean daily price curves of the imbalanced settlement prices *SSP* and *SBP* in the beginning week.

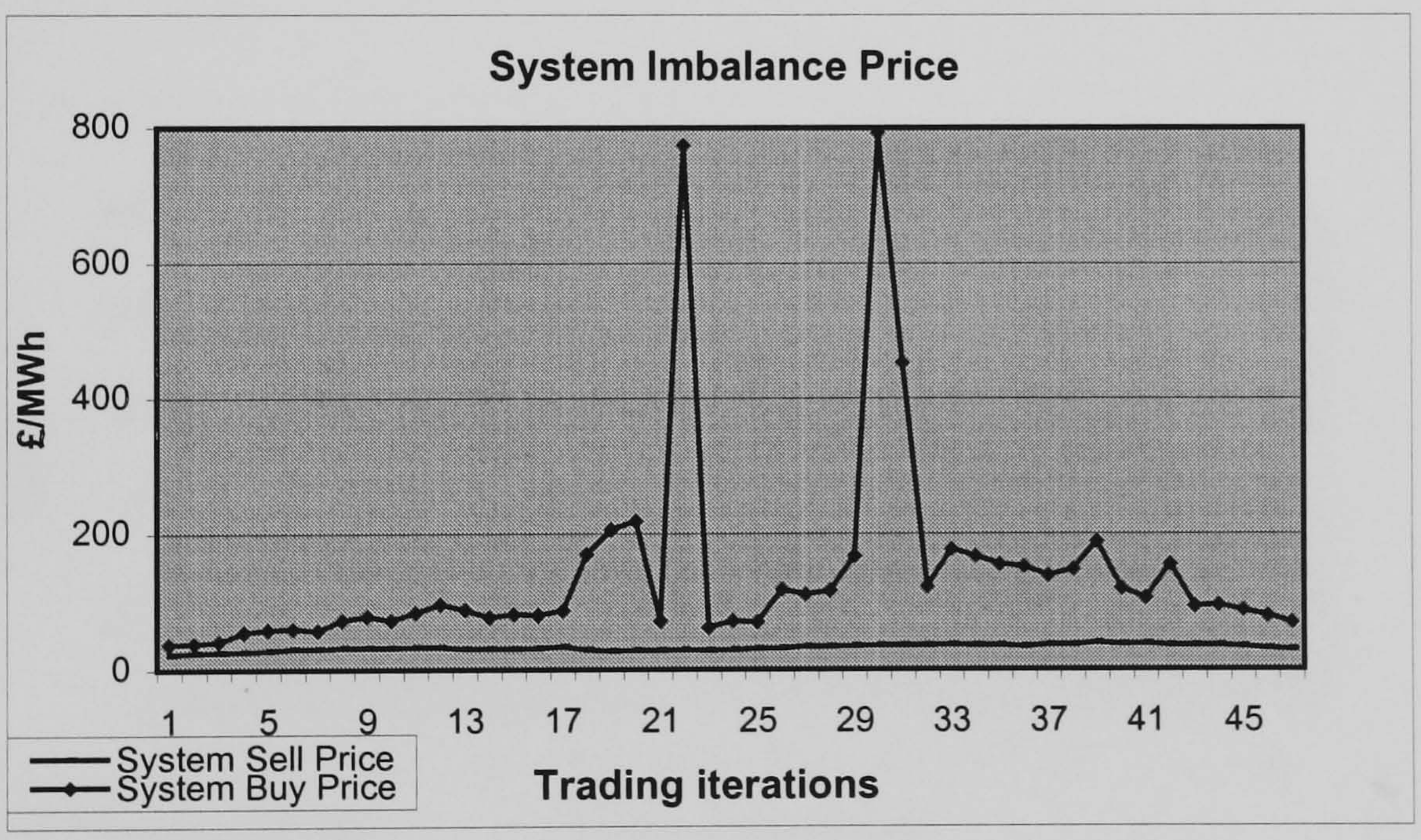

Figure 6.6: Mean daily System Imbalance Price in the first week

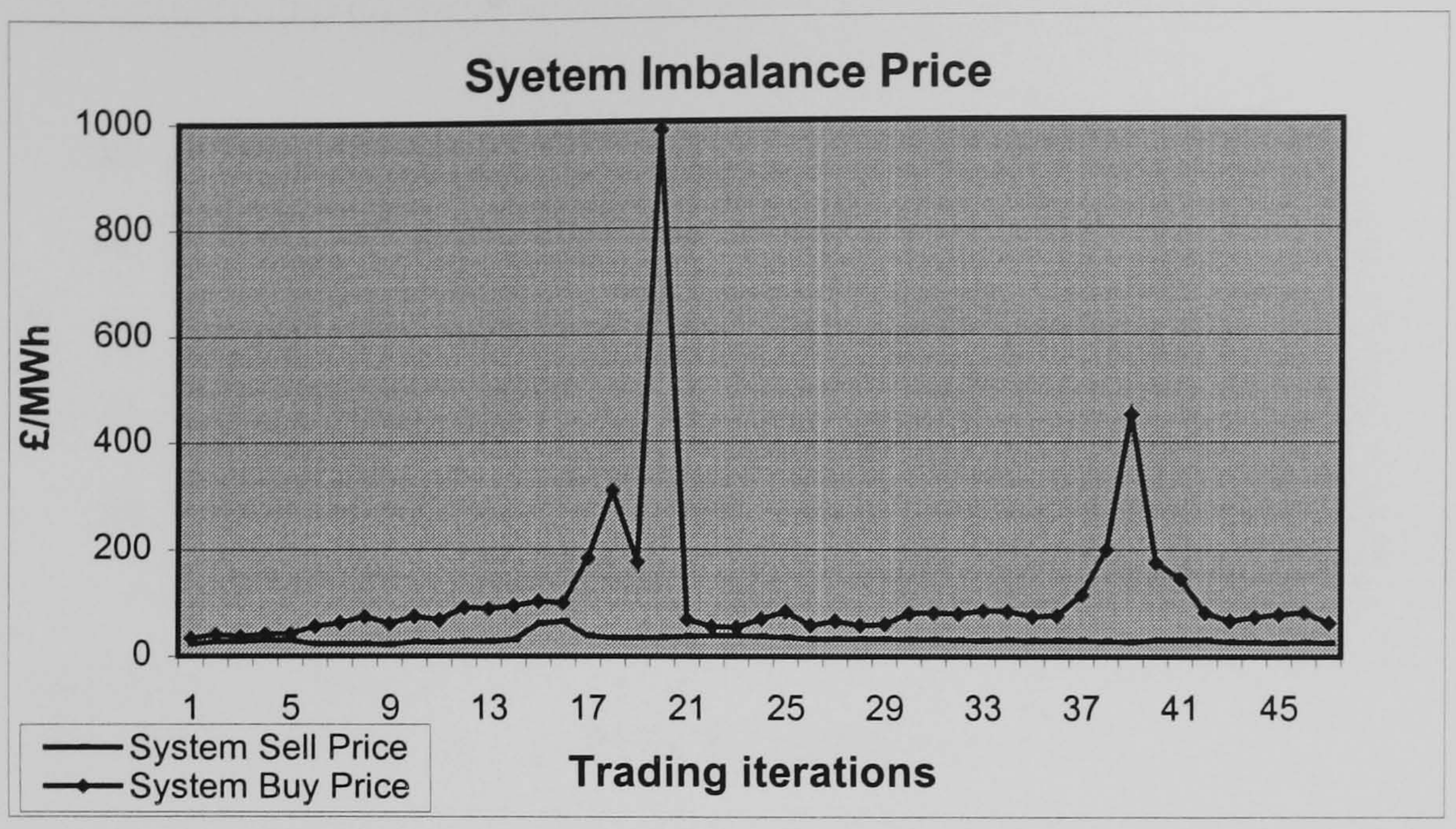

Figure 6.7: Mean daily System Imbalance Price in the second week

Figure 6.7 shows the mean daily price curves of the imbalanced settlement prices *SSP* and *SBP* in the second week. There is evident observation that both of *SSP* and *SBP* stay stable at much higher degrees than previous experiment data in most of the trading rounds.

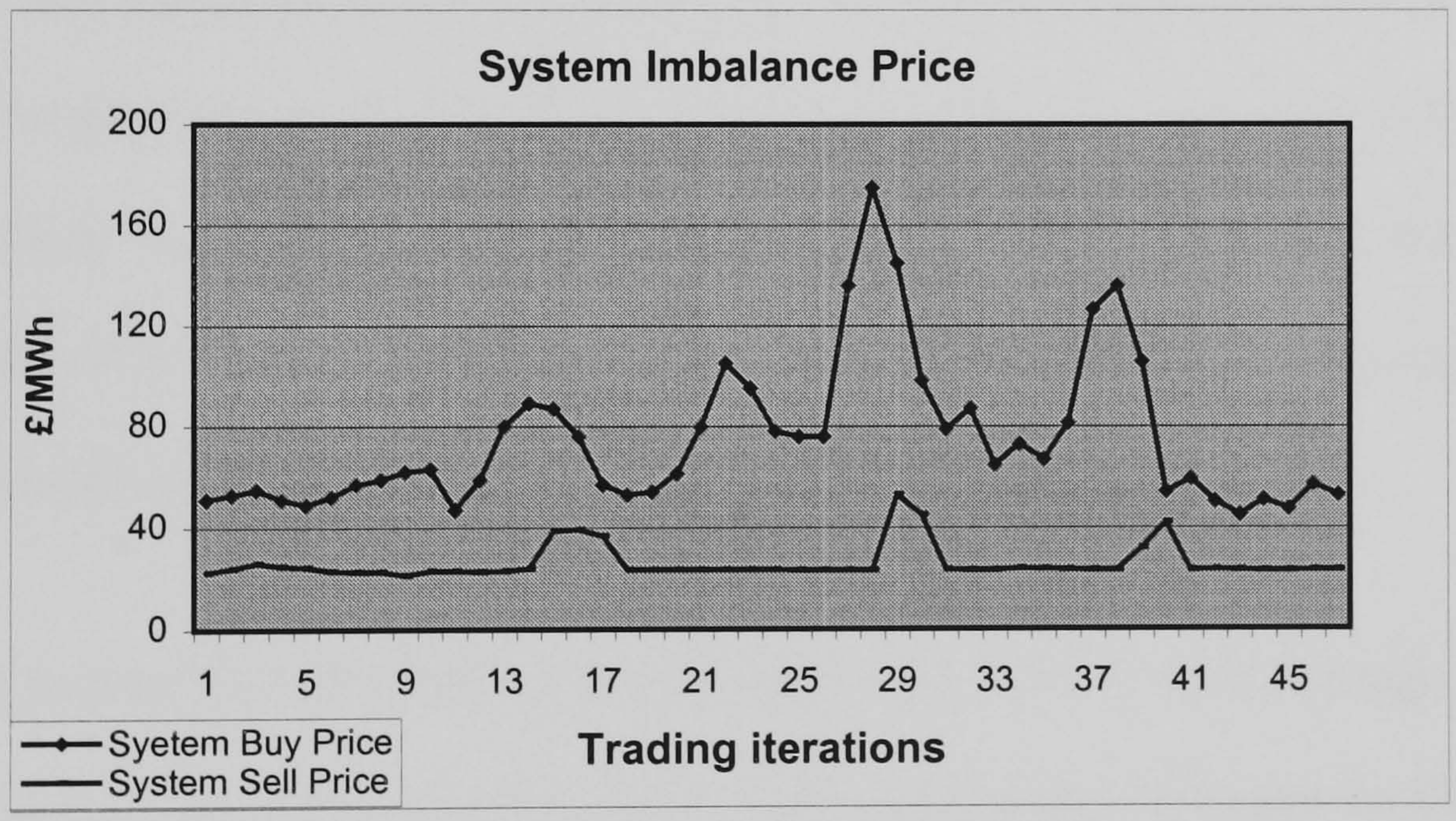

Figure 6.8: Mean daily System Imbalance Price in the third week

Figure 6.8 shows the development of mean daily imbalanced settlement prices in the third week.

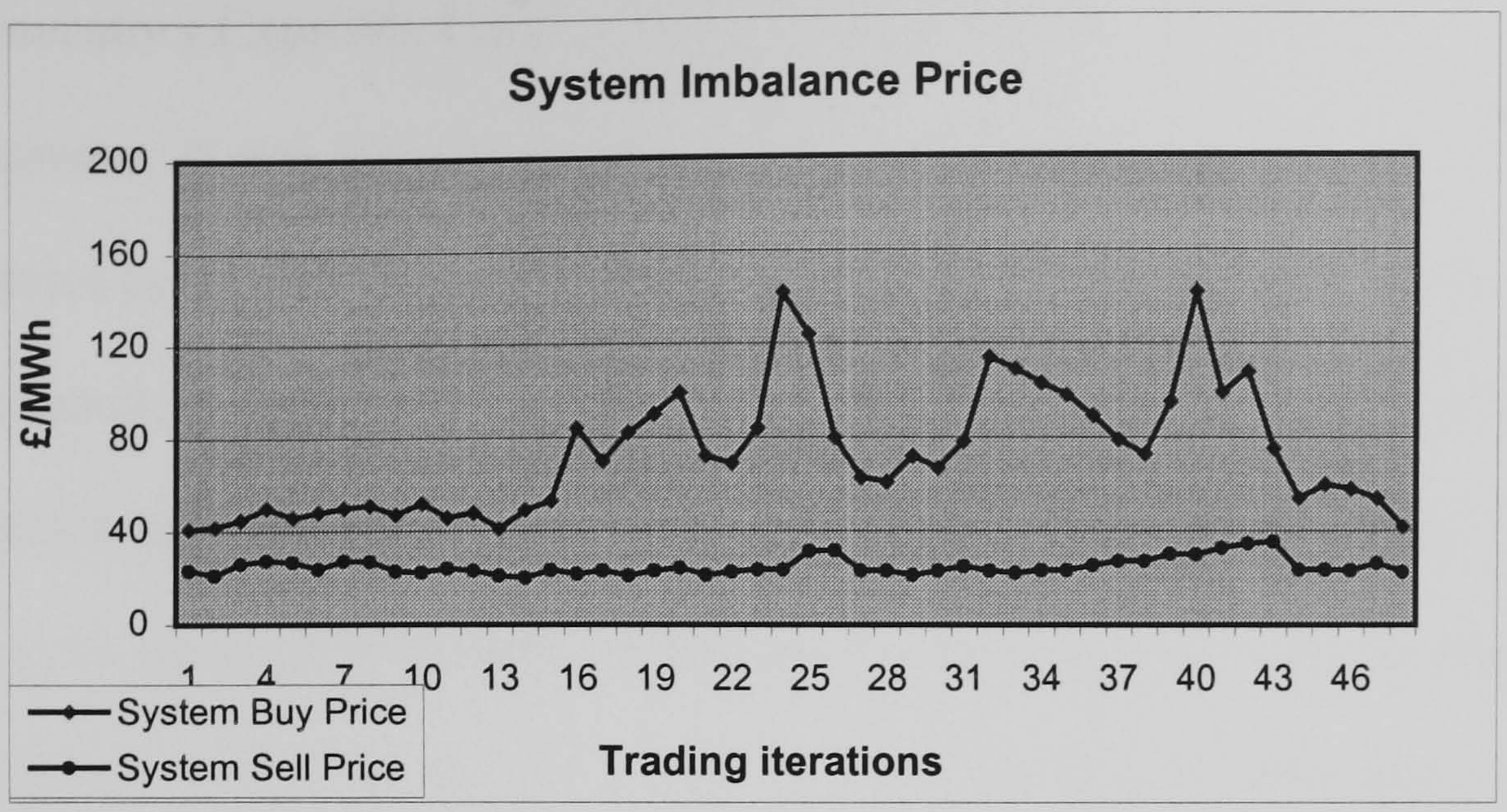

Figure 6.9: Mean daily System Imbalance Price in the forth week

The model's mean daily imbalanced settlement prices in the last trading week are introduced in Figure 6.9.

6.3.1.3 Discussion of Results

Based on the experiment results demonstrated above, significantly different to the results in last experiments at which generators only employ non-cooperative strategy, the *PXP* is driven to very high degrees during demand peak times and in the rest of trading times the *PXP* remains on similar level to the experimental data in last experiment with no cooperative strategy employed. The reason will be discussed in the section of summary.

Also, the System Buy Price *SBP* is varied within an extremely wide of range, between 40£/MWh to 790£/MWh. Further, much more price spikes emerges in SBP rather than only at the three peak periods, 9:00am to 11:00am, 14:00am to 16:00am, and 20:00pm to 22:00pm, in previous experiments, due to sharper supply function's shape.

6.3.2 Generators Capacity Used

As we assume, if and only if, that the market clearing prices, PXP, is in either of average price period or high price period of a "opportunistic collusive" generator, and its used capacity is in low demand period, this "opportunistic collusive" generator will quit coalition agreement and trade independently in market. If either of these two conditions is unsatisfied, it will rejoin the collusive group. The generator used capacity is an important reference to measure the efficiency of generators' strategies and individual generator's position in this environment. For the "opportunistic collusive" generators it is also a reference parameter to decide the next move on the trading. Figure 6.10 shows the individual mean used capacity of the all five types generators in the first week.

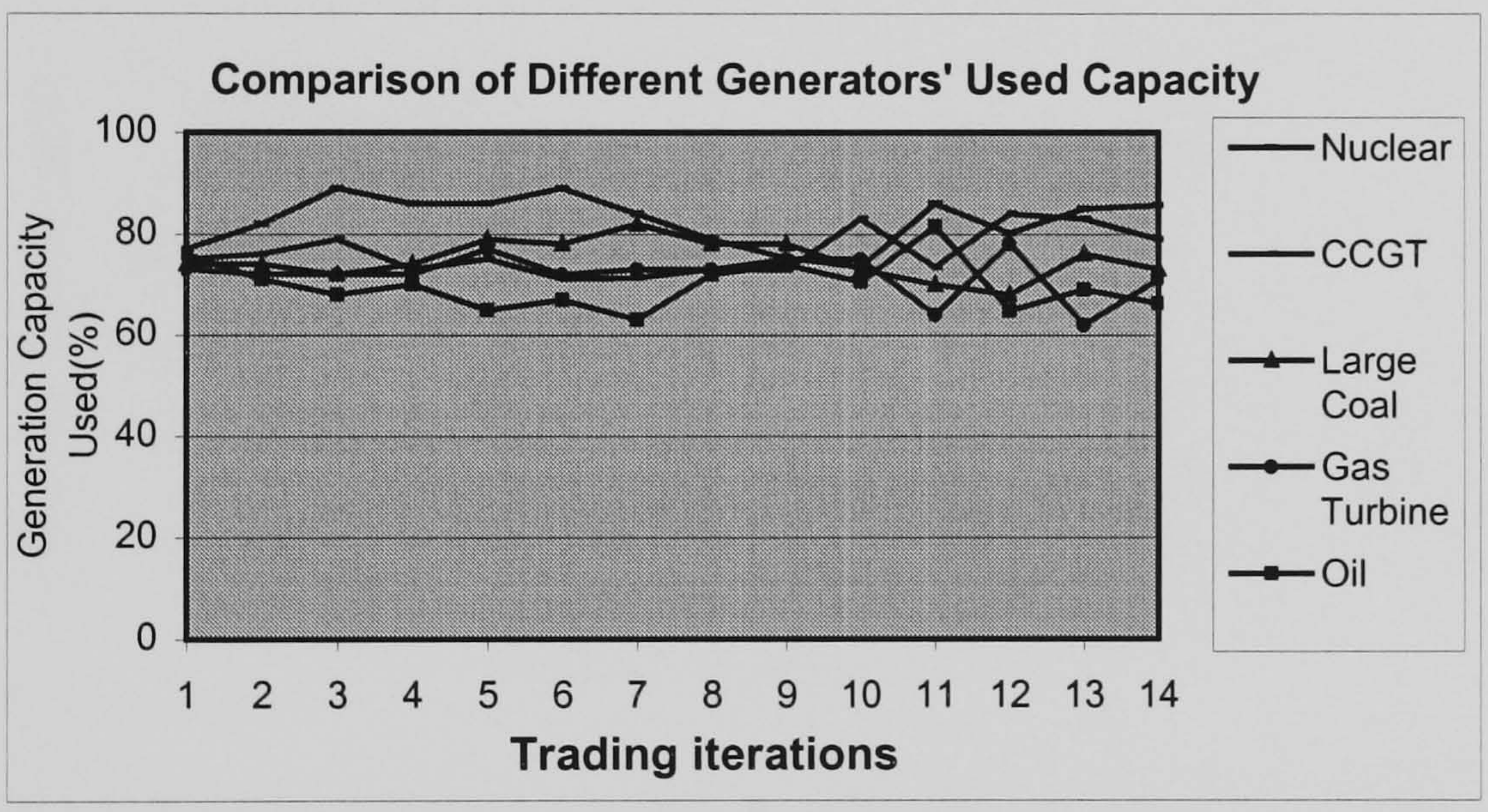

Figure 6.10: Comparison of used capacity for different generators in the first week

It is clear in Figure 6.10 that the type of nuclear stations, assumed as "loyal cooperator", has the largest market share in the initial stage. The experiment results show that suppliers often use nuclear plant as base-load plants because of its continuous running feature to avoid the risk of having to buy and sell in this way through the Balancing Mechanism with its very volatile prices.

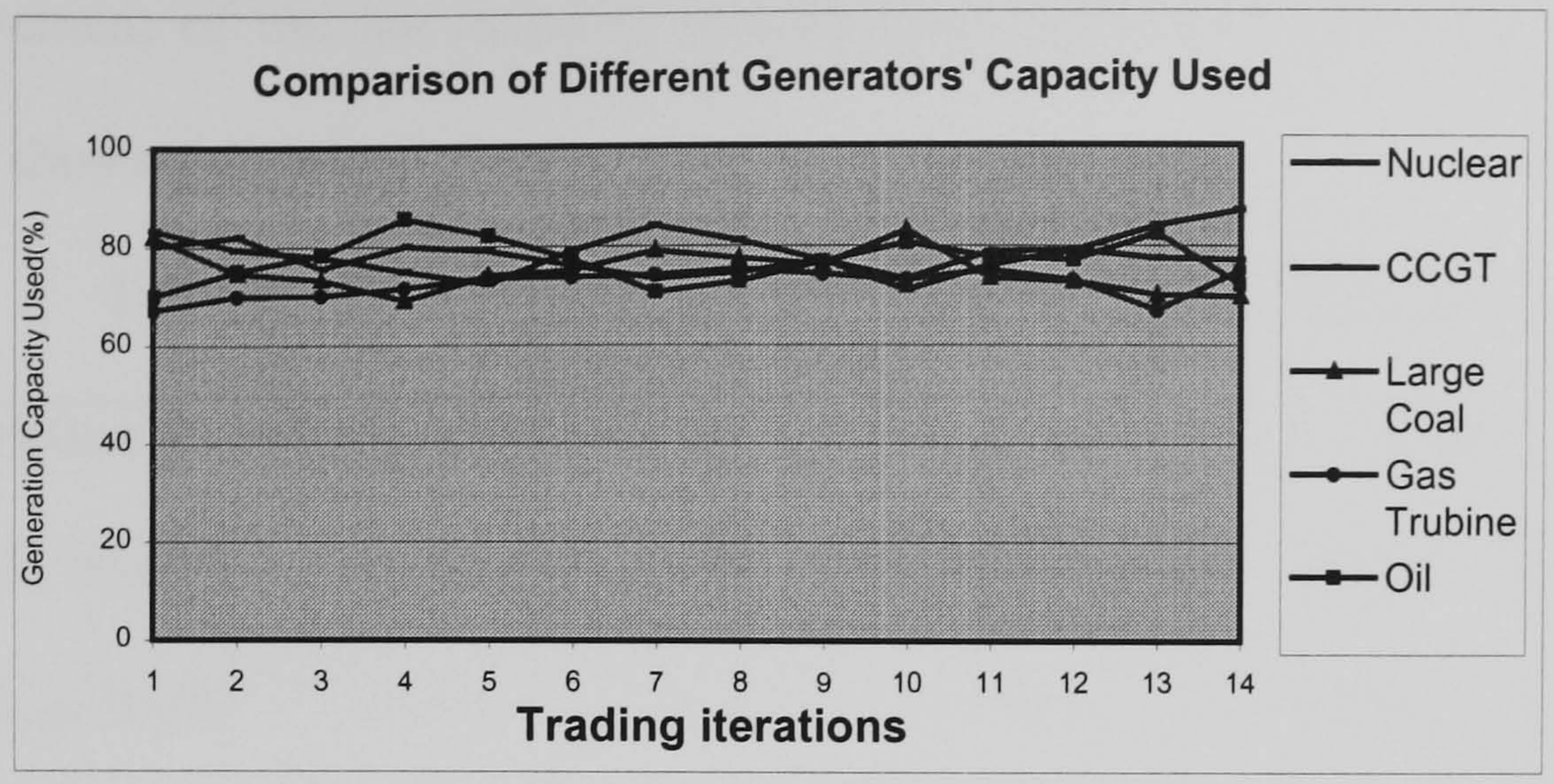

Figure 6.11: Comparison of used capacity for different generators in the second week

Figure 6.11 and Figure 6.12 have shown that the generation types with more flexibility have sold more power to the market than base-load plants, given the nuclear.

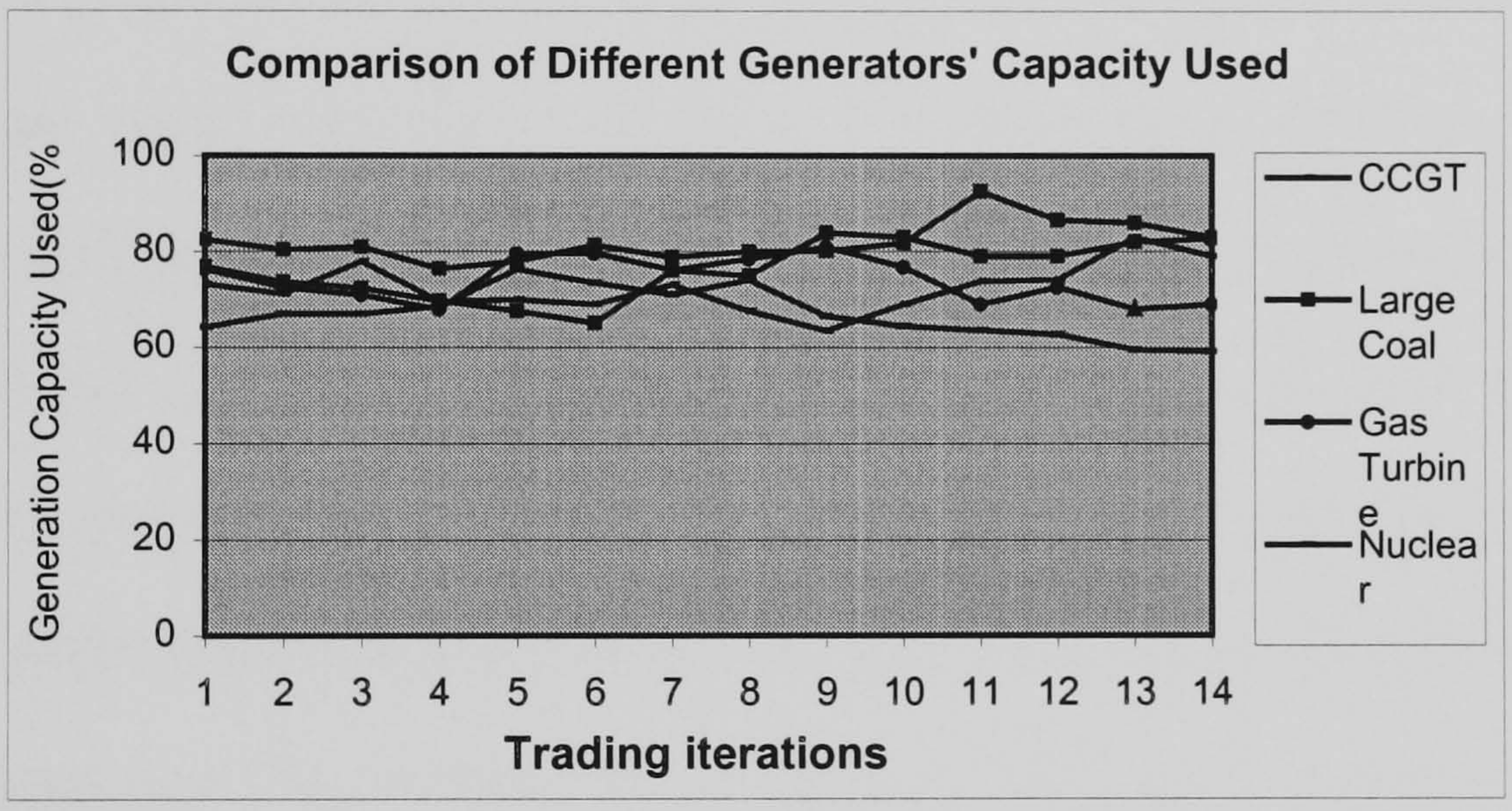

Figure 6.12: Comparison of used capacity for different generators in the third week

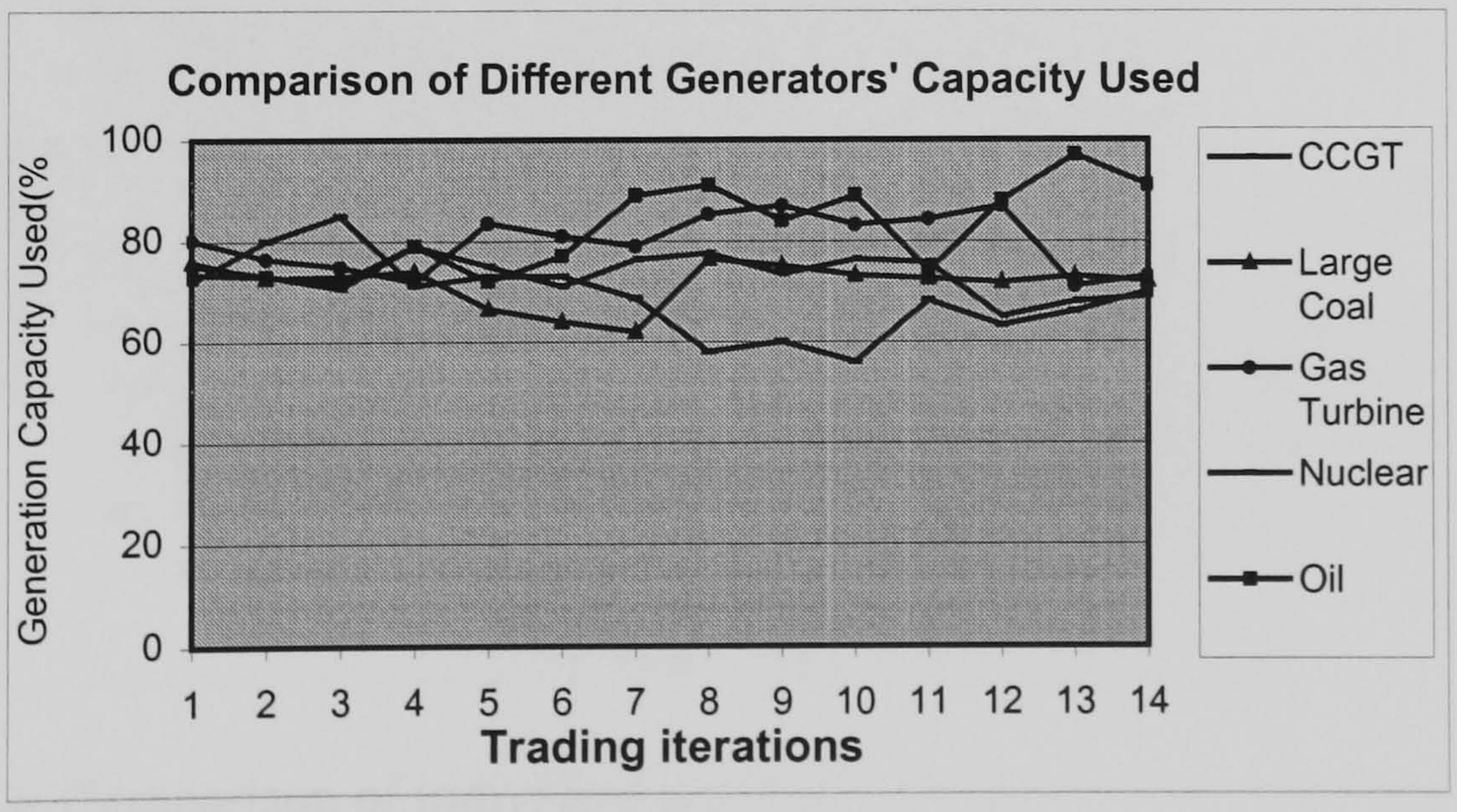

Figure 6.13: Comparison of used capacity for different generators in the fourth week

The evolvement of the use capacity of individual generation type is these trading process is shown following.

Table 6.2: Mean Percentage of Used Generation Capacity

Generation Type	*Nuclear*	*CCGT*	*Large coal*	*Gas turbine*	*Oil*
First Week	0.802	0.763	0.736	0.724	0.703
Second Week	0.712	0.770	0.749	0.729	0.754
Third Week	0.659	0.742	0.766	0.775	0.807
Forth Week	0.685	0.749	0.741	0.780	0.832

6.3.3 Profitability Prediction of Individual Generators

As we know, there are five sorts of power generation systems run into this model, including gas turbine, oil, coal, combined cycle gas turbine (CCGT) and nuclear plants. For each generation type, the weekly individual profit is represented by mean daily individual profit. The mean daily individual profit of each generation type is calculated by function 4.4. In order to compare their strategy's efficiency, the mean individual profit of nuclear generator on each trading day is divided by the other four type's, respectively. The calculated results are shown below from Figure 6.14 to 6.17.

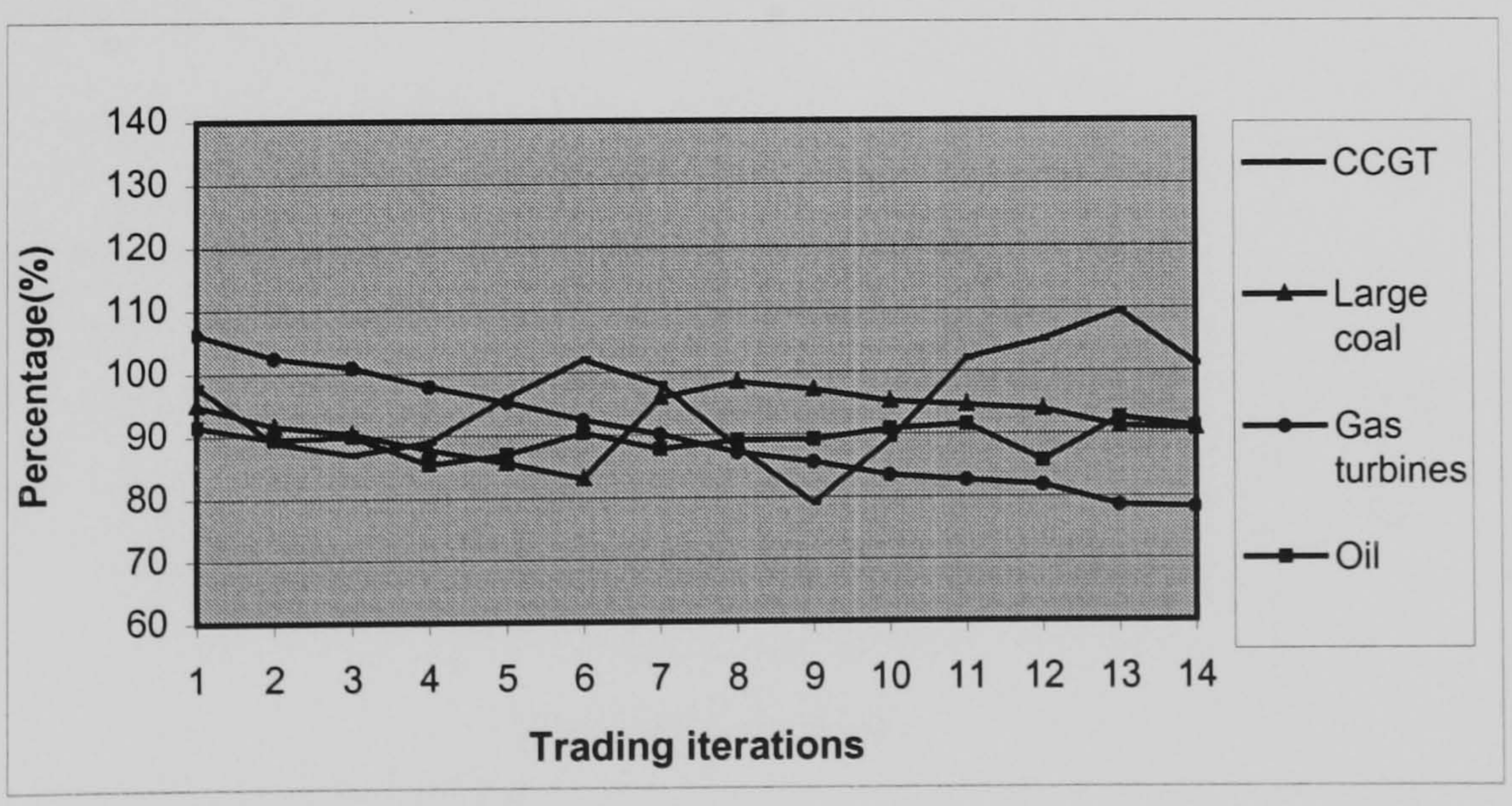

Figure 6.14: Comparison of individual profit of each generation type in the first week

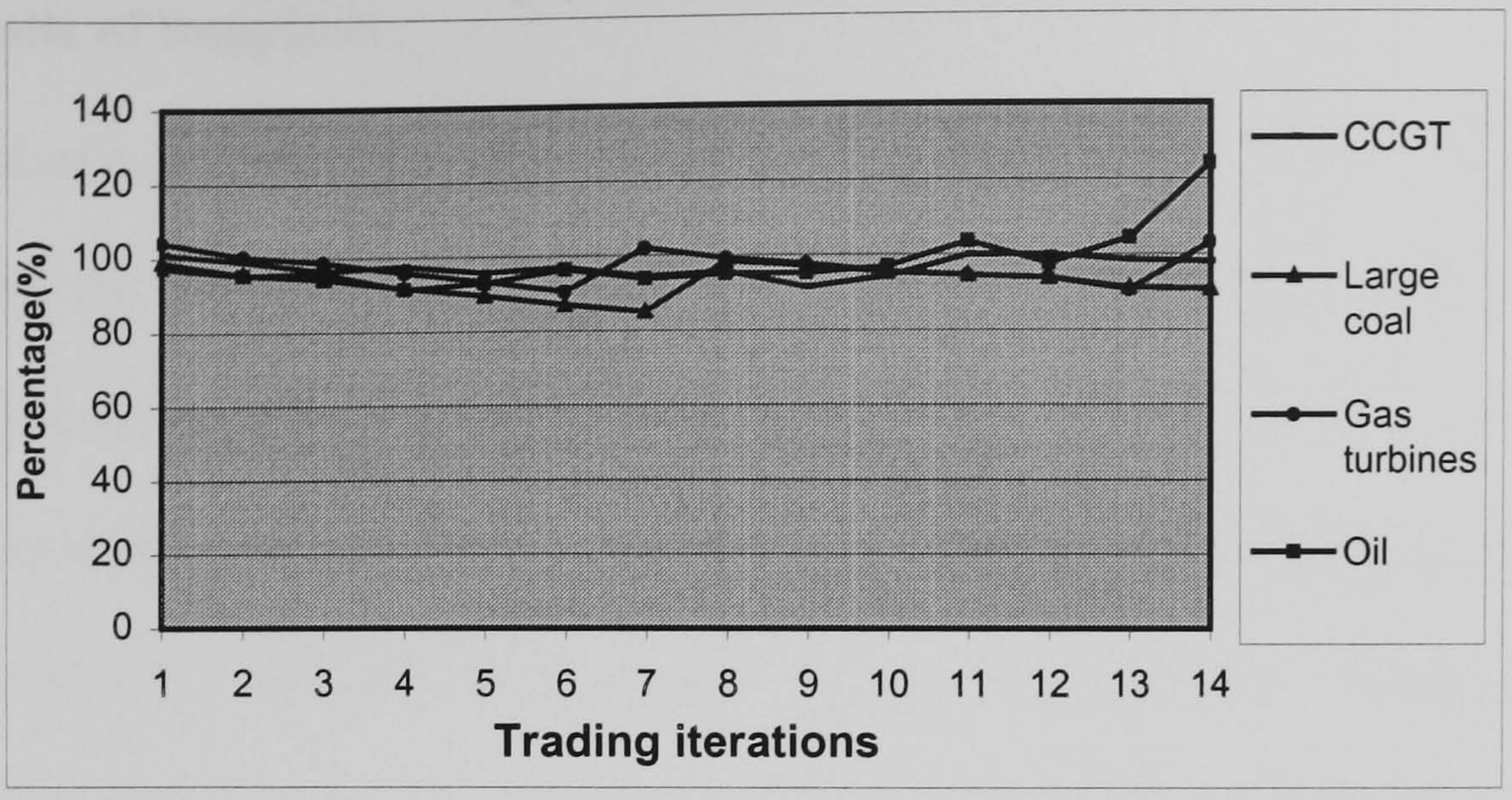

Figure 6.15: Comparison of individual profit of each generation type in the second week

Based on the figures shown here, the individual profit of each generation type has very similar development trend to the case of their used capacity.

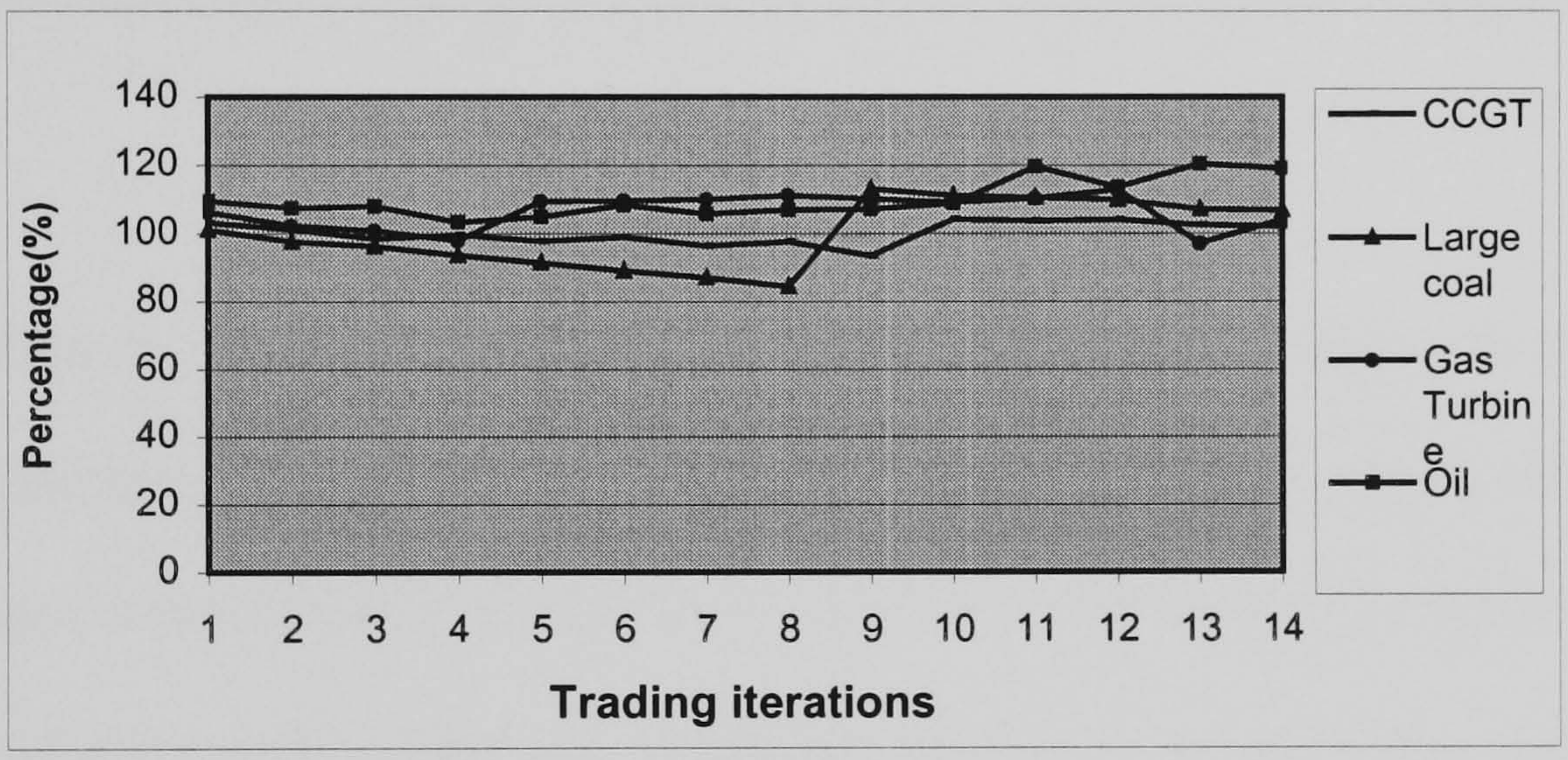

Figure 6.16: Comparison of individual profit of each generation type in the third week

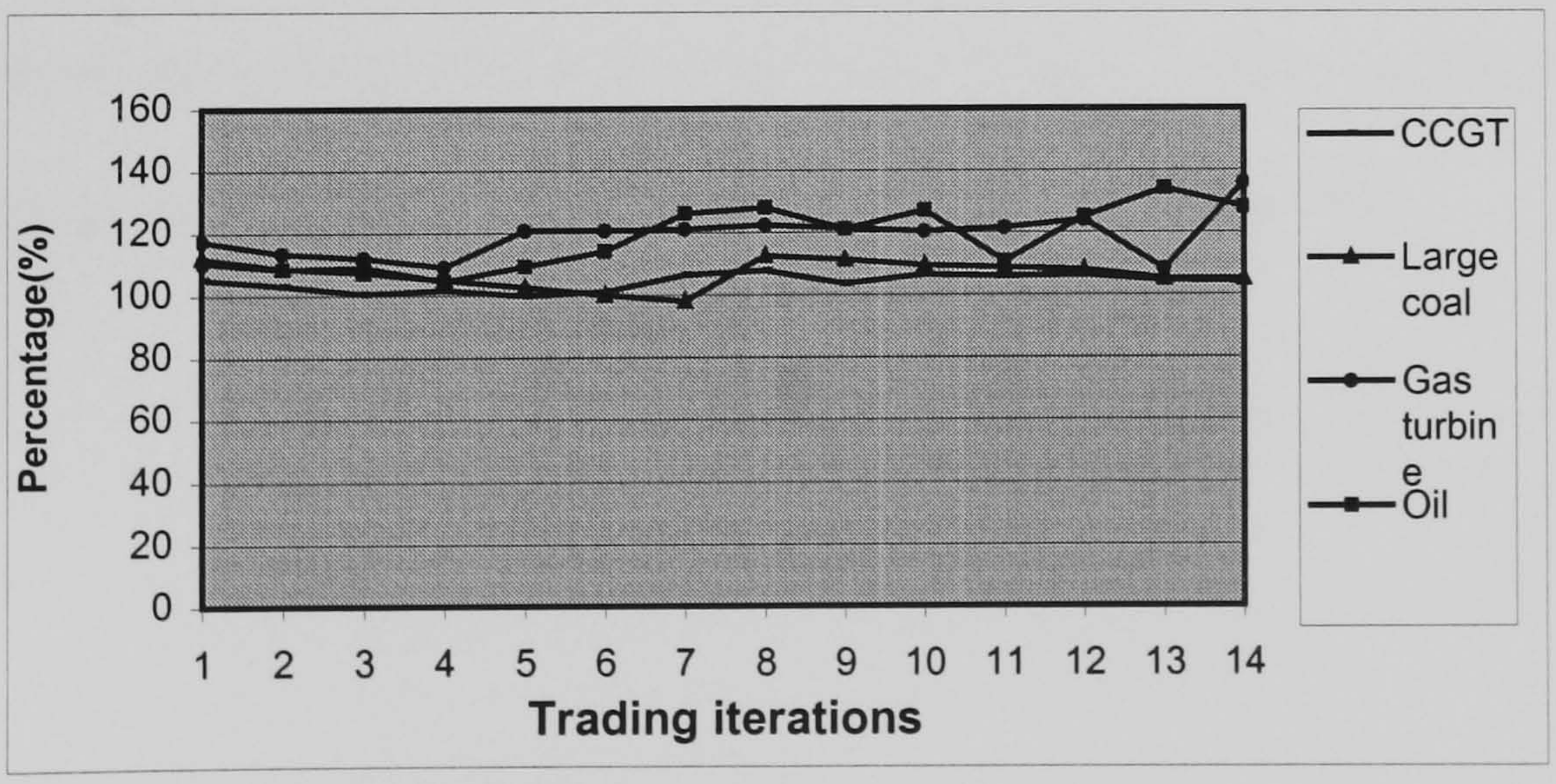

Figure 6.17: Comparison of individual profit of each generation type in the fourth week

6.3.4 Results of Suppliers

Each supplier's objective is to optimize its contract position, as well as trading prices, to minimize the cost of contracting in order to maximize total daily profits. Although in NETA the demand side service is full incorporated, the position of suppliers is still subordinate in this marketplace. Some may argue that demand service providers can withdraw demand from the PX market to counter the generator's strategy. On one hand, NETA's transition rules limited the ability of the major providers to do this by requiring that they purchase a majority of their needs from the PX markets. On the other hand, even when demand providers can move their purchases between markets, the generators always have an advantage. Once the PX market clears, generators can use System Operator load forecasts to know how much energy is required by the market.

As described in previous part, the suppliers have adopted a strategy to respond to NETA imbalance prices by over-contracting to reduce exposure to the penalty in BM. The strategy is represented by functions 4.2 and 4.3. A percentage premium, which is used to evaluate supplier's strategy and profit efficiency, can be defined as $(C_S / C_L) * 100$; the lower the premium the more efficient the strategy. The mean daily premium on each round are presented week by week. The efficiency of the suppliers' strategy optimization is clearly demonstrated in the Figure 6.17 to Figure 6.20.

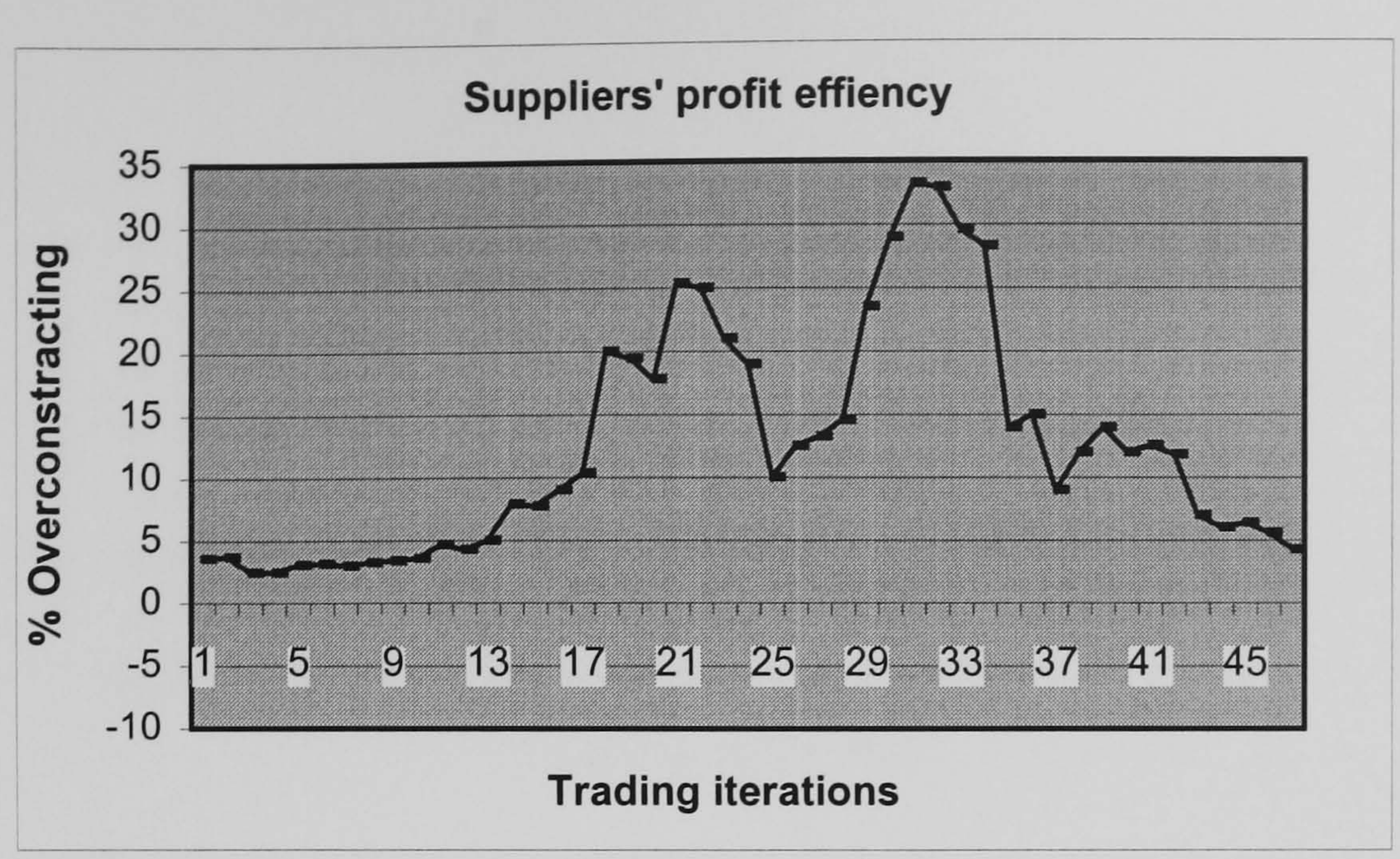

Figure 6.18: Average suppliers' percentage of overcontracting in the first week

In each of the four trading weeks, the suppliers' percentage of overcontracting is represented by a set of mean daily overcontracting points. Figure 6.18 shows the suppliers overcontract situation in the initial stage.

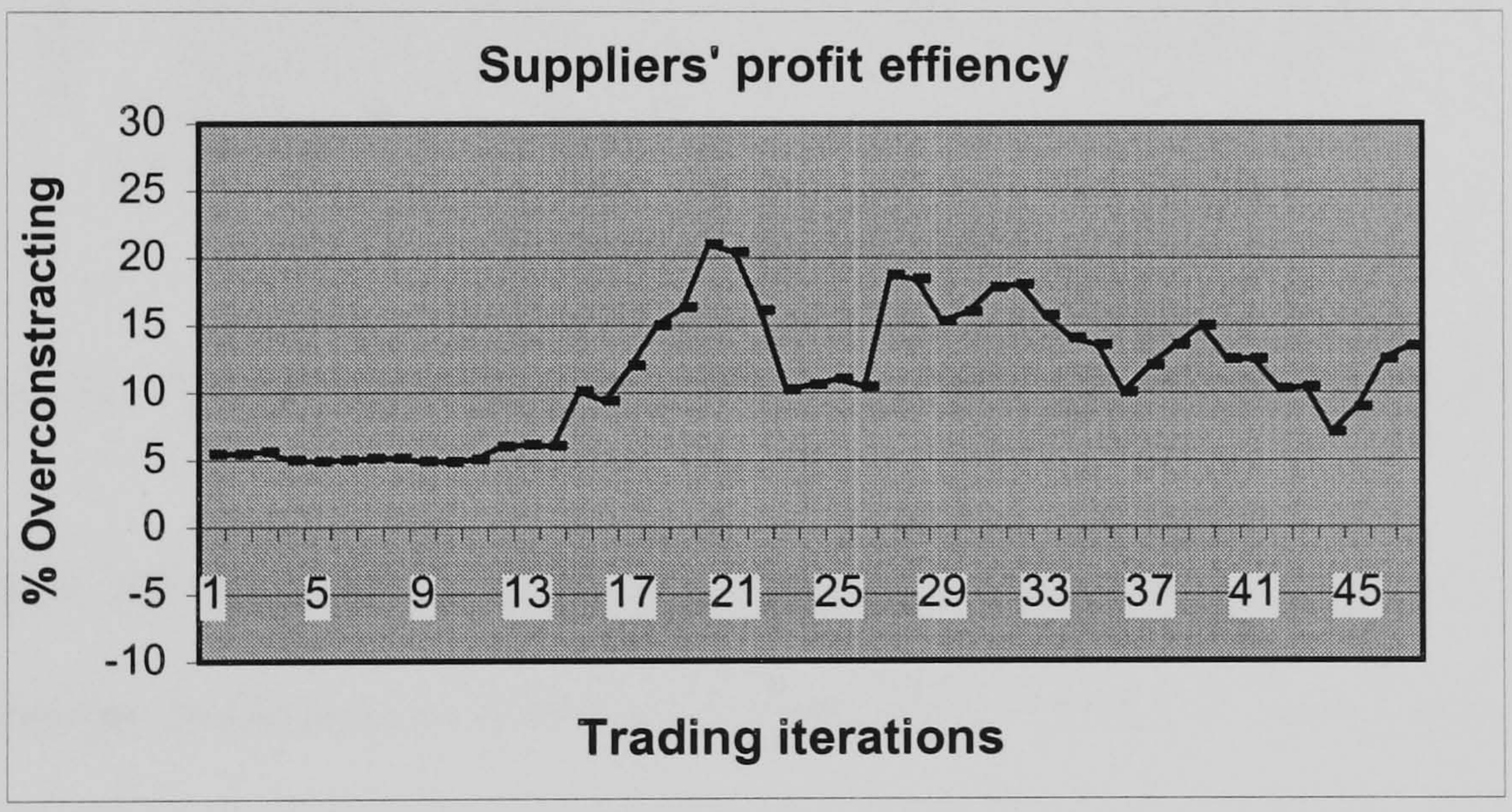

Figure 6.19: Average suppliers' percentage of overcontracting in the second week

Figure 6.19 and 6.20 present the development of suppliers' overcontracting when the model is running in the midway.

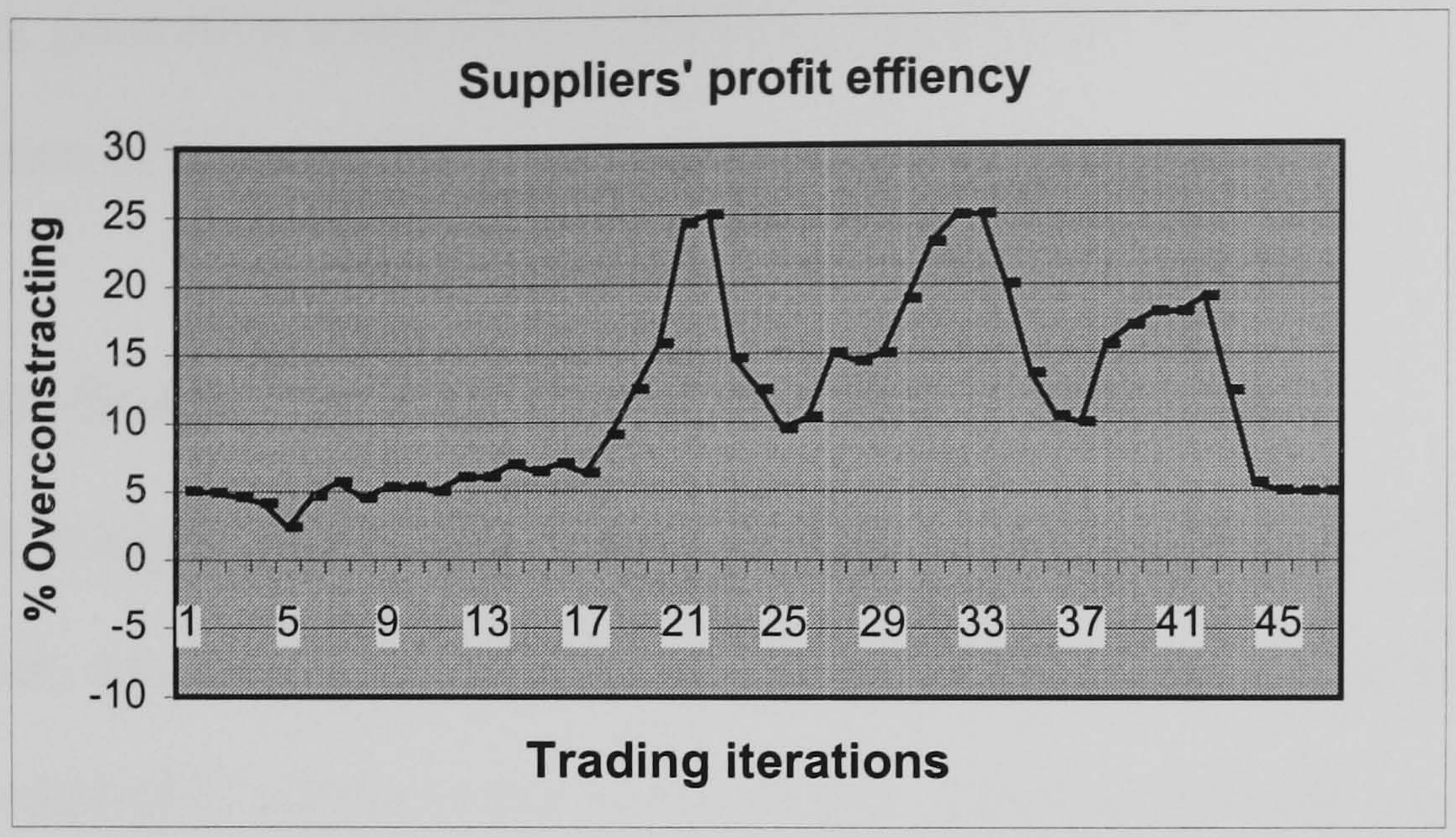

Figure 6.20: Average suppliers' percentage of overcontracting in the third week

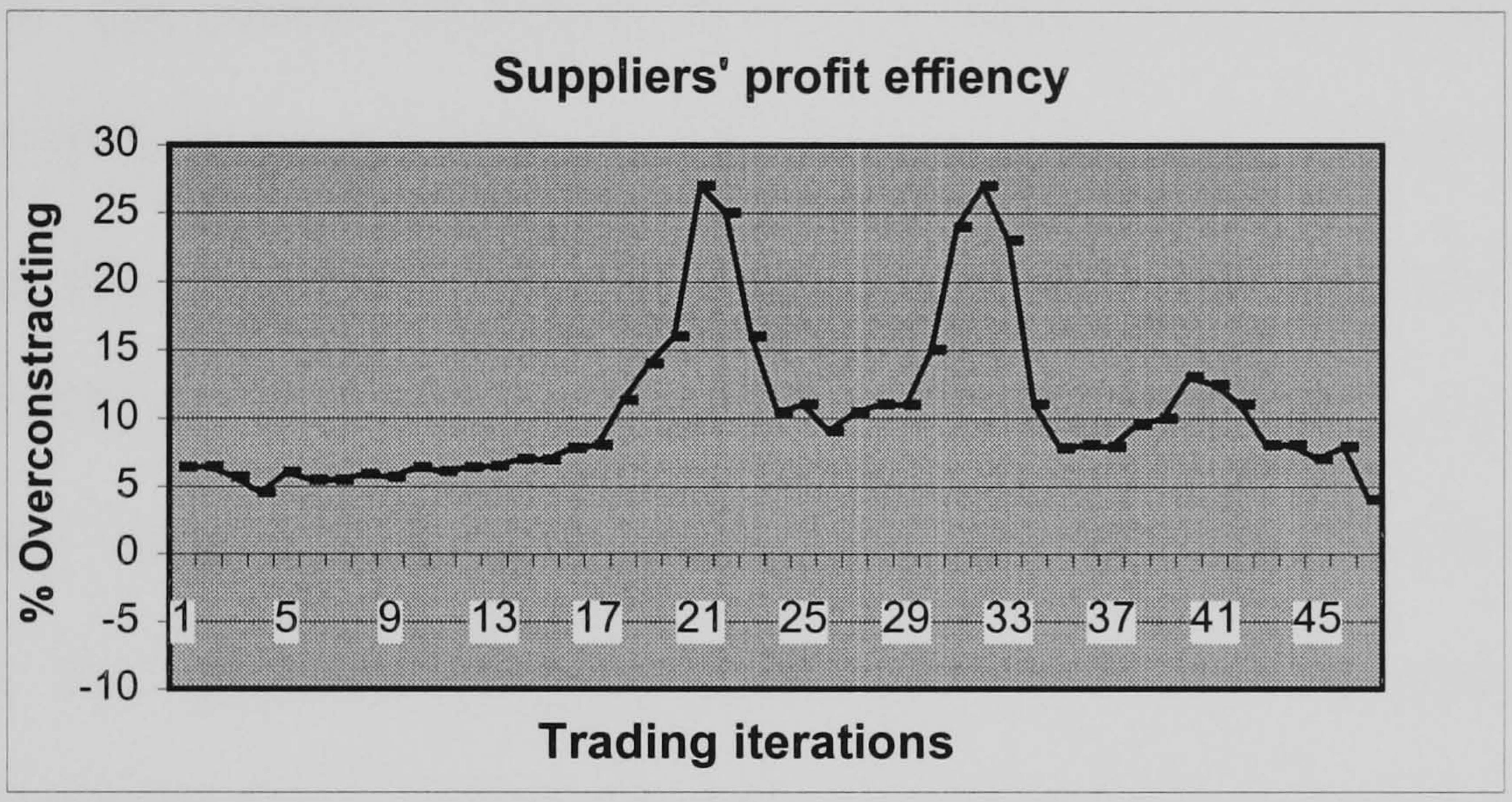

Figure 6.21: Average suppliers' percentage of overcontracting in the forth week

According to results above, the suppliers' strategy effectiveness is quite poor when gaming strategy is adopted by a number of generators. The over-contracting maintains serious especially in peak periods when the risks of being short and cost for imbalance are high.

6.3.5 Summary

Based on the application experimental results presented above, it has been proved that gaming generators have the potential to unilaterally raise the market price by withholding generation under certain situation. The detailed analysis will be taken in the last section of this chapter.

6.4 Large-Scale Model Experiment and Verification

In order to compare the effects of market player strategies under different market circumstance, the second application experiment is taken on a large-scale model which is comparably similar to the NETA market. The total available capacity is set same as the experimental model at which the non-cooperative strategy is employed, say 66.7GW. The number of generators, *m*, is assumed to 15, and suppliers', *n*, is assumed to 10 in this experiment as well. There are five sorts of power generation systems run into this model, including gas turbine, oil, coal, combined cycle gas turbine (CCGT) and nuclear plants. The generators of the same type are assumed to have similar marginal costs and generation capacity. The generators' system parameters, i.e. estimated marginal generation costs P_{mc}^{i}, assumed maximal generation capacity, Q_{smax}^{i}, of each generator on each generation type are presented in Table 6.3 below. The total available generation capacity is set as 66.7GW. Oppositely, the maximal market demand is 50GW, which is same as the market scale of the NETA, so that the average maximal demand, Q_{dmax}^{i}, of each supplier is 1125MW. The ratio of maximal market demand to total available generation capacity is set as 0.75, following the real situation in NETA. The large-scale experiments are based on the same winter daily demand profile introduced in the previous experiment.

Table 6.3 Generators' system self-parameters

Type of generation plants	**Nuclear**	**Combined cycle Gas turbine (CCGT)**	**Large Coal**	**Gas Turbines**	**Oil**
Marginal generation cost (£/MWH)	24.50	9.72	33.23	66.95	87.91
Maximal generation capacity (MW)	4450	4450	4450	4450	4450

6.4.1 Modelling Results

6.4.1.1 Traded Market Clearing Prices in Power Exchange

The method to analyse the experimental results is same as in the last experiment. These major trading results, including market clearing price *PXP*, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP*, generators used capacity, individual profit are shown and assessed.

In each trading week, the PX market clearing price, is represented by a set of mean daily market clearing price. There are overall 4 sets of experimental results corresponding to the four consecutive trading weeks.

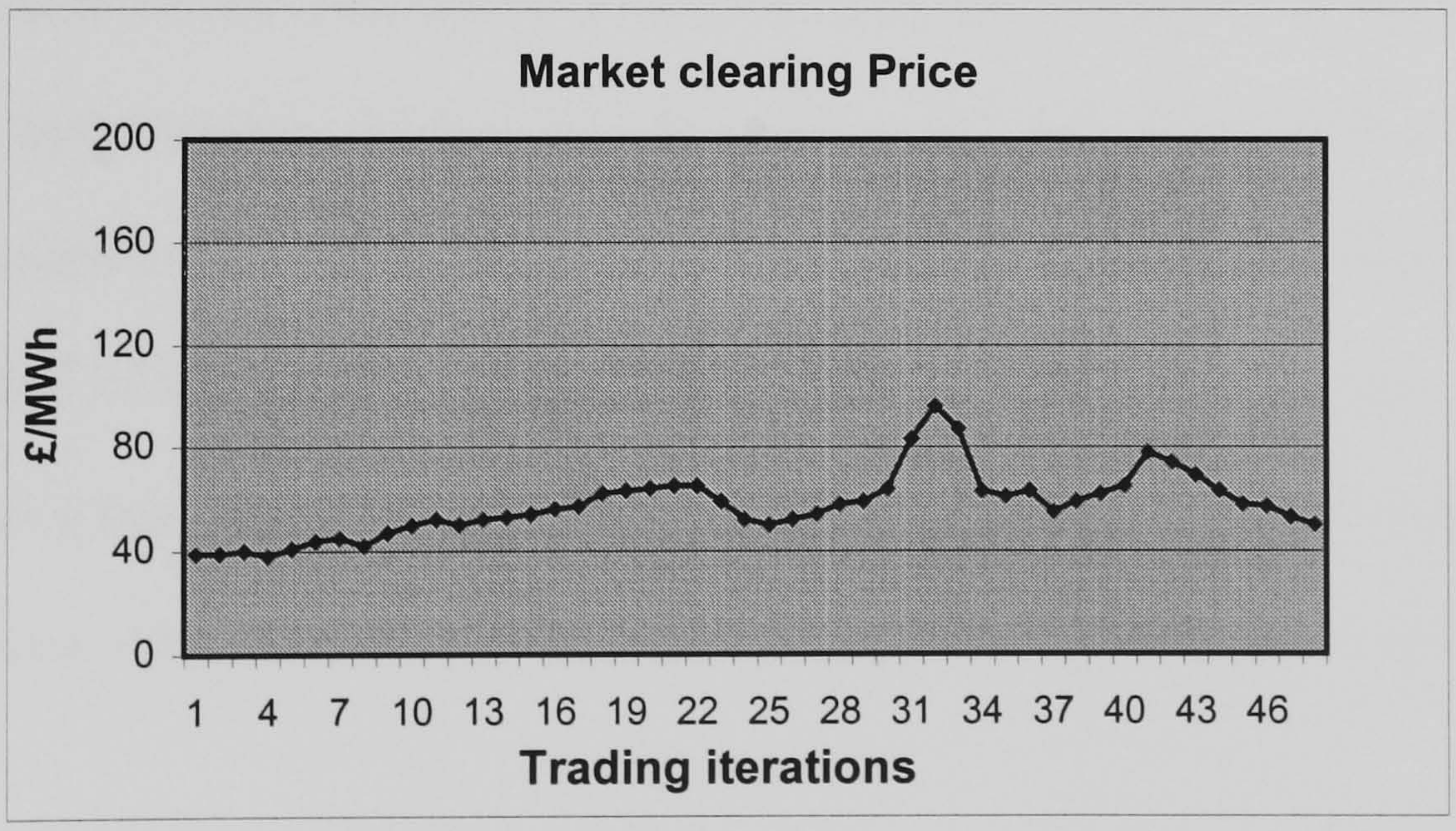

Figure 6.22: Mean daily market clearing price in PX in the first trading week

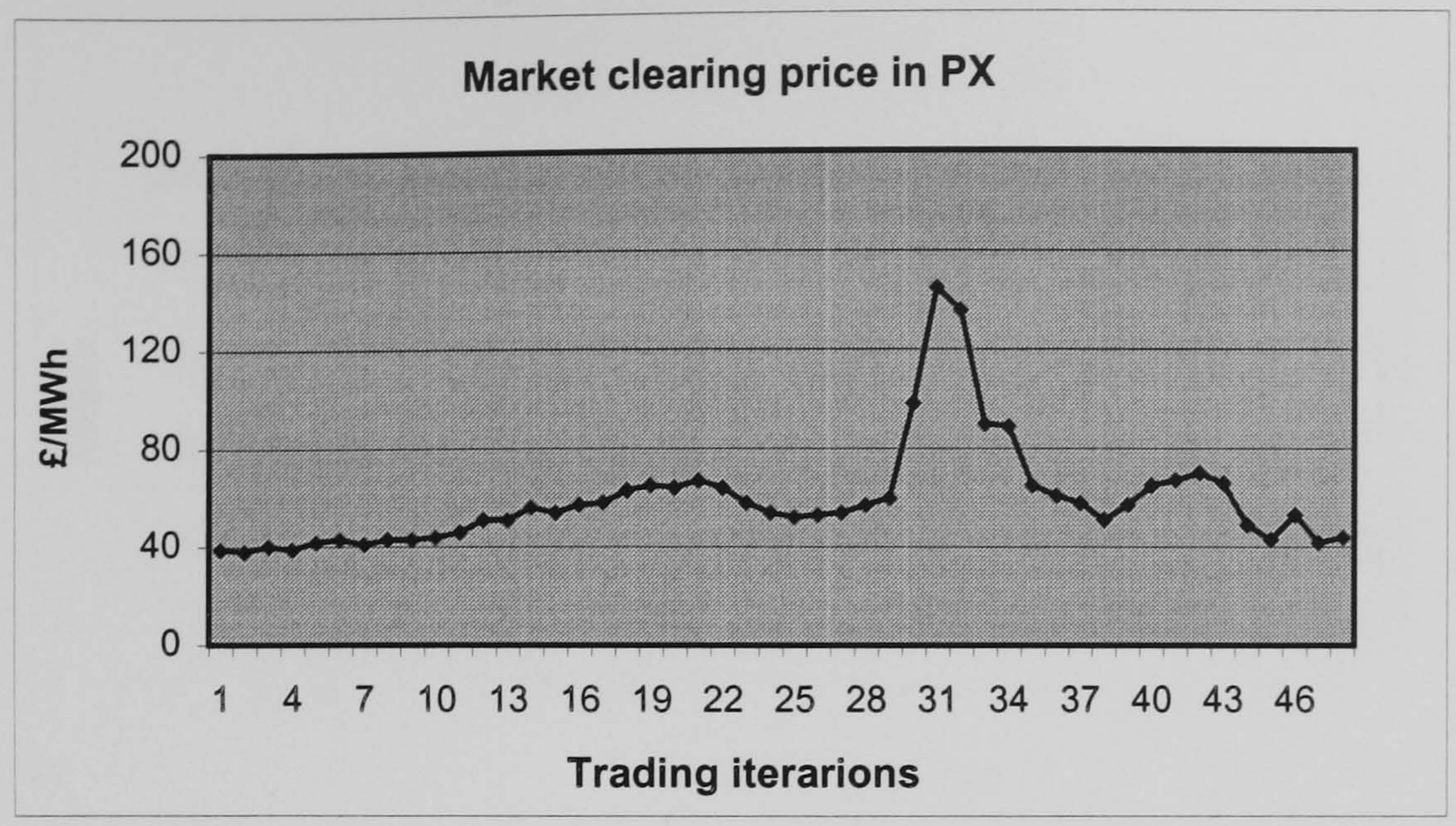

Figure 6.23: Mean daily market clearing price in PX in the second trading week

From the diagraphs above, there is an interesting trend arising, that the wholesale price *PXP* under cooperative situation in the first small-scale model is more higher than in the large-scale model with same trading strategy. There are a few price spikes on wholesale market price *PXP* happened in the later model as compared with in former where the price spikes arise even when sufficient supply is available. Whereas, in the second model these price spikes only emerge when the demand is on peak times, 10:00am to 12:00am, and 19:00pm to 21:00pm. Also, in the second experiment, the *PXP* in the rest of trading rounds are very close to the *PXP* in the model at which market participants adopt non-cooperative strategy. Hence, in order to get better understanding of how the strategies work, we adjust an crucial gaming strategy parameter, *X*, which represents the percentage of how much output capacity each member of the coalition agreement intends to withhold in its total generation capacity, to a new range between 10% and 40%, which was set between 10% and 25%. The new variable is experimented in the third and forth trading weeks.

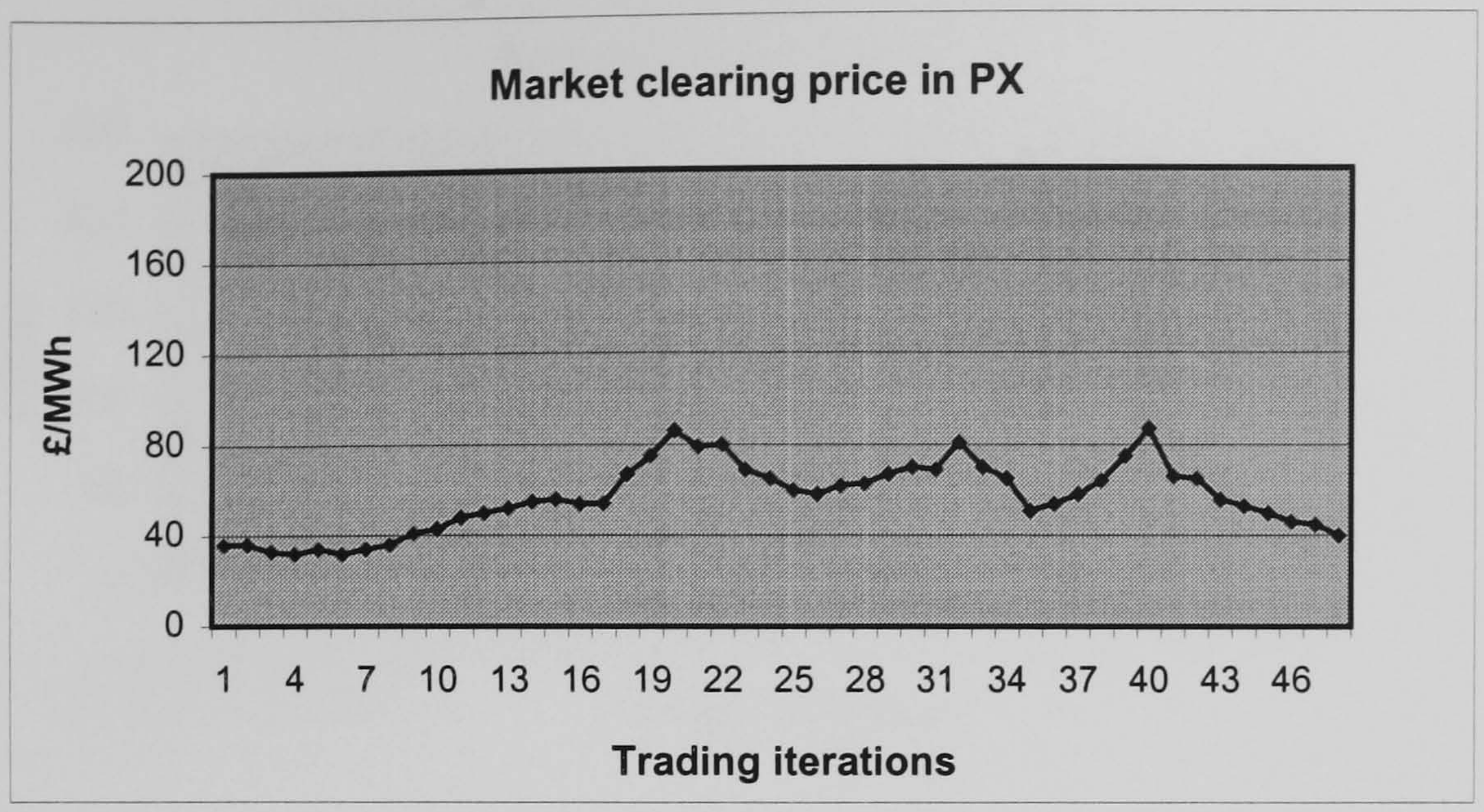

Figure 6.24: Mean daily market clearing price in PX in the third trading week

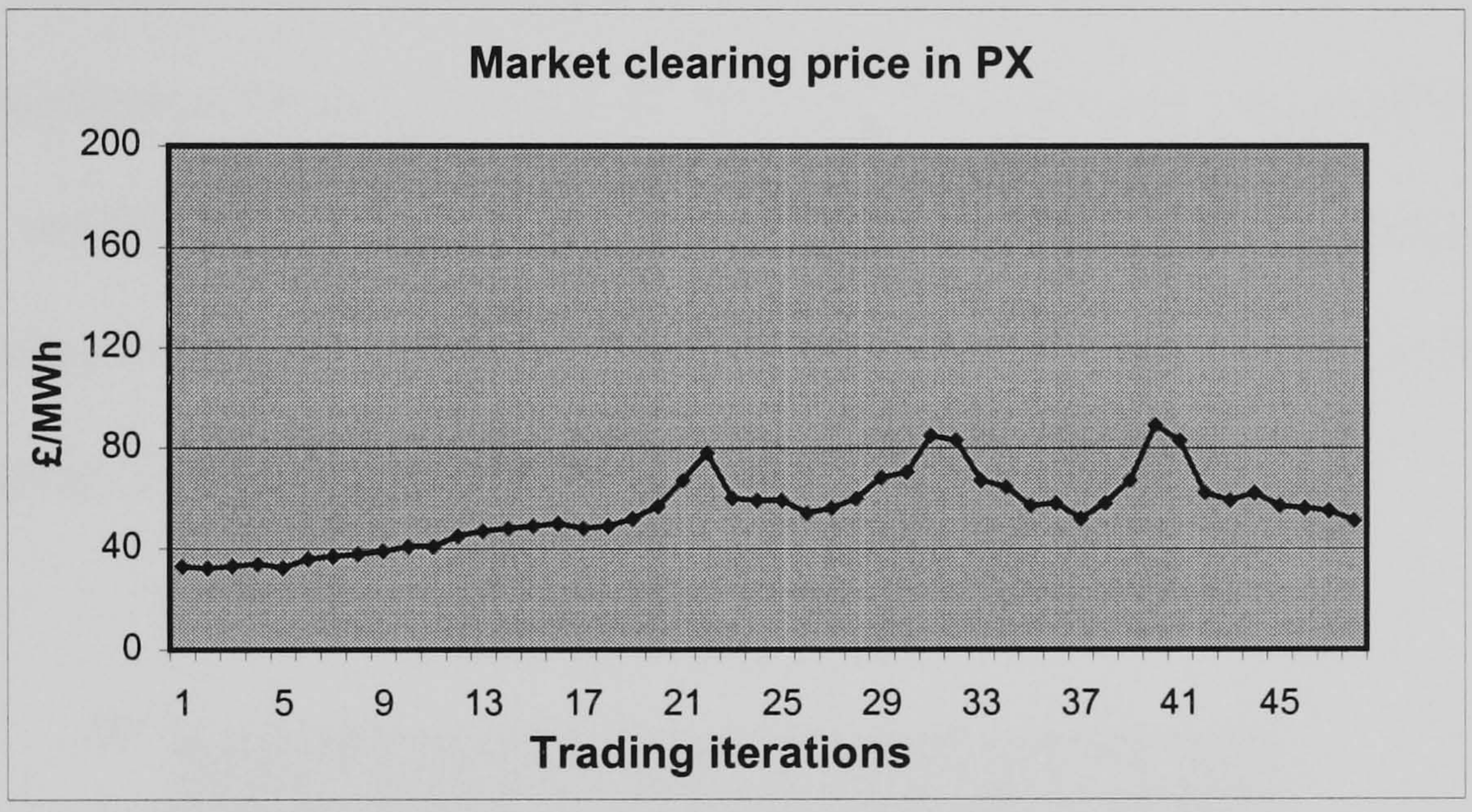

Figure 6.25: Mean daily market clearing price in PX in the forth trading week

On the last two experiments, the emergence of price spikes keeps same as in the first two experiments. The discussion for this feature will be carried out later on.

6.4.1.2 Traded Prices in Imbalance Settlement System – System Sell Price and System Buy Price

Imbalance Settlement prices are parameters to observe the efficiency of gaming generators strategy and how market players' performance influence on the market.

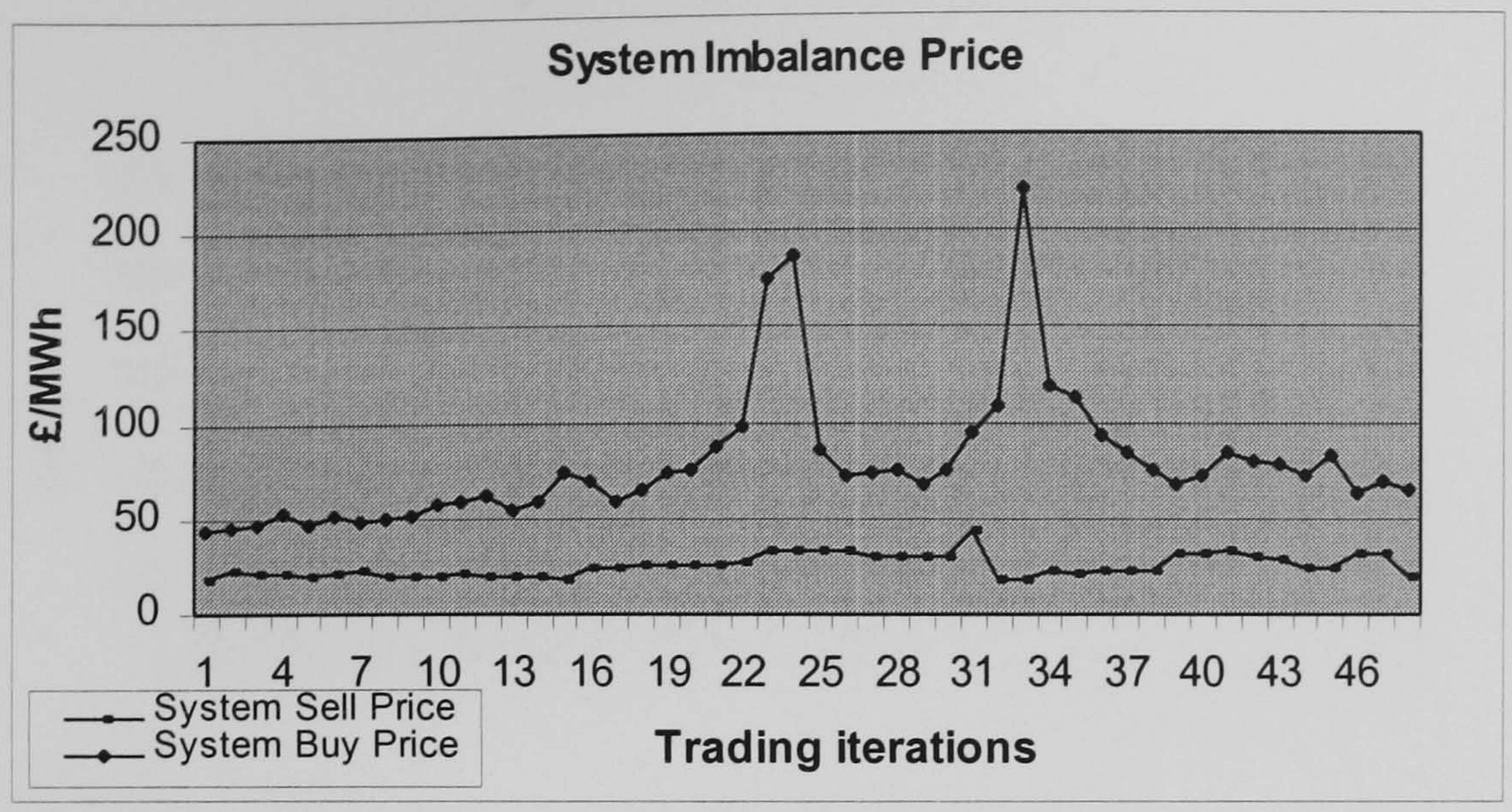

Figure 6.26: Mean daily System Imbalance Price in the first week

Figure 6.26 to Figure 6.29 reveal the impact of market participants' strategies on the Imbalance Settlement Process in terms of showing the other two important reference parameters, imbalanced settlement prices System Buy Price *SBP* and System Sell Price *SSP*. Figure 6.26 demonstrates the mean daily price curves of the imbalanced settlement prices *SBP* and *SSP* in the beginning week.

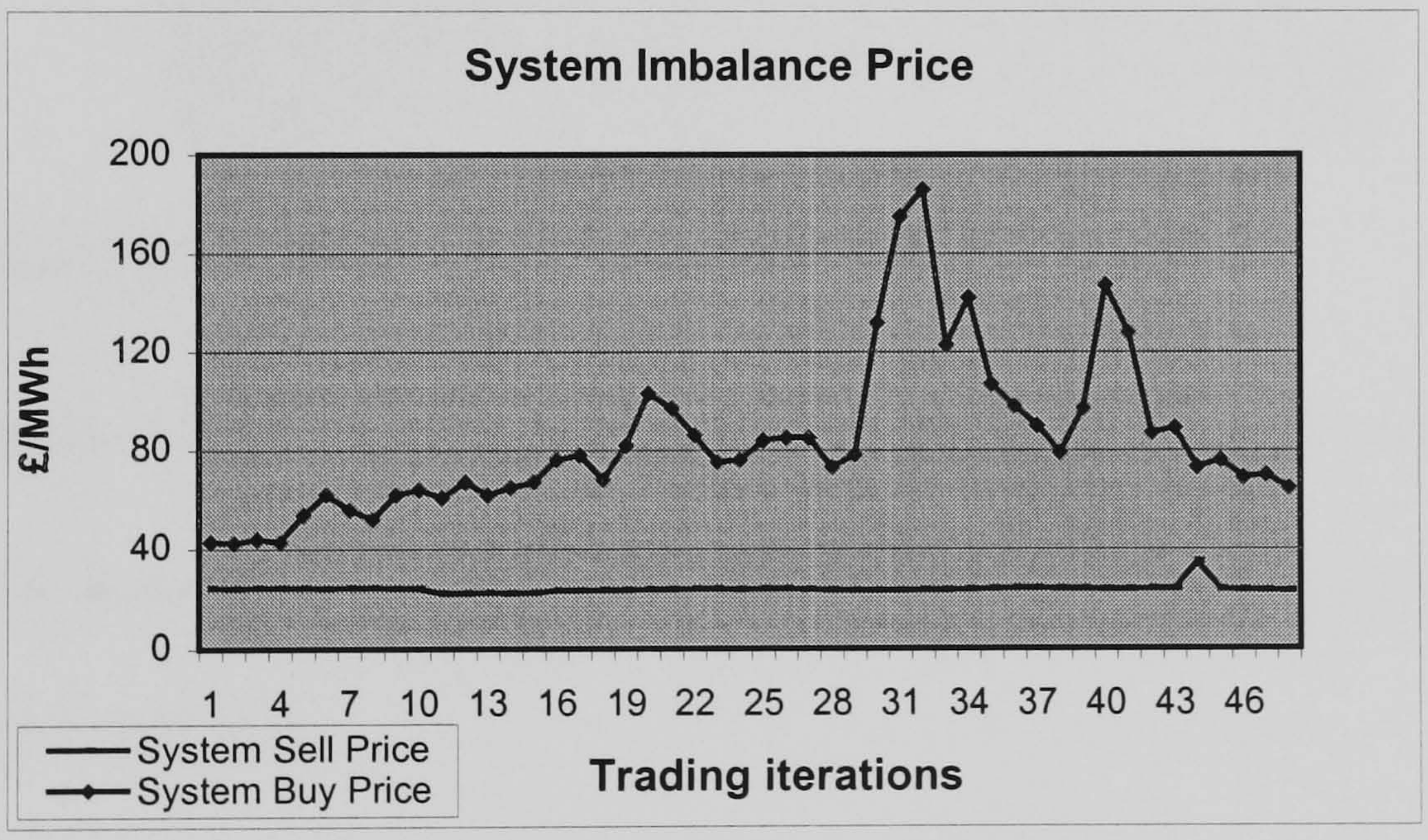

Figure 6.27: Mean daily System Imbalance Price in the second week

Figure 6.27 and 6.28 present the development of mean daily System Imbalance price when the model is running in the midway. It is clear that the price spikes only emerge in peak demand periods in the model.

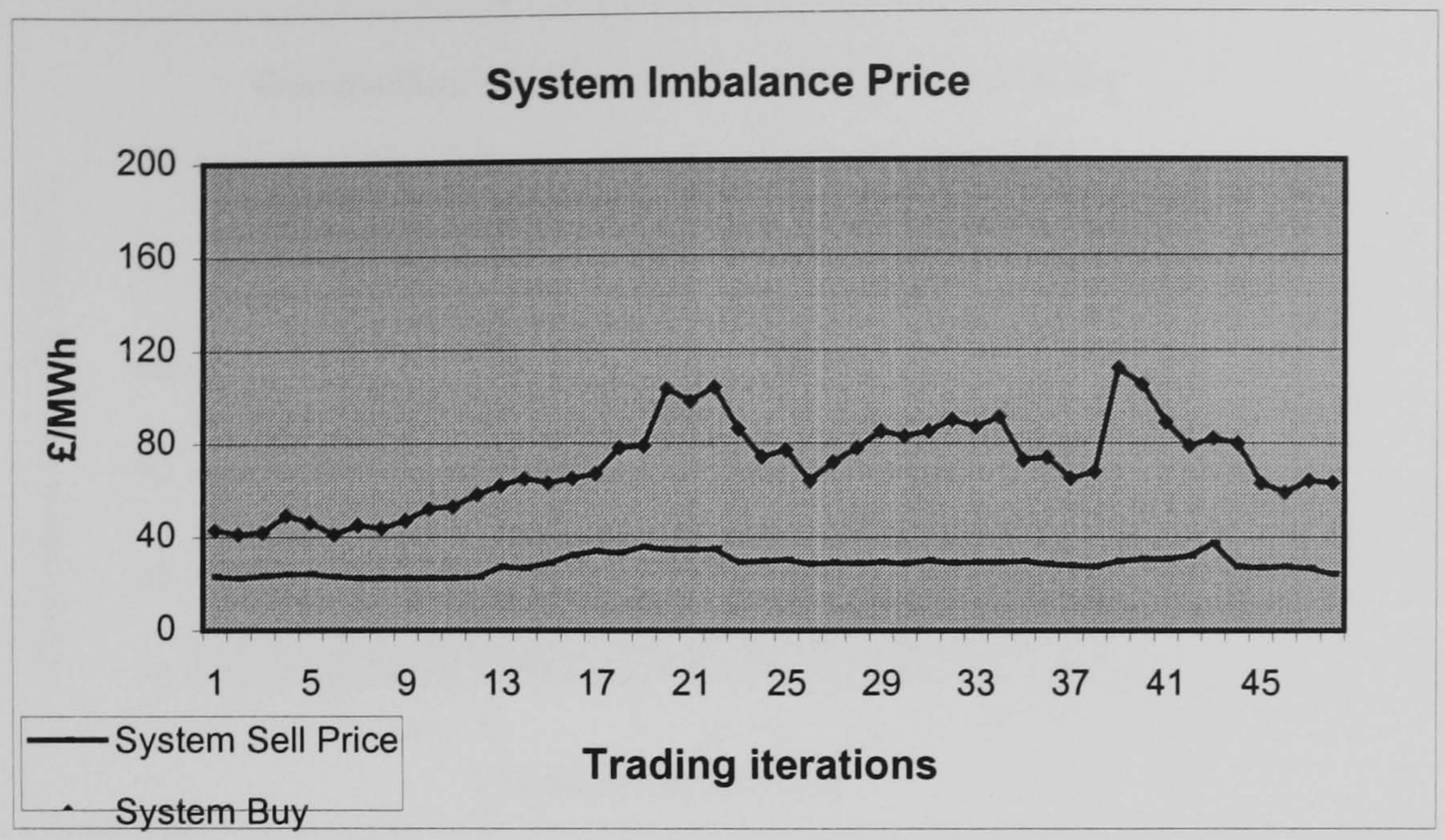

Figure 6.28: Mean daily System Imbalance Price in the third week

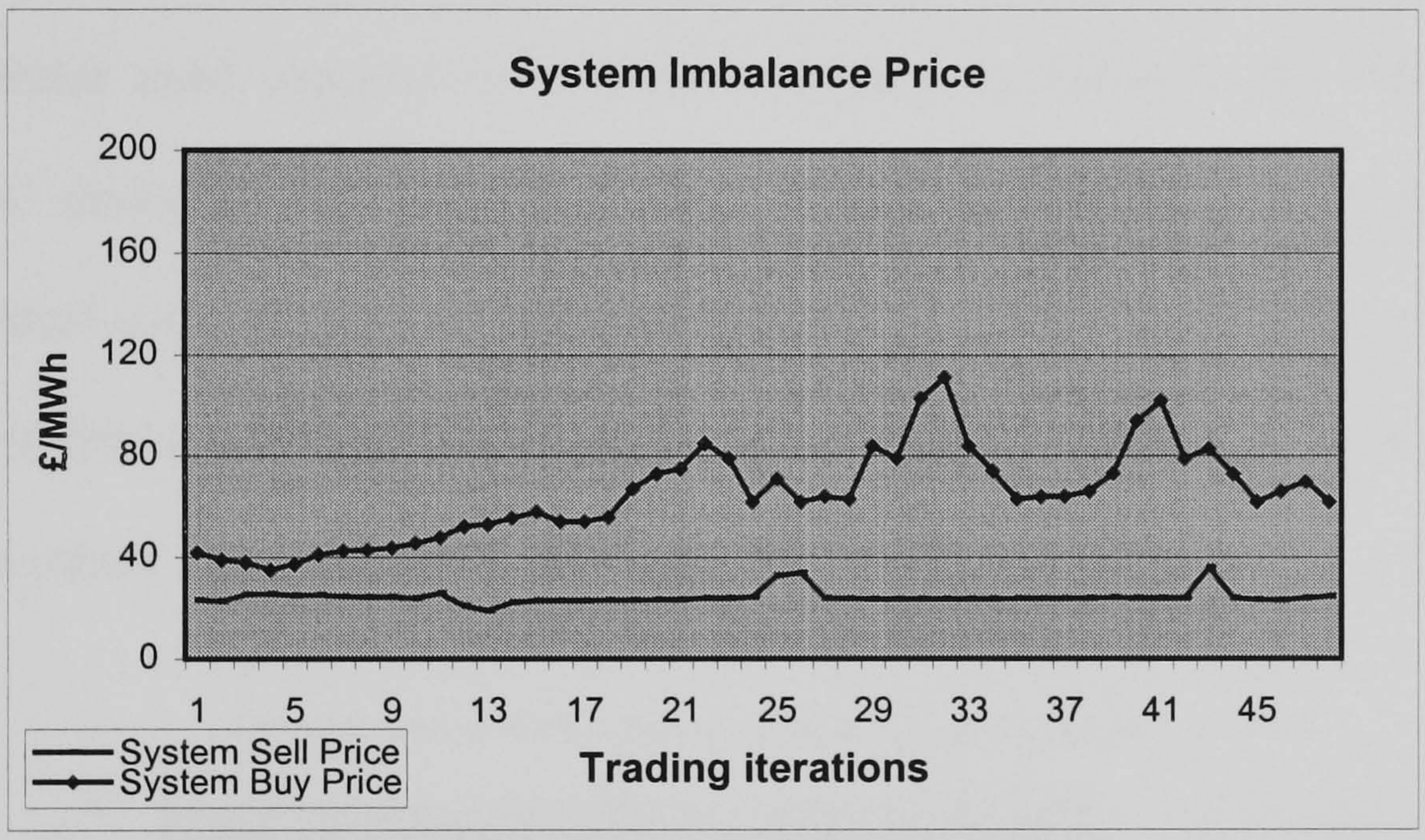

Figure 6.29: Mean daily System Imbalance Price in the forth week

The model's mean daily imbalanced settlement prices in the last trading week are illustrated in Figure 6.29.

6.4.1.3 Generators Capacity Used

The traded generation output volumes from different types of generators are presented as following by week:

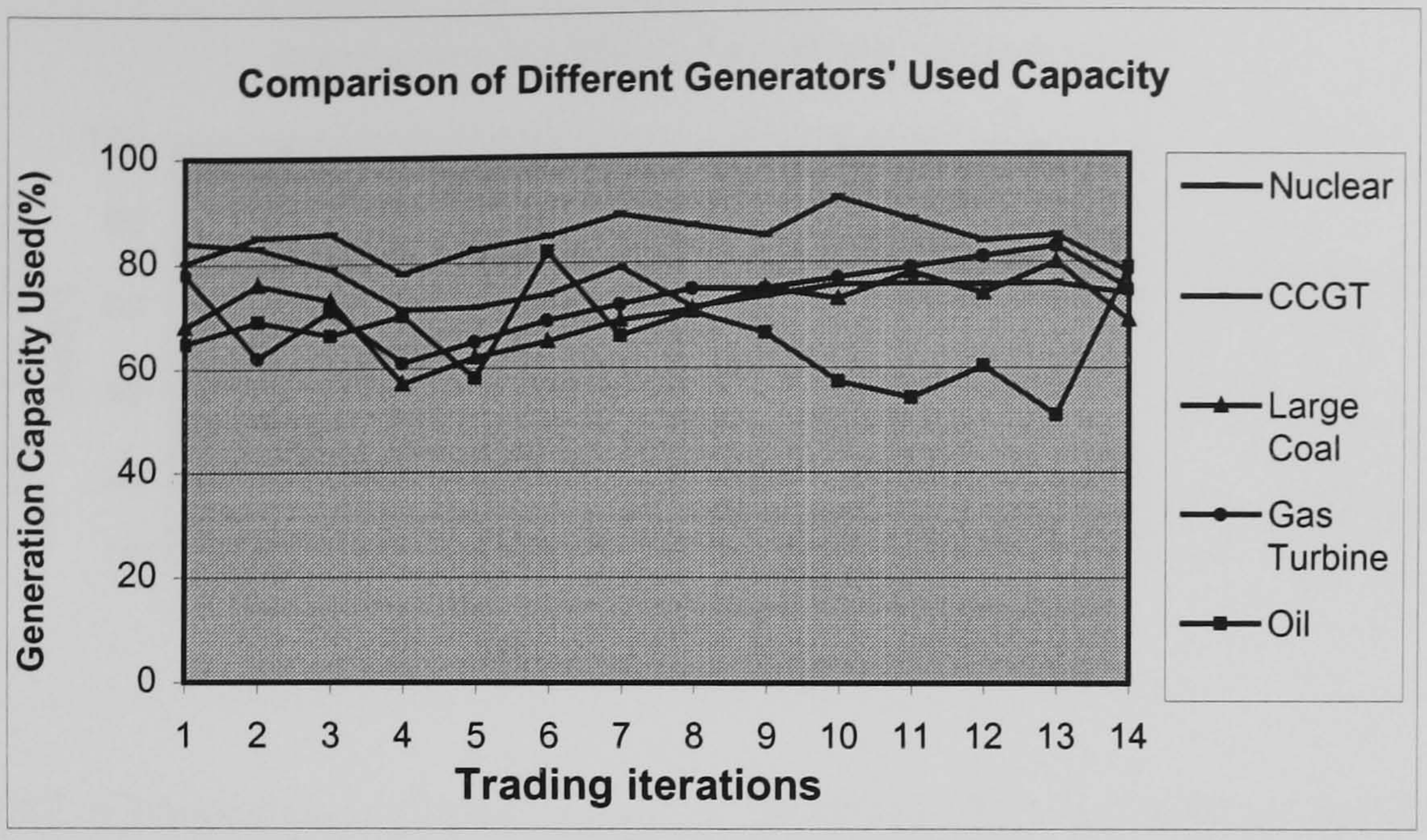

Figure 6.30: Comparison of used capacity for different generators in the first week

The generator used capacity is a crucial reference to measure the efficiency of generators' strategies and to decide the next move on the trading. Figure 6.30 shows the individual used capacity for different generators in the first week. Similar to the last experiment carried out in a small-scale model, the nuclear plants get more market share than others in the initial stages.

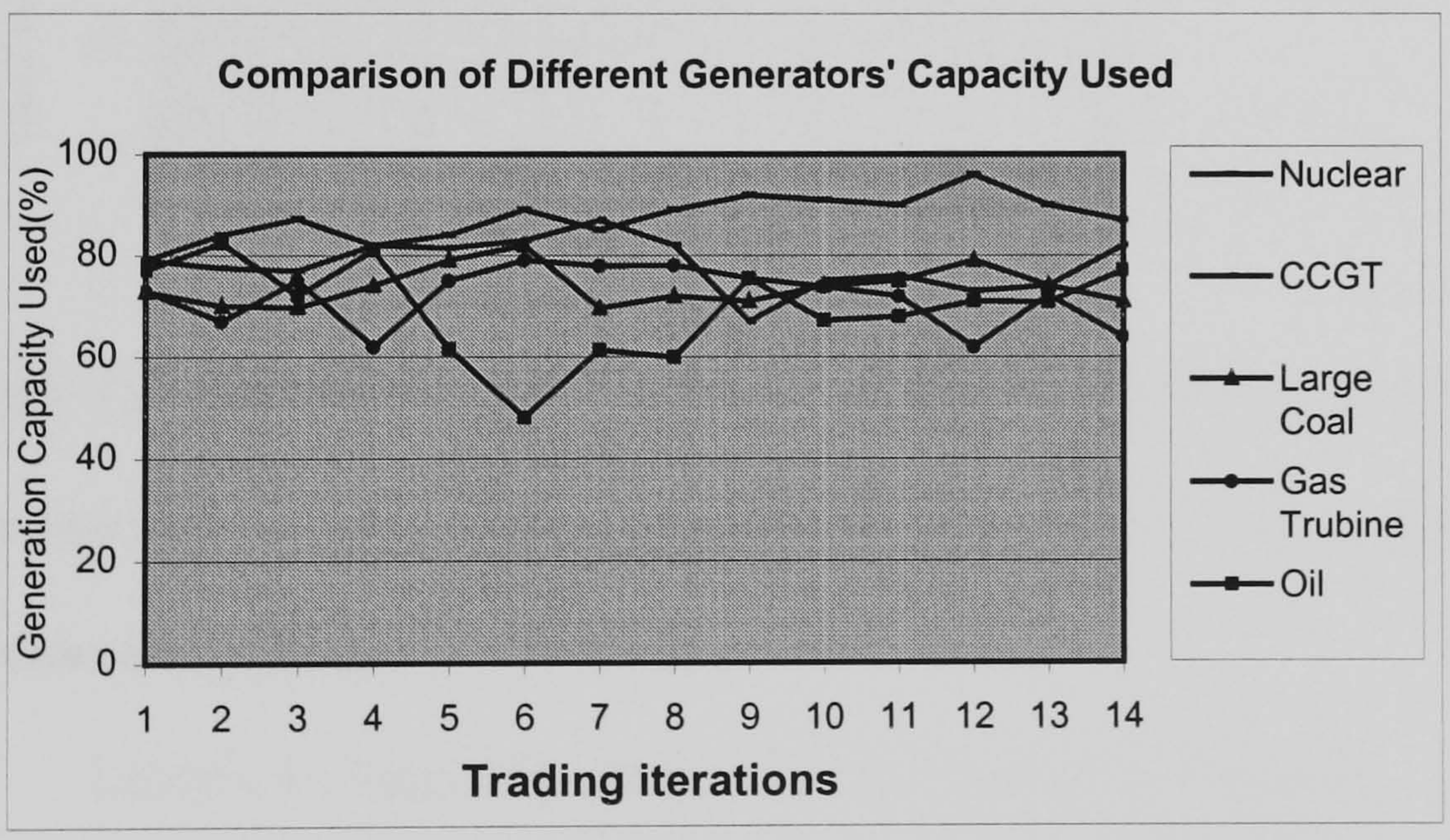

Figure 6.31: Comparison of used capacity for different generators in the second week

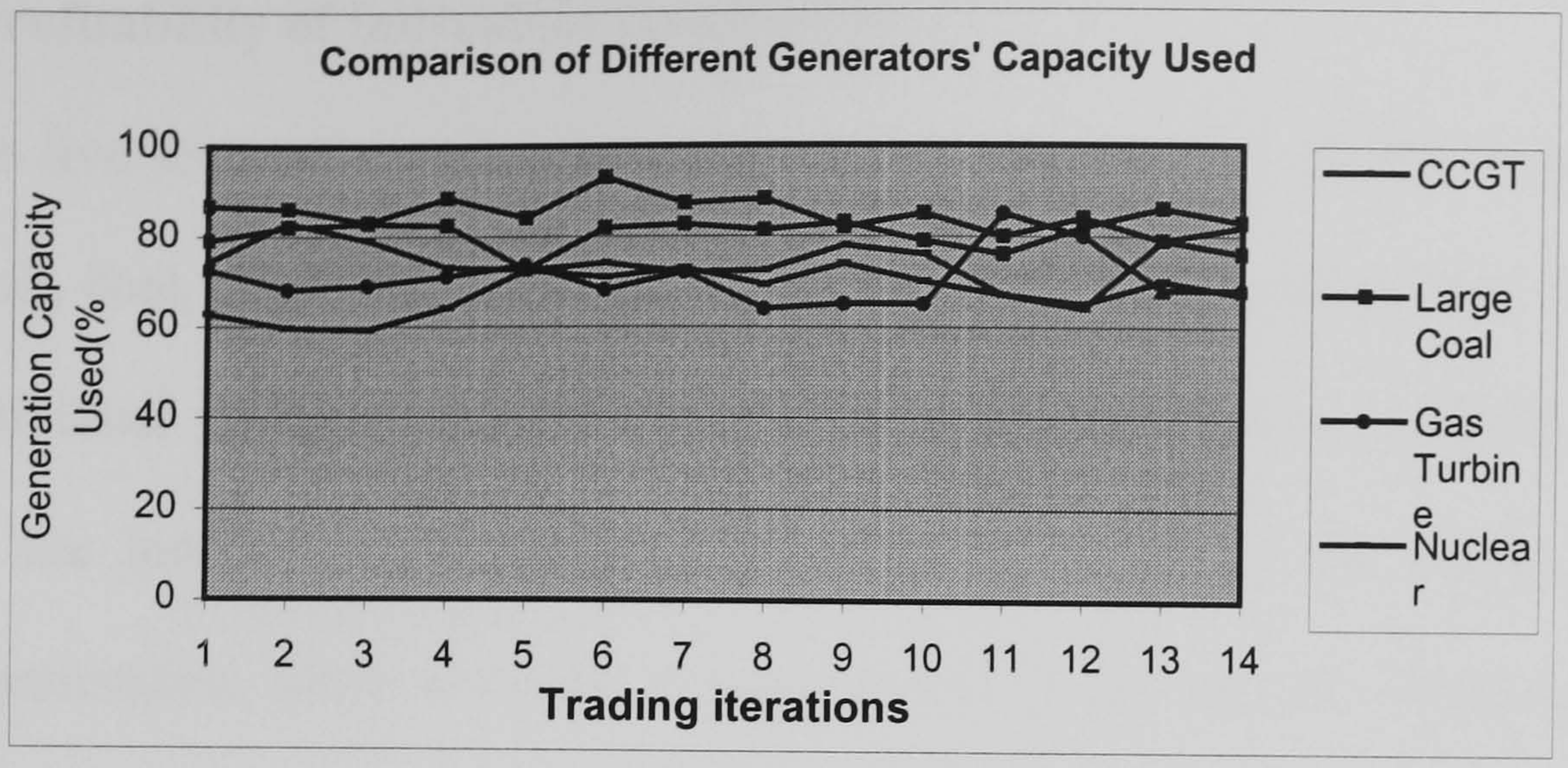

Figure 6.32: Comparison of used capacity for different generators in the third week

Figure 6.32 shows the development of used capacity for different generators in the third week.

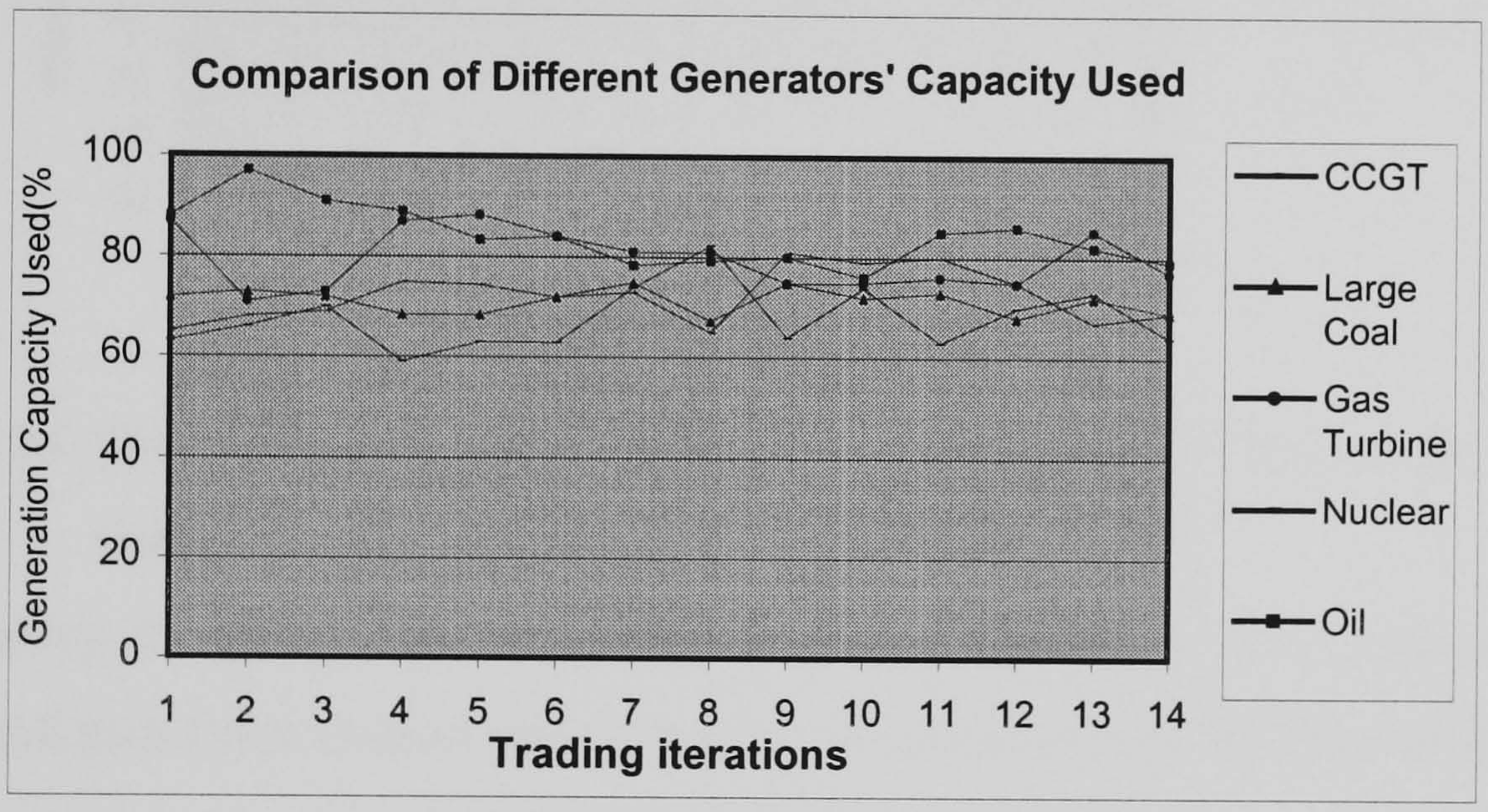

Figure 6.33: Comparison of used capacity for different generators in the forth week

The evolvement of the use capacity of individual generation type is these trading process is shown following.

Table 6.4: Mean Percentage of Used Generation Capacity

Generation Type	*Nuclear*	*CCGT*	*Large coal*	*Gas turbine*	*Oil*
First Week	0.829	0.755	0.729	0.728	0.727
Second Week	0.832	0.778	0.748	0.722	0.728
Third Week	0.68	0.729	0.782	0.727	0.75
Forth Week	0.685	0.734	0.713	0.761	0.82

6.4.1.4 Profitability of Individual Generators

There are five sorts of power generation systems run into this model, including gas turbine, oil, coal, combined cycle gas turbine (CCGT) and nuclear plants. The mean daily individual profit of each generation type is calculated by function 4.4. To compare the individual generation sort's strategy efficiency, the mean profit of nuclear generation plant on each trading round is set as the benchmark. The experiment results are shown below.

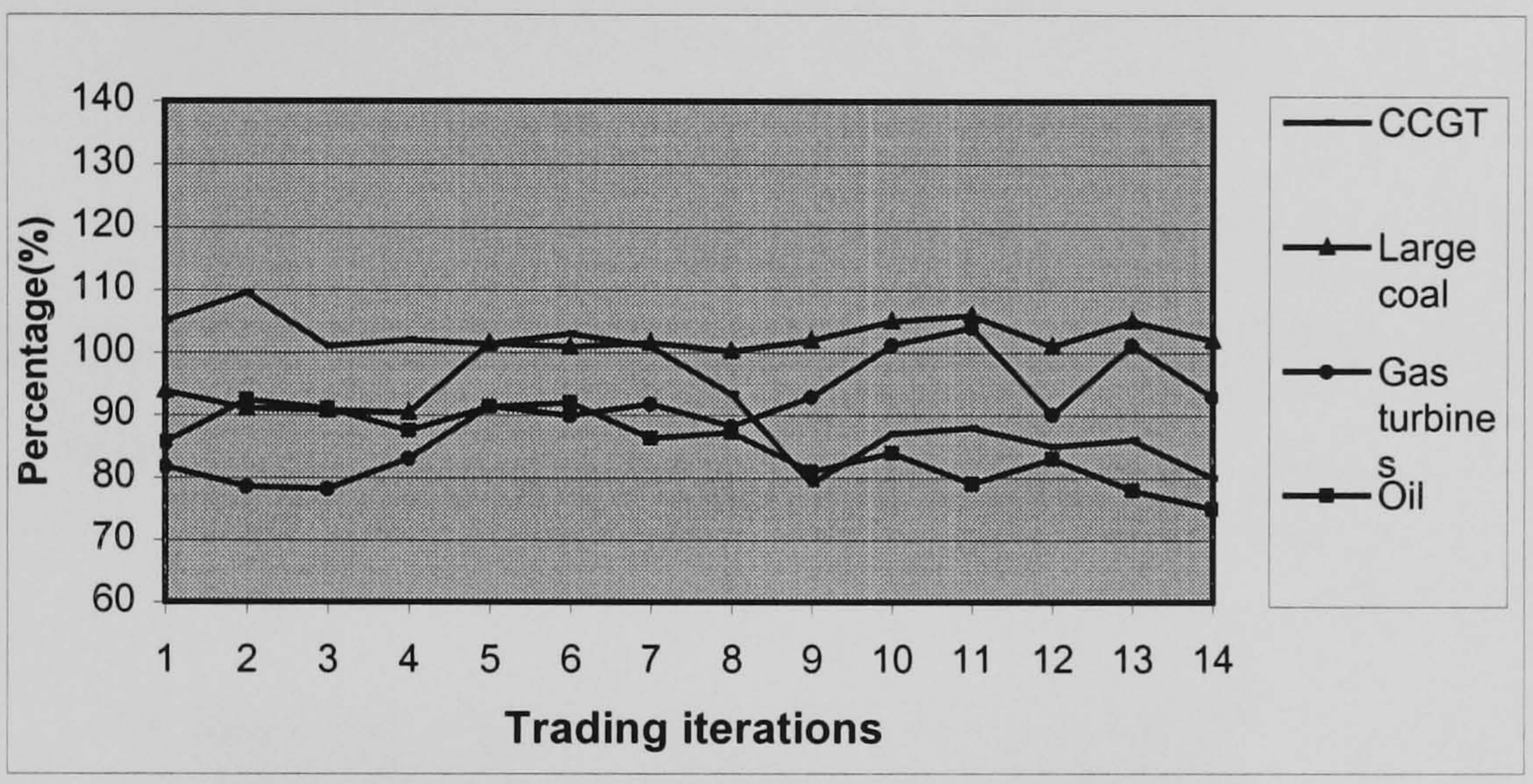

Figure 6.34: Comparison of individual profit of each generation type in the first week

Corresponding to the situation at which the nuclear plant has more used generation capacity and gain more market share, its profit is the highest in the beginning.

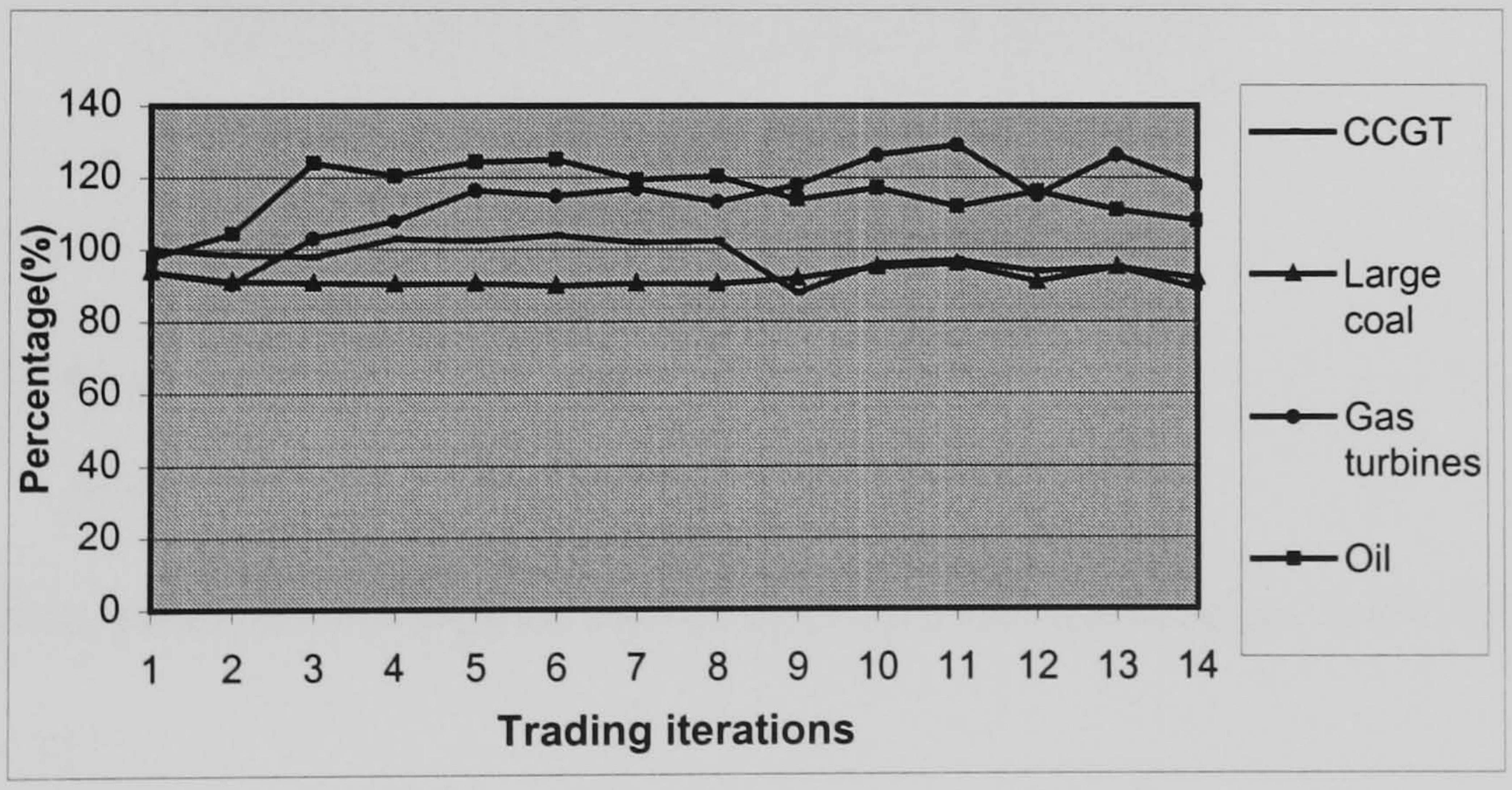

Figure 6.35: Comparison of individual profit of each generation type in the second week

The evolvement of the individual profit when the trading is running in midway is shown in Figure 6.35 and Figure 6.36.

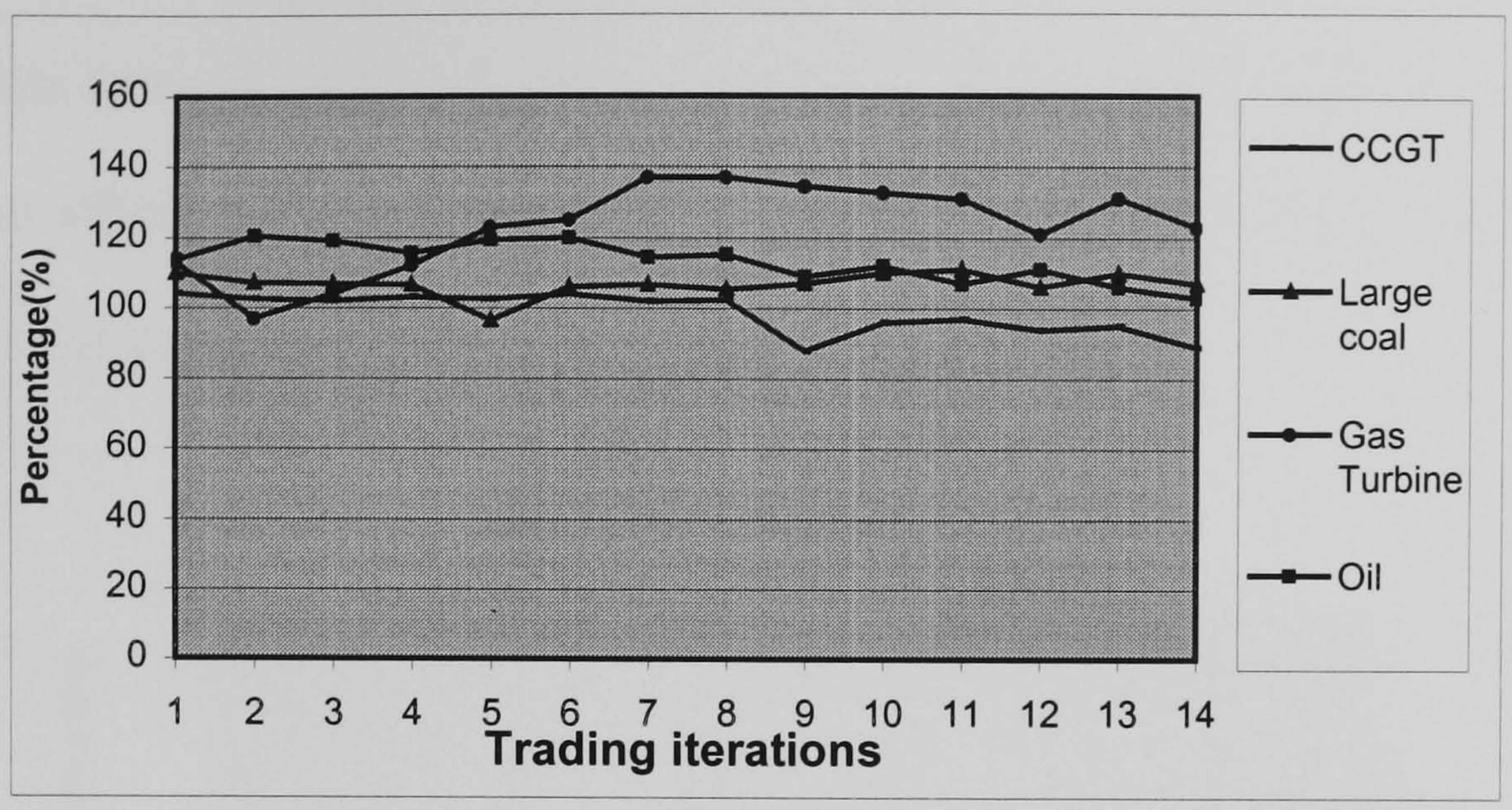

Figure 6.36: Comparison of individual profit of each generation type in the third week

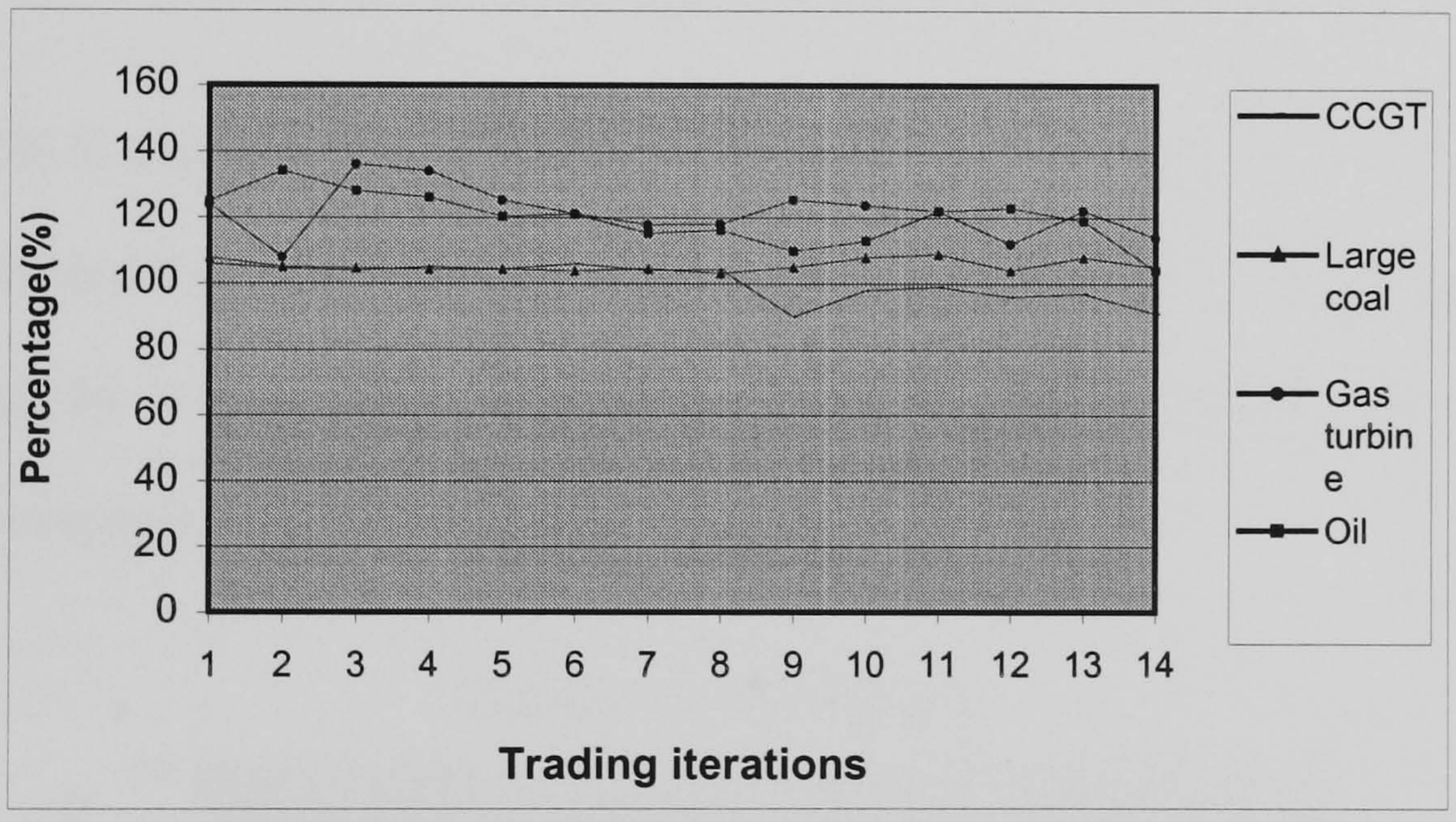

Figure 6.37: Comparison of individual profit of each generation type in the forth week

The individual profit of each generation type from the last trading week are presented in Figure 6.37.

6.4.2 Results of Suppliers

A percentage premium, which is used to evaluate supplier's strategy and profit efficiency, is calculated by equations 4.2 and 4.3. The lower the premium the more efficient the strategy. The mean daily premium on each round are presented week by week. The efficiency of the suppliers' strategy optimization is clearly demonstrated from these figures.

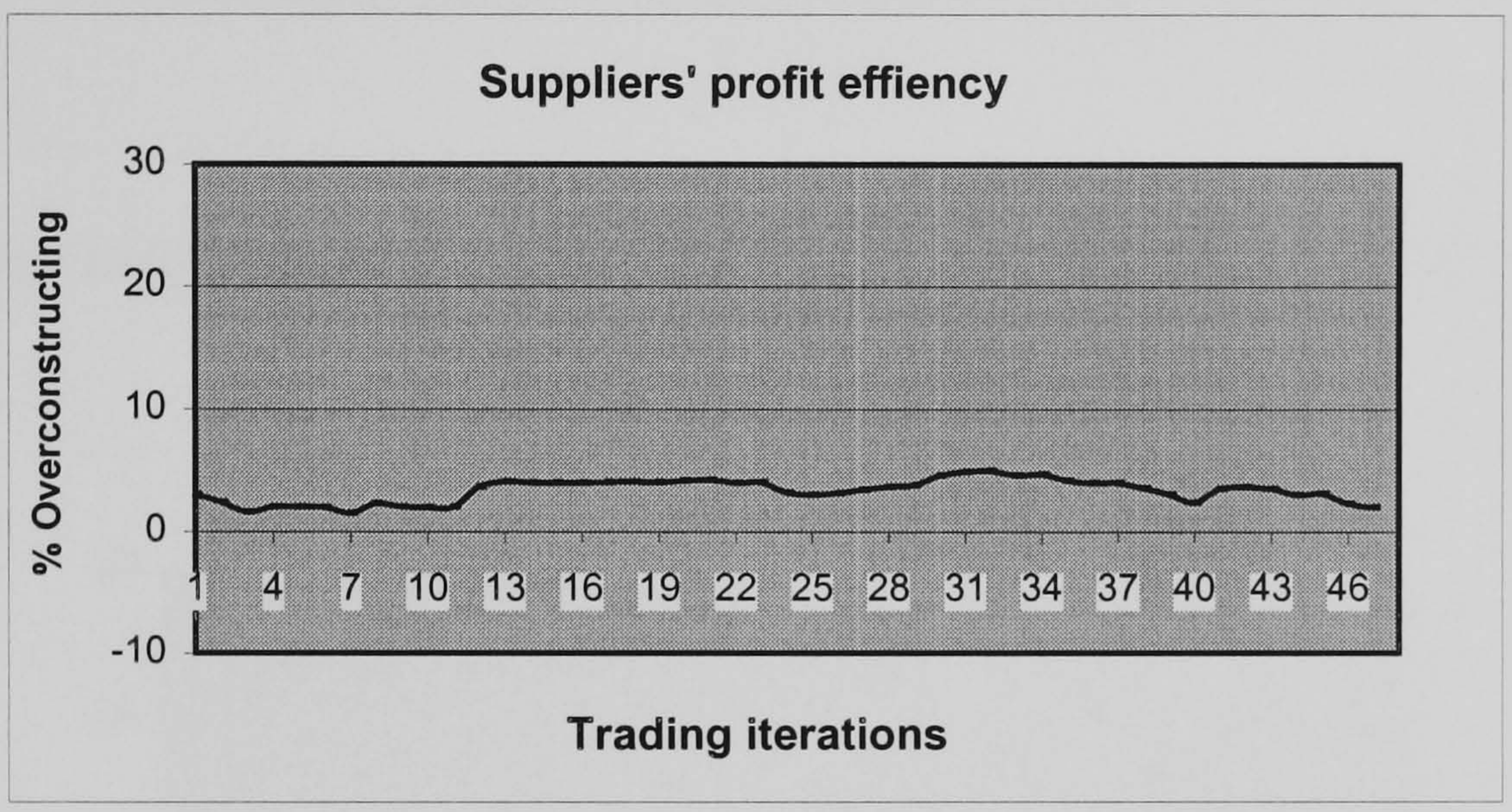

Figure 6.38: Comparison of suppliers' percentage of overcontracting in the first week

In each of the four trading weeks, the suppliers' percentage of overcontracting is represented by a set of mean daily overcontracting points. Figure 6.38 shows the suppliers overcontract situation in the initial stage.

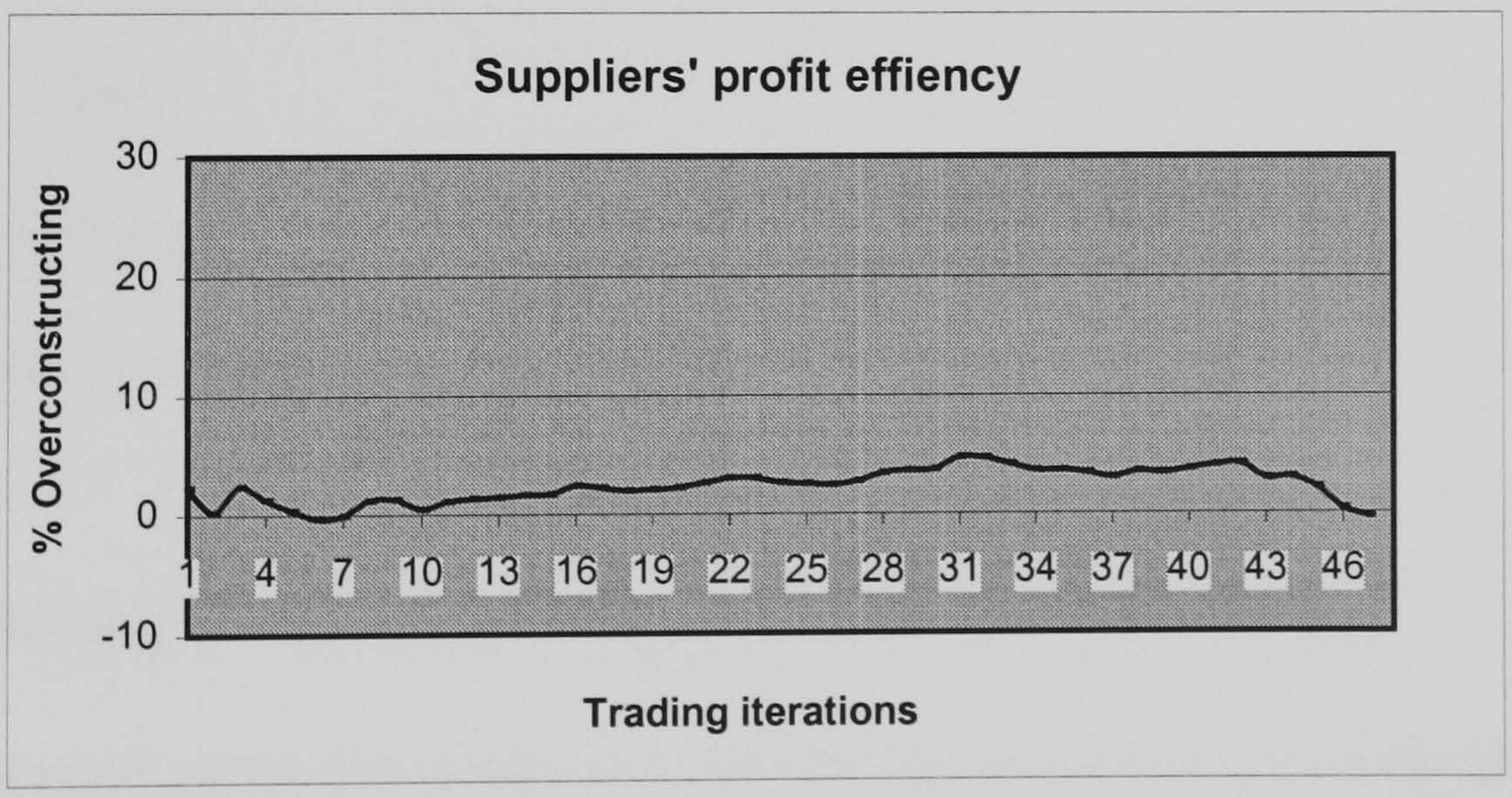

Figure 6.39: Comparison of suppliers' percentage of overcontracting in the second week

In the first two stages, the suppliers' percentage of overcontracing is around 5%.

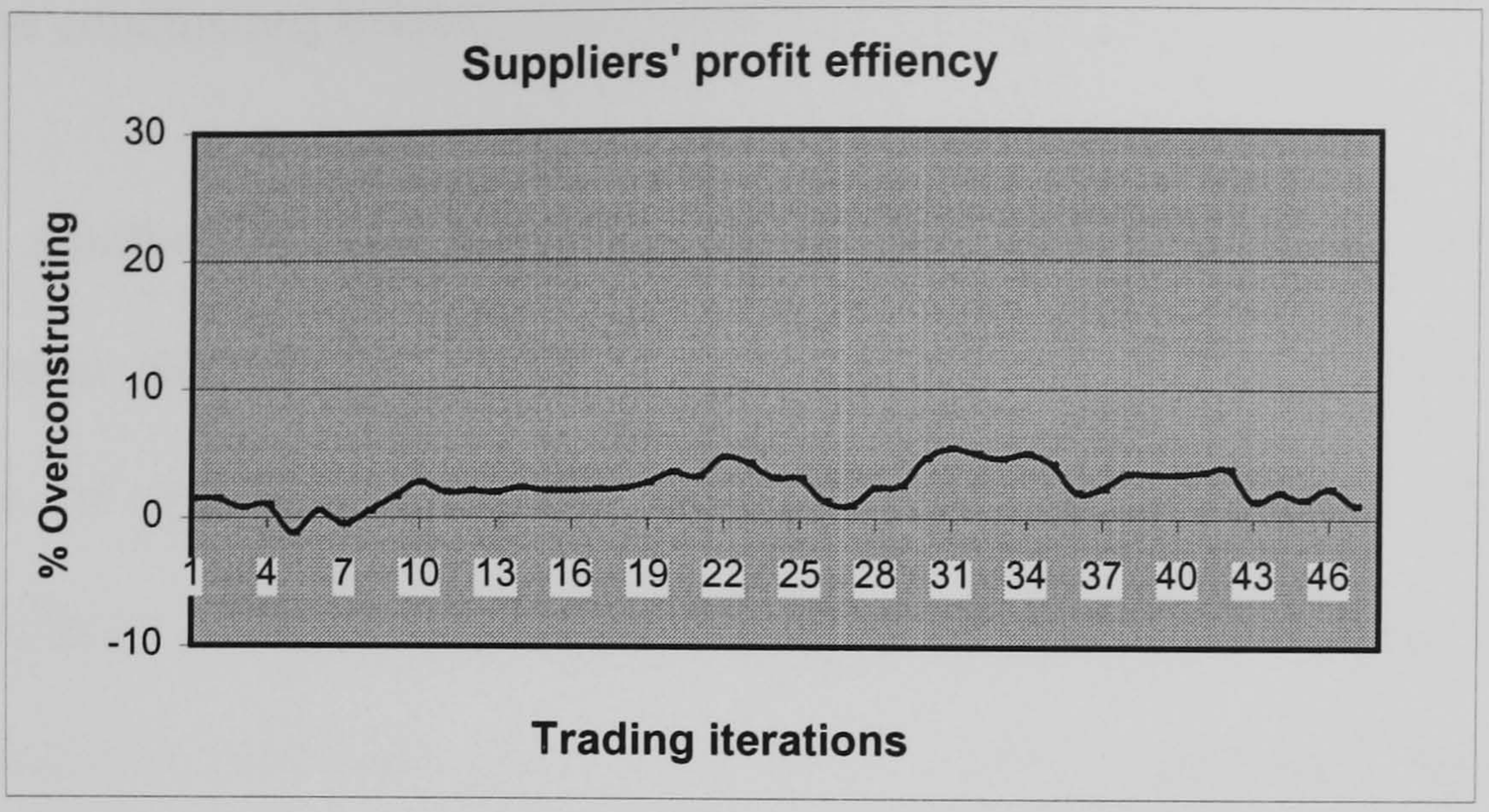

Figure 6.40: Comparison of suppliers' percentage of overcontracting in the third week

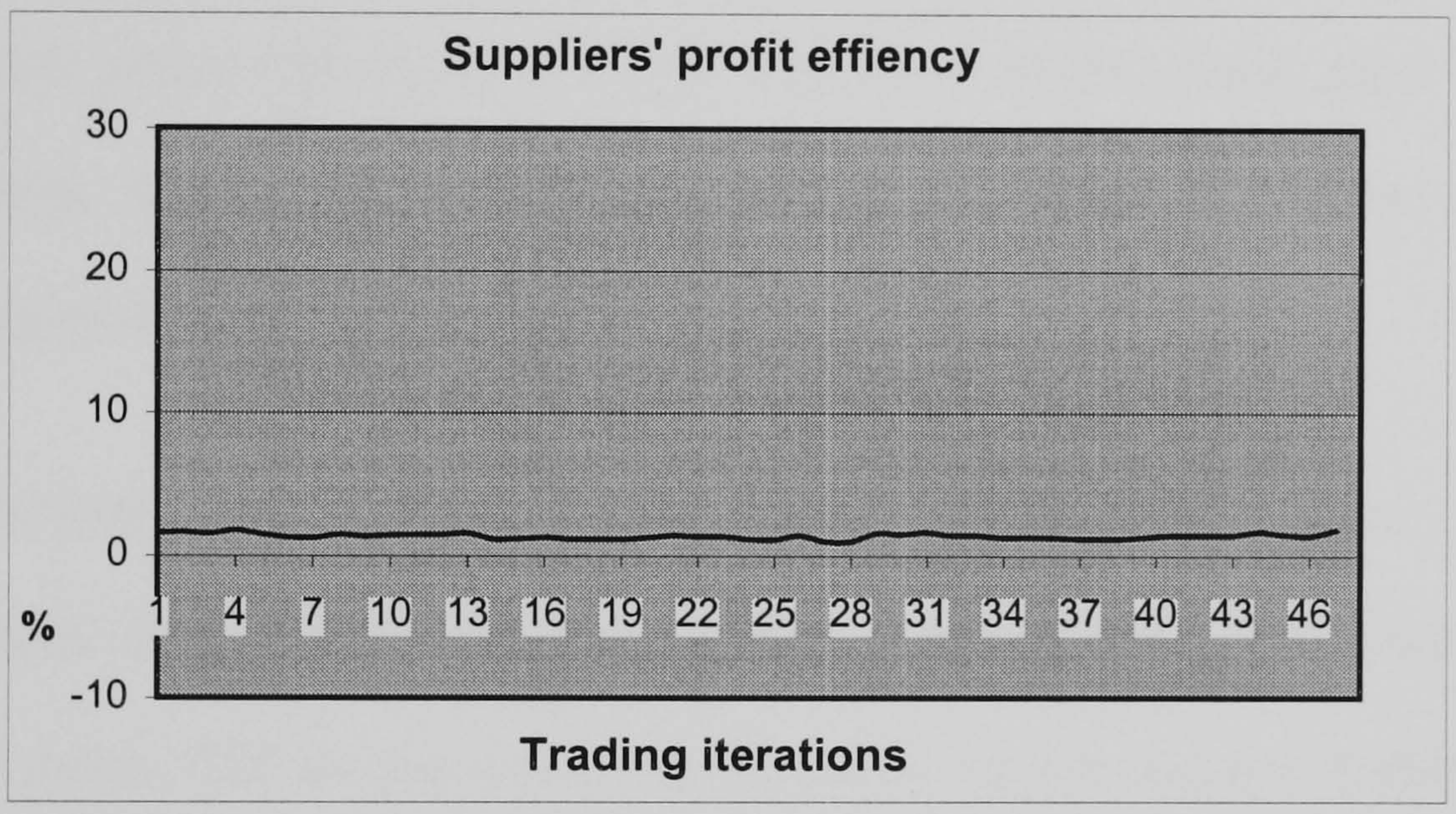

Figure 6.41: Comparison of suppliers' percentage of overcontracting in the fourth week

We can observe that the evolution of supplier strategy has significantly made less overcontracting in last stage.

6.5 Summary

From the generalisation and prediction experiments carried out, the experiment results have revealed some significant changes and differences among the outputs of the models with different trading strategies and two different scale models, they have also drawn some conclusions below.

1. In the small-scale model where the market size is similar to the scale of Californian electricity market, but much smaller than the reality in NETA, a number of generation companies adopt cooperative strategy. The market circumstance has been successfully changed by gaming generation companies. The Imbalance Settlement price *SBP* is driven up to a significantly high level and the PX market price *PXP* has a number of sharp price spikes which are not affordable for electricity suppliers. Further, the individual profit of gaming players are much higher than in both of the large-scale model where some generation companies adopt same cooperative strategy and the model where all trading participants employ non-cooperative strategy.

2. Experimental results from the large-scale model where some generation companies adopt cooperative strategy have revealed that, on one hand, the PX market prices *PXP* are not obviously influenced by the strategic trading imposed by some gaming generators, whereas the *PXP* results are close to the results in the model with all using non-cooperative strategy, even when the percentage of withheld output capacity of individual coalition member is tuned to 40% of its maximal generation volume; on the other hand, the Imbalance Settlement prices *SBP* and *SSP* have caused lots of serious price spikes in demand peak times. And individual profit of gaming players is comparably higher than other market participants employing non-cooperative strategy. Experimental results expose that one of major reasons for this phenomena in which the trading outcomes from two models are obviously different is that, in the large-scale market place where a

large number of participants are involved, a minority group of players do no have significant effect on market share. Another reason is that the "opportunistic collusion" generators do not always join the agreement to withhold output and, according to their strategy evaluation results, in some trading rounds they choose non-cooperative strategy to work independently and try to make their individual profit maximized in the market place.

3. Experimental results also illustrate that implementing both physical (bid only a portion of one's capacity) and economic (bid a portion at a very high price) withholding generation capacity is an efficient methodology to change the market circumstance, given causing price spikes. Theoretically which type of withholding a generator should choose depends on the market structure. In NETA circumstance, all markets (forwards and futures markets, short-term Power Exchange and BM) are continuate and interchangeable. Therefore both of physical and economic withholding is employed to make the maximal profit by gaming generators.

4. It is evident that a number of price spikes do emerge on PX market price *PXP* and Imbalance Settlement Prices, no matter in our designed models or in actual NETA market. In the experiment with non-cooperative strategy the price spikes often emerge when the demand is on peak times, 10:00am to 12:00am, and 19:00pm to 21:00pm. When the market is driven to an oligopoly situation in the small-scale model, much more price spikes arises. For most industries, standard economic theory suggests that, under perfect competition, where no individual supplier has market power, the bids offered by each supplier should equal their marginal production costs. Under this scenario, price spikes should only occur when

demand exceeds supply. However, in virtually all electric power markets, price spikes giving profits much in excess of marginal costs have been observed, even when sufficient supply is available.

5. Based on the experimental results, the power plants in base-load position with lower marginal costs, like nuclear power generators, have sole out more generation volume and got comparably higher profits in initial weeks. Along with the development of strategy and algorithms optimization, the other power generation with lower startups which are flexible in Balancing Mechanism are meeting the mechanism's system balance requirements and learning to improve their trading strategies. In the later weeks, the power plants with flexibility which means their generation features allow them to start up a numbers of times within one day to respond the 48-round market trading in one day, whereas the power plants with inflexible technology have to run continuously, have sold more volumes and won significantly high profits from the BM.

In general, the performance of developed models and the experimental results have proved that, on one hand, there is no evidence that on a non-naturally oligopoly electricity market where the market scale is similar to the NETA, the effort that a part of generators make a coalition of withholding output capacity to drive the market to an oligopoly circumstance could achieve its original targets, when the generation capacity of these gaming generators do not account for significant share of the total market supply; on the other hand, withholding capacity may have an extreme impact on the imbalance settlement prices, hence cause extra profit for related generators.

7. Evaluation Experiments of Developed Model and Method

7.1 Introduction

In order to assess the performance of the proposed NETA market model and the evolving trading strategy, it is necessary to compare them against other related works.

A comparably similar simulation model with its developed strategies from [34] is chosen to be examined in this Chapter. In this chosen research work, the designed model's scale is close to the model proposed in this thesis. The trading agents in this model use Genetic Algorithm coupled with various price forecasting techniques to select appropriate bidding strategies for the current market conditions. The bidding strategies adapt, or evolve, as other traders change their trading behavior. The research results from this work are compared with my experimental results following.

7.2 Evaluation Results

To evaluate the efficiency of the two different developed strategies, three major system parameters from two models, the ratio of PX market clearing price *PXP* to mean marginal cost *MC*, the individual generator capacity used, and the market imbalance volume, are compared respectively.

7.2.1 Traded Market Clearing Prices in Power Exchange

Because the PX is the marketplace where most trades are made and its clearing price *PXP* is one of the most important model outputs, the ratio of *PXP* to mean marginal cost MC, *PXP/MC*, is a significant reference which directly assess the effect of generation companies' gaming strategy on the wholesale market, and also measures the interaction between the market environment and the market player's payoff.

As introduced previously, the model's running process, given 20 days, is divided into four consecutive stages, week by week. The *PXP/MC*, in each trading week, are respectively represented by a set of mean daily trading results. There are 4 sets of experimental results corresponding to the four trading weeks, and one set includes 48 calculated values. Figure 7.1 demonstrates the mean daily *PXP/MC* in the first week.

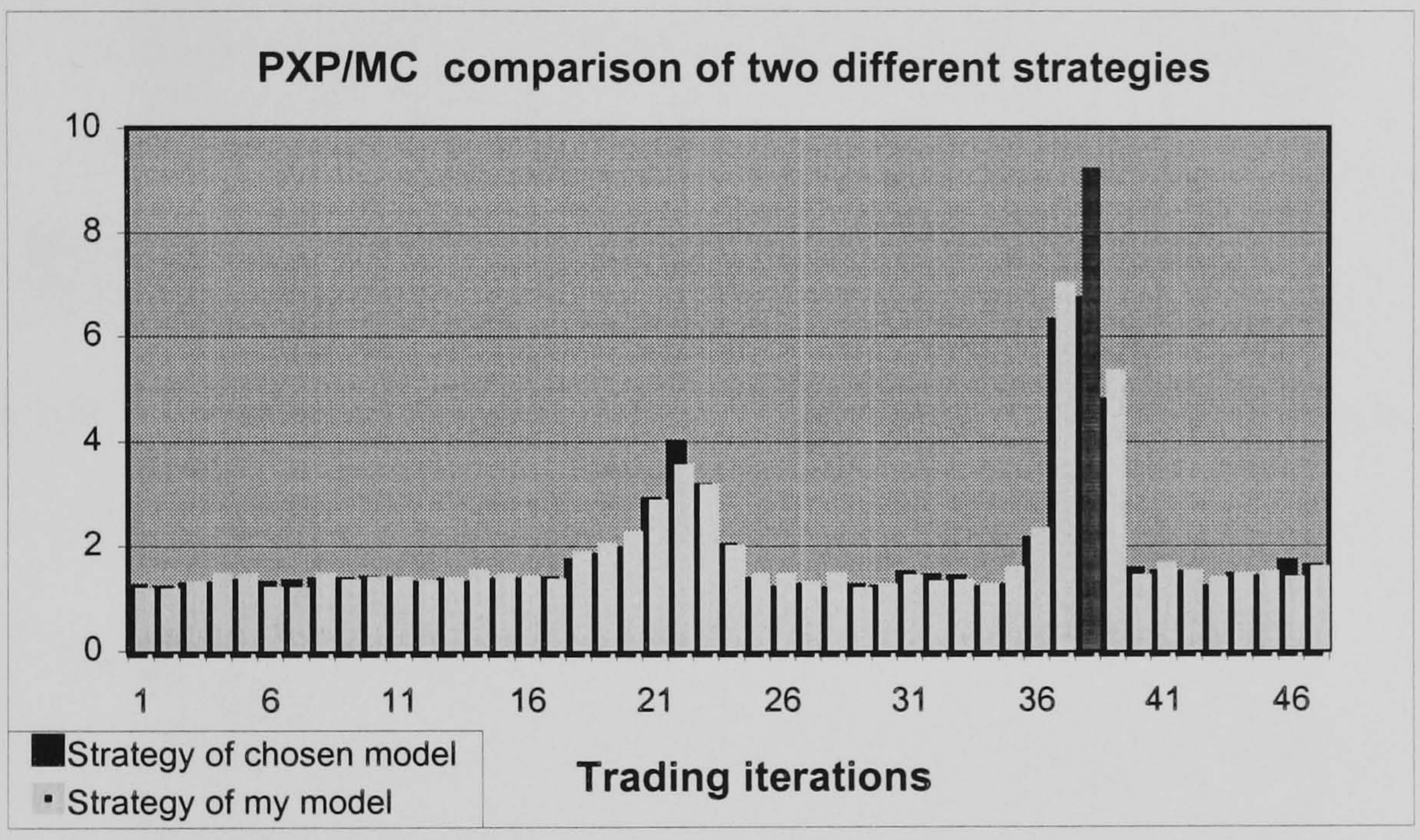

Figure 7.1: Comparison of PXP/MC from two strategies in the first trading week

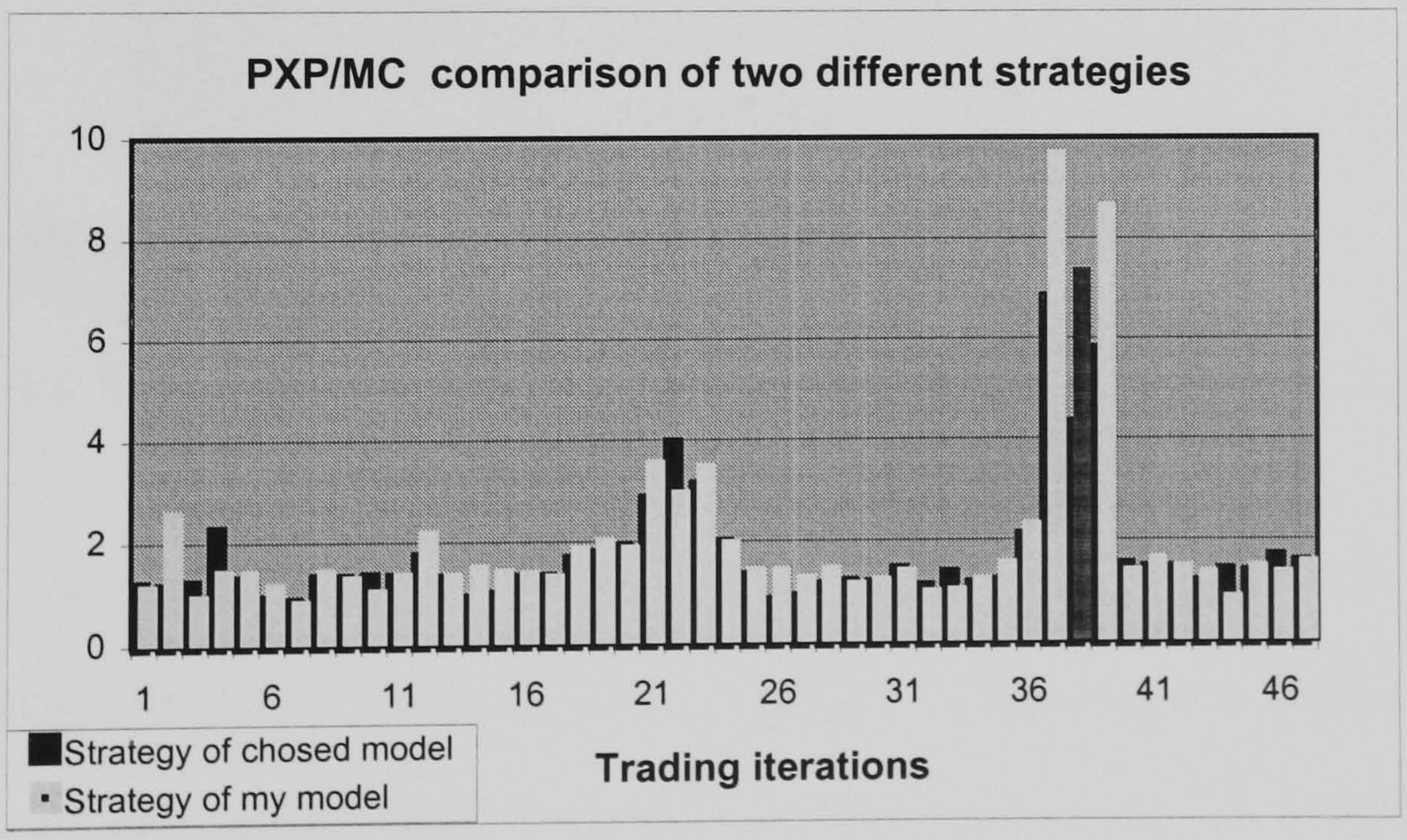

Figure 7.2: Comparison of PXP/MC from two strategies in the second trading week

According Figure 7.1 and Figure 7.2 above, during the first two weeks the two strategies have similar performance in most trading rounds. The trading strategy proposed by this thesis works better in demand peak periods.

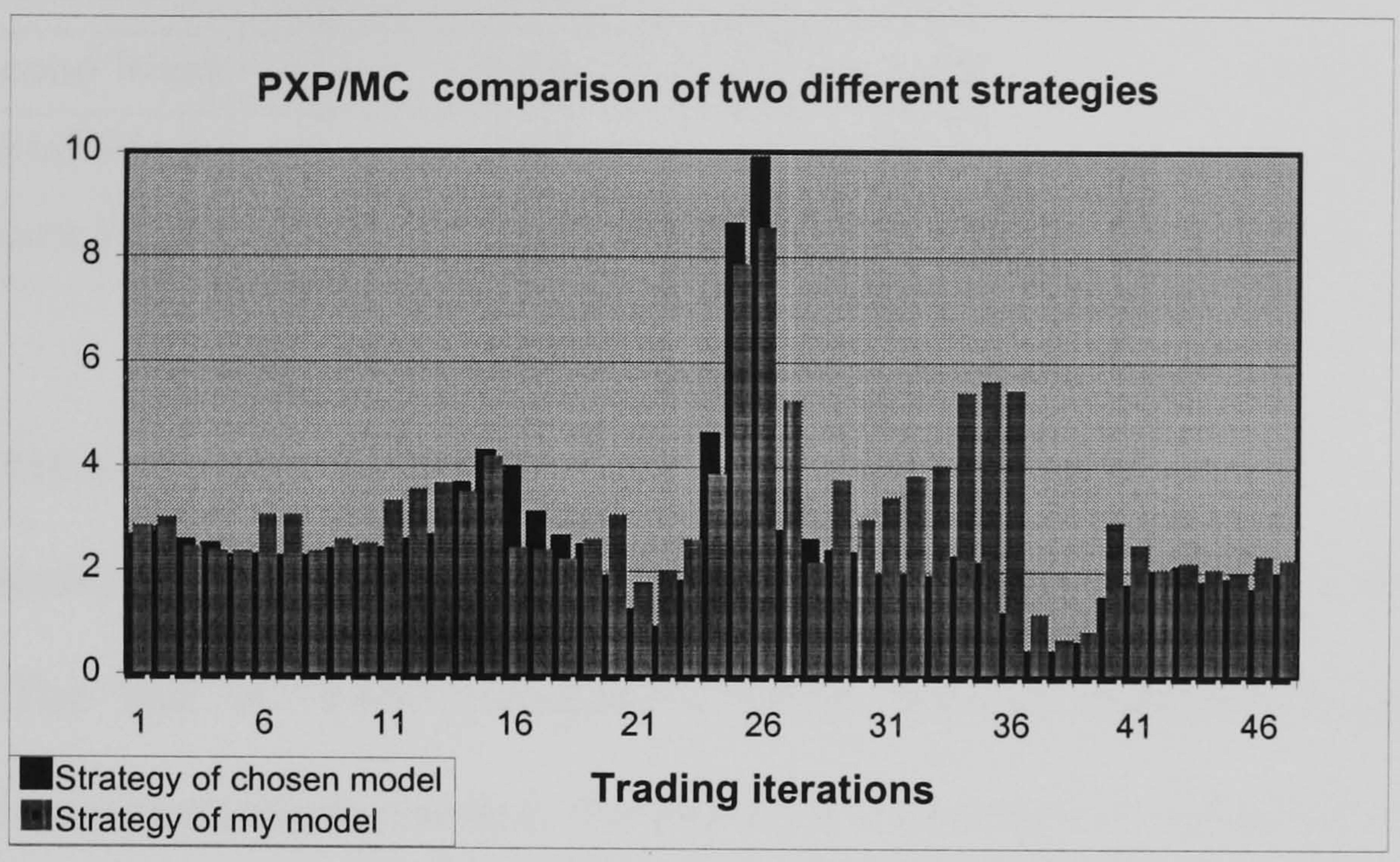

Figure 7.3: Comparison of PXP/MC from two strategies in the third trading week

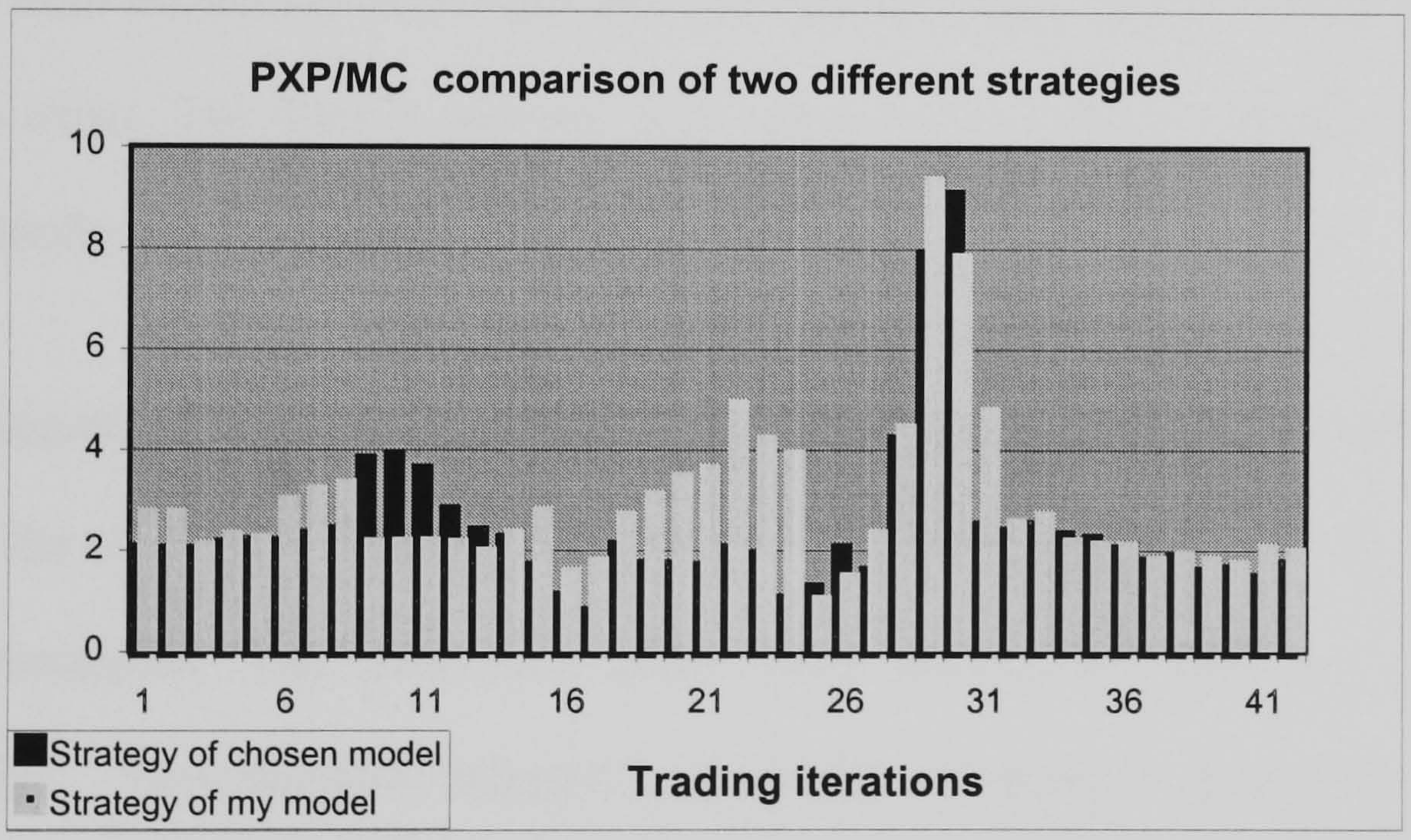

Figure 7.4: Comparison of PXP/MC from two strategies in the fourth trading week

Based on the experiment results demonstrated above, the difference of two strategies is calculated through dividing the mean *PXP/MC* of the chosen model by mean *PXP/MC* of my model. There is significant evidence that the latter has stronger influence on the PX prices.

Table 7.1 Comparison of PXP/MC from two strategies

Comparison of *PXP/MC* from two strategies	***Mean PXP/MC of chosen model***	***Mean PXP/MC of my model***	***Ratio of two PXP/MC***
First Week	1.72	1.83	6.40%
Second Week	1.68	1.93	14.88%
Third Week	2.39	2.98	24.69%
Forth Week	2.40	2.83	17.92%

7.2.2 Generators Capacity Used

As we assume, there are three kinds of generation companies playing in the trading system. The first is "loyal cooperator", which "always" withhold a portion in anticipation of coalition agreement. The second is "opportunistic collusive" generator. They follow an "opportunistic collusion" strategy whereby generators withhold capacity from the market only when they perceive an "opportunity" to raise profits by doing so exists. The third is assumed only adopt non-cooperative strategy and trade independently in power market.

As we introduced earlier, the generator used capacity is an important reference to measure the efficiency of generators' strategies and individual generator's position in this environment. The individual mean used generation capacities of "loyal cooperator", "opportunistic collusive" generator, competitive generator and the generator in the chosen model are shown below from Figure 7.5 to 7.8.

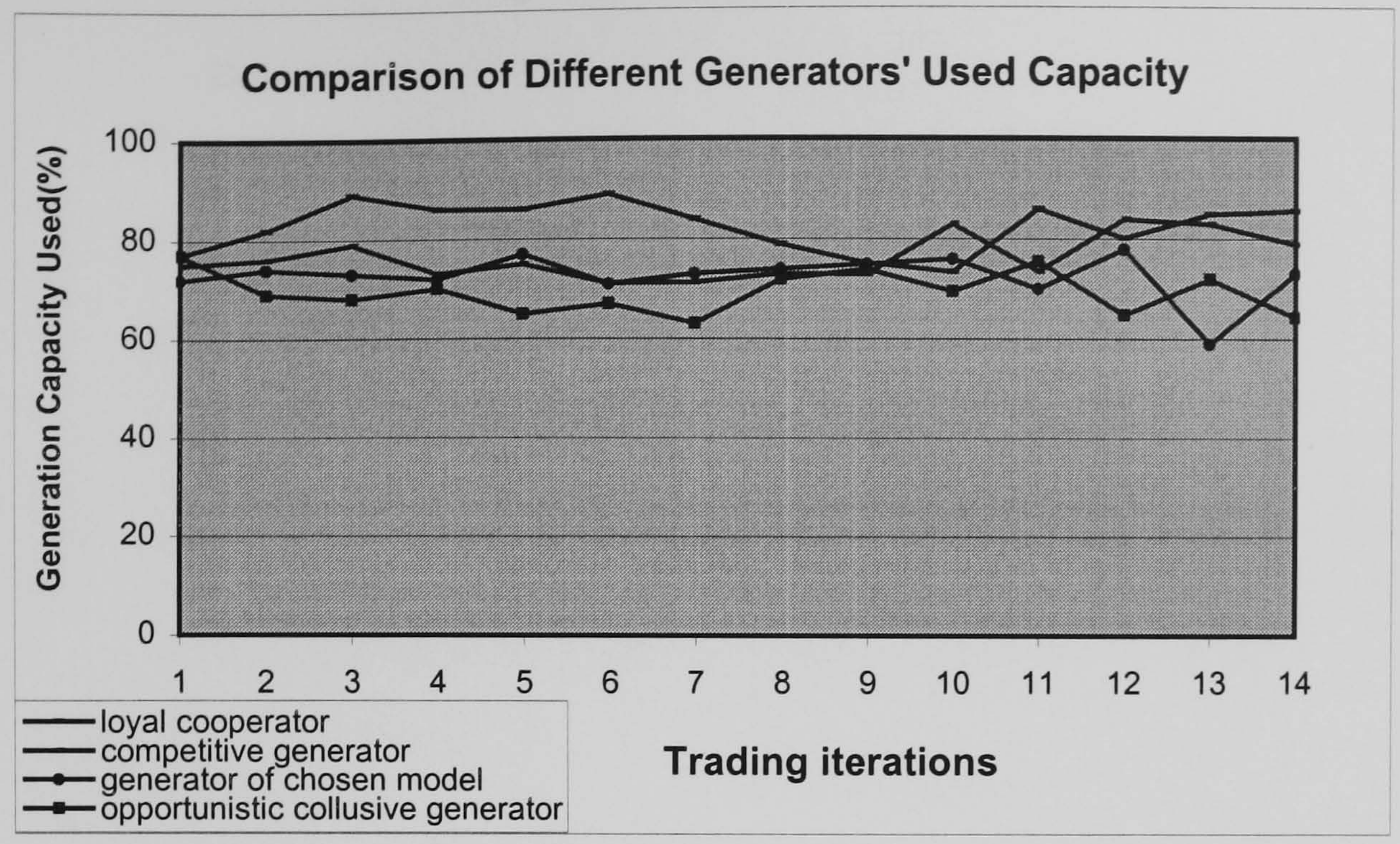

Figure 7.5: Comparison of used capacity for different generators in the first week

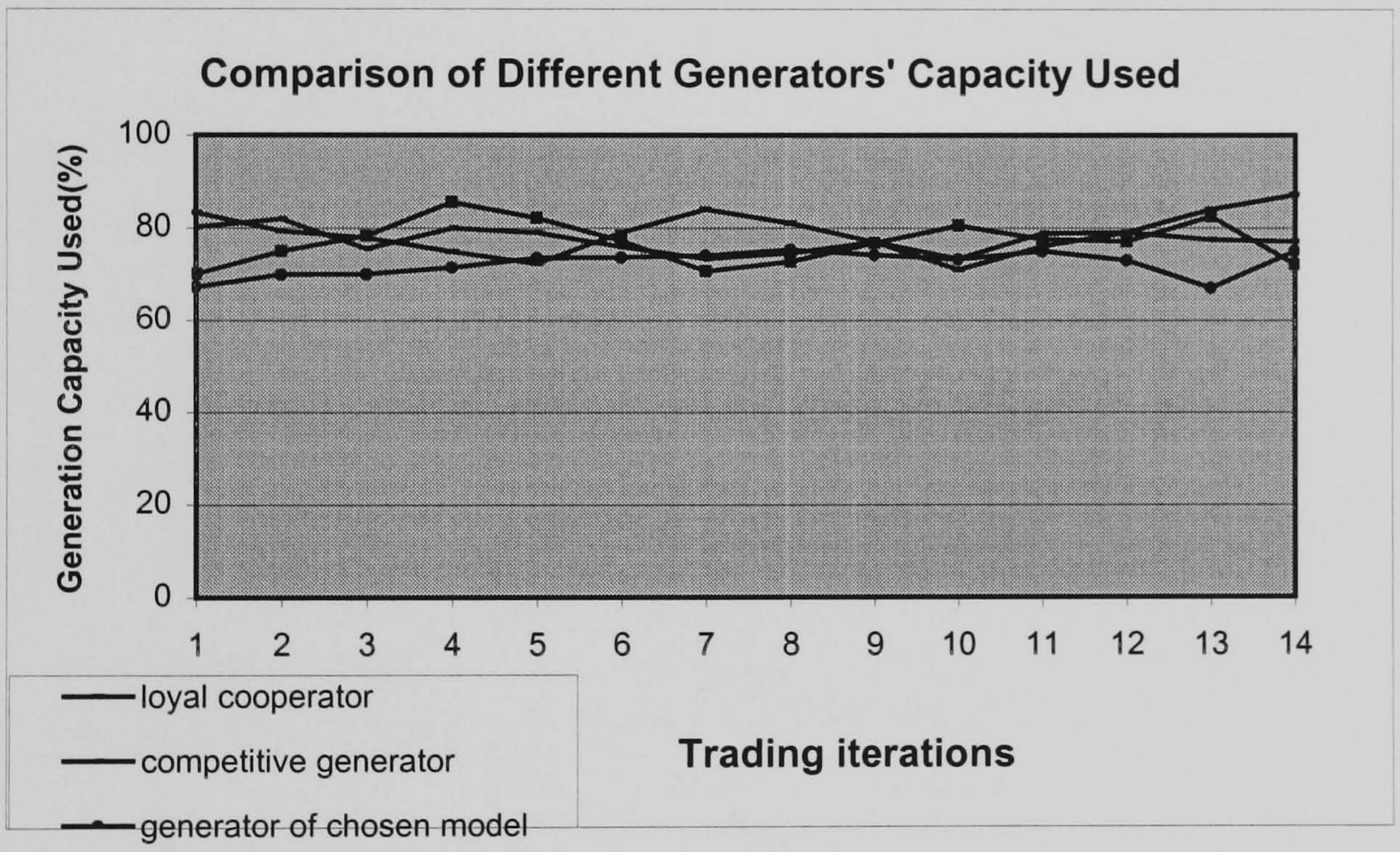

Figure 7.6: Comparison of used capacity for different generators in the second week

It is clear in Figure 7.1 and Figure 7.2 that the "loyal cooperator" and competitive generators have sold more generation volumes in the initial stage.

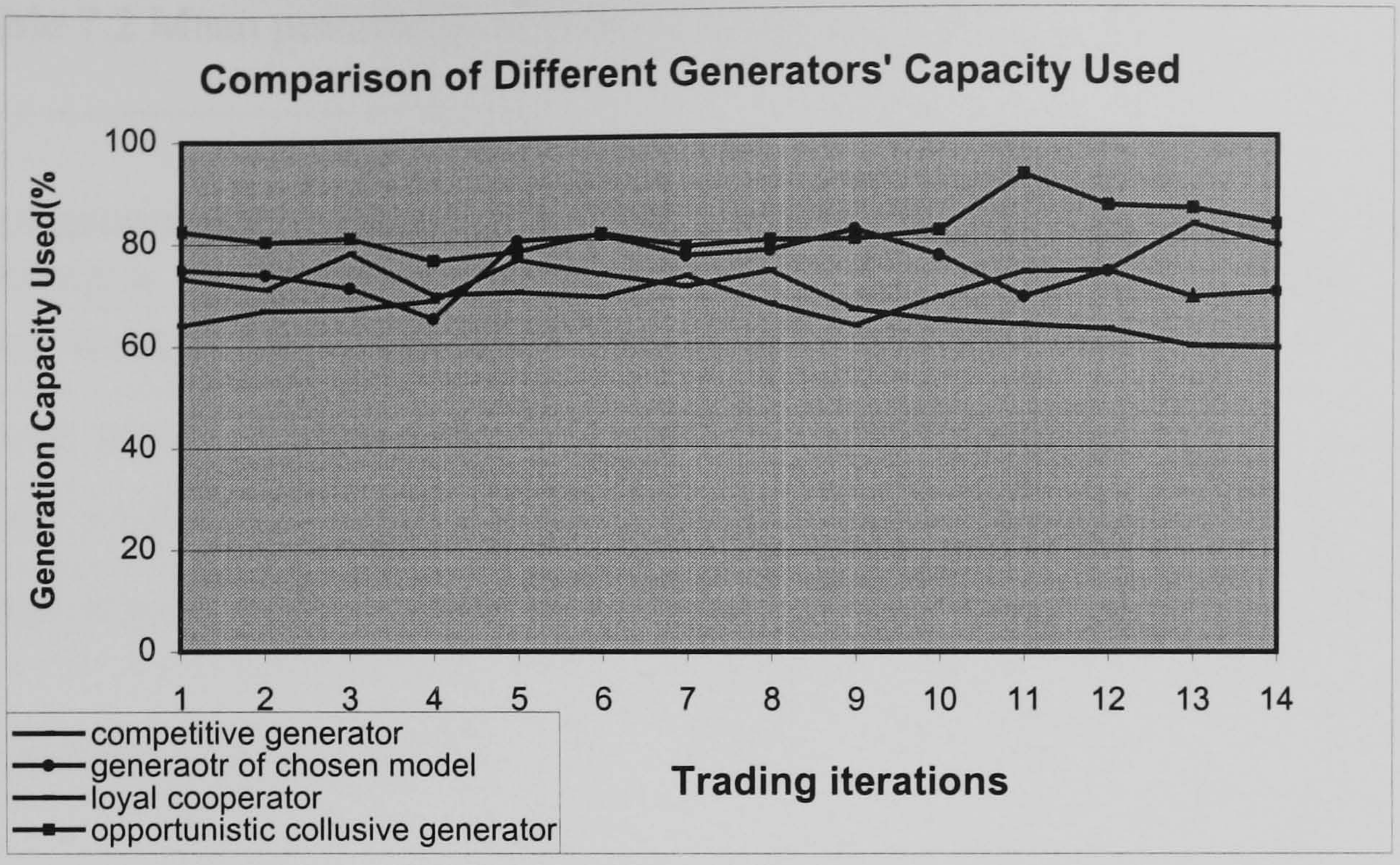

Figure 7.7: Comparison of used capacity for different generators in the third week

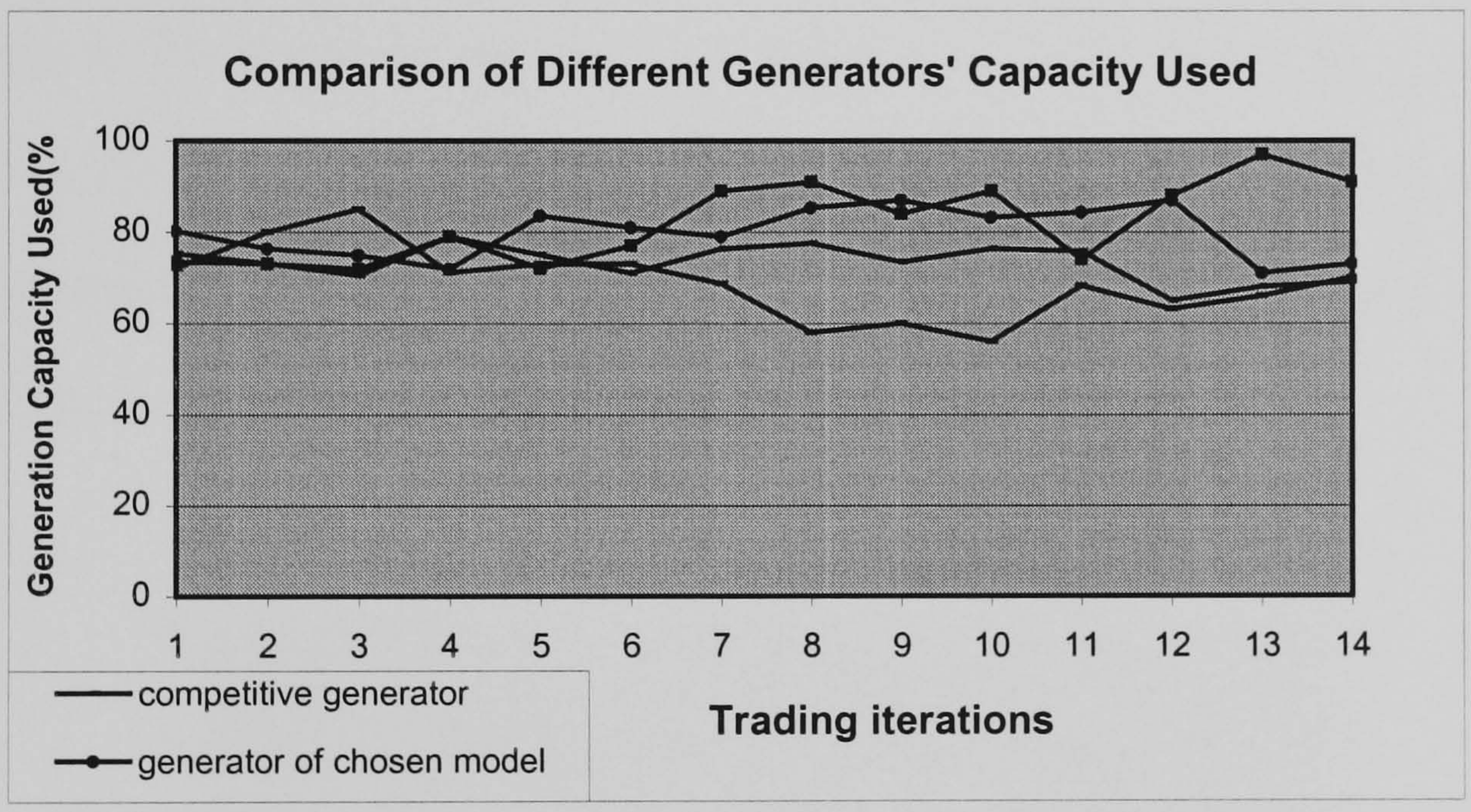

Figure 7.8: Comparison of used capacity for different generators in the fourth week

The evolvement of the use capacity of individual generation type is these trading process is shown in Table 7.2.

Table 7.2 Mean percentage of used generation capacity of different strategies

Kinds of generators' strategies	**Loyal cooperator**	**Competitive generator**	**opportunistic collusive" generator**	***Generator of chosen model***
First Week	0.82	0.76	0.69	*0.72*
Second Week	0.79	0.77	0.77	*0.72*
Third Week	0.67	0.72	0.82	*0.74*
Forth Week	0.69	0.73	0.82	*0.76*
Mean Used Capacity	0.74	0.75	0.78	*0.74*

7.2.3 Imbalance Volume In PX of Two Strategies

The fundamental objective of gaming generators is to make up supply/demand imbalance in PX and drive the market into an oligopoly situation. The imbalance volume in PX is the major parameter to assess the efficiency of the strategy. The mean imbalance volume in PX on each trading week are shown below from Figure 7.9 to 7.12.

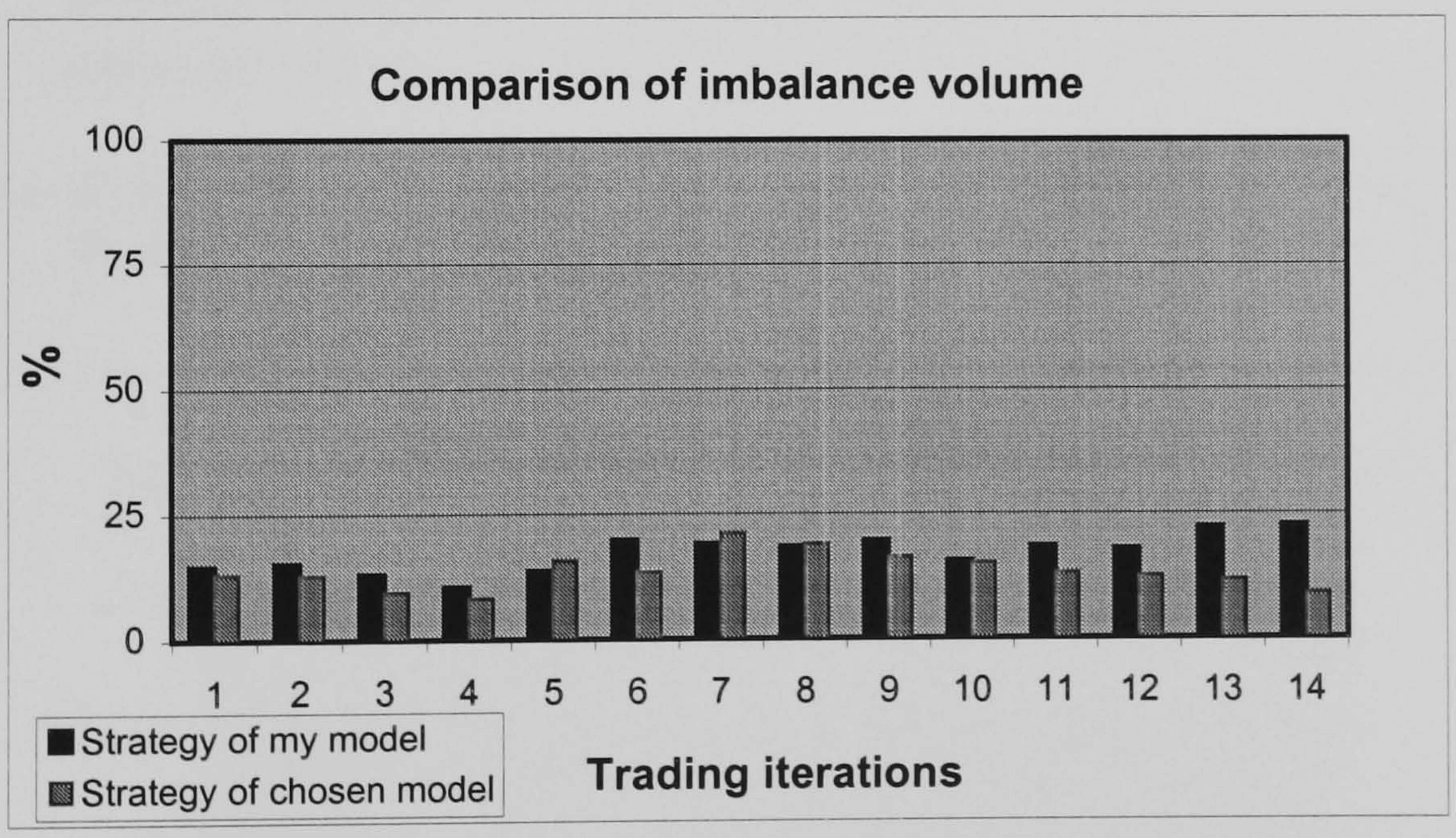

Figure 7.9: Comparison of imbalance volume for different generators in the first week

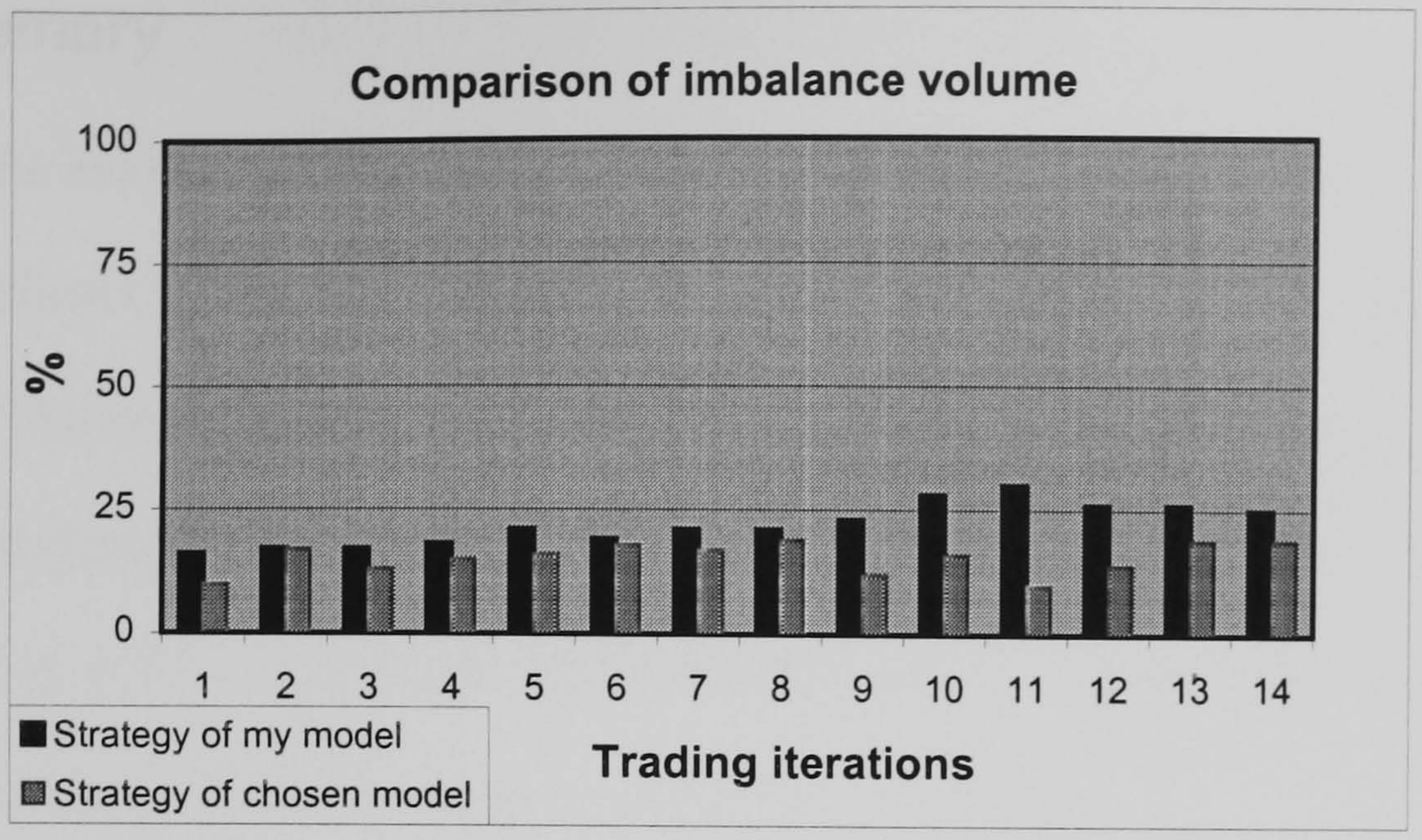

Figure 7.10: Comparison of imbalance volume for different generators in the second week

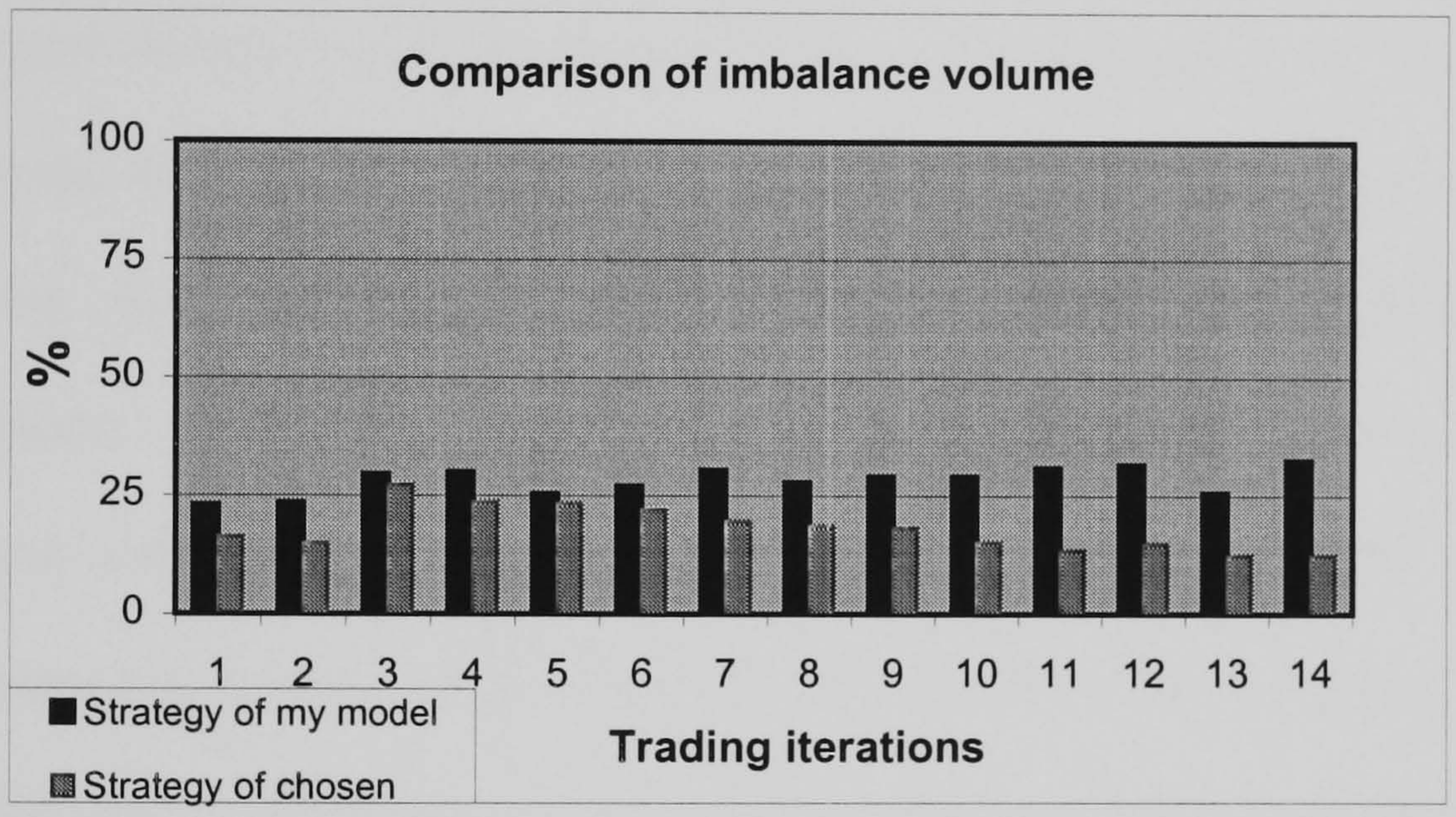

Figure 7.11: Comparison of imbalance volume for different generators in the third Week

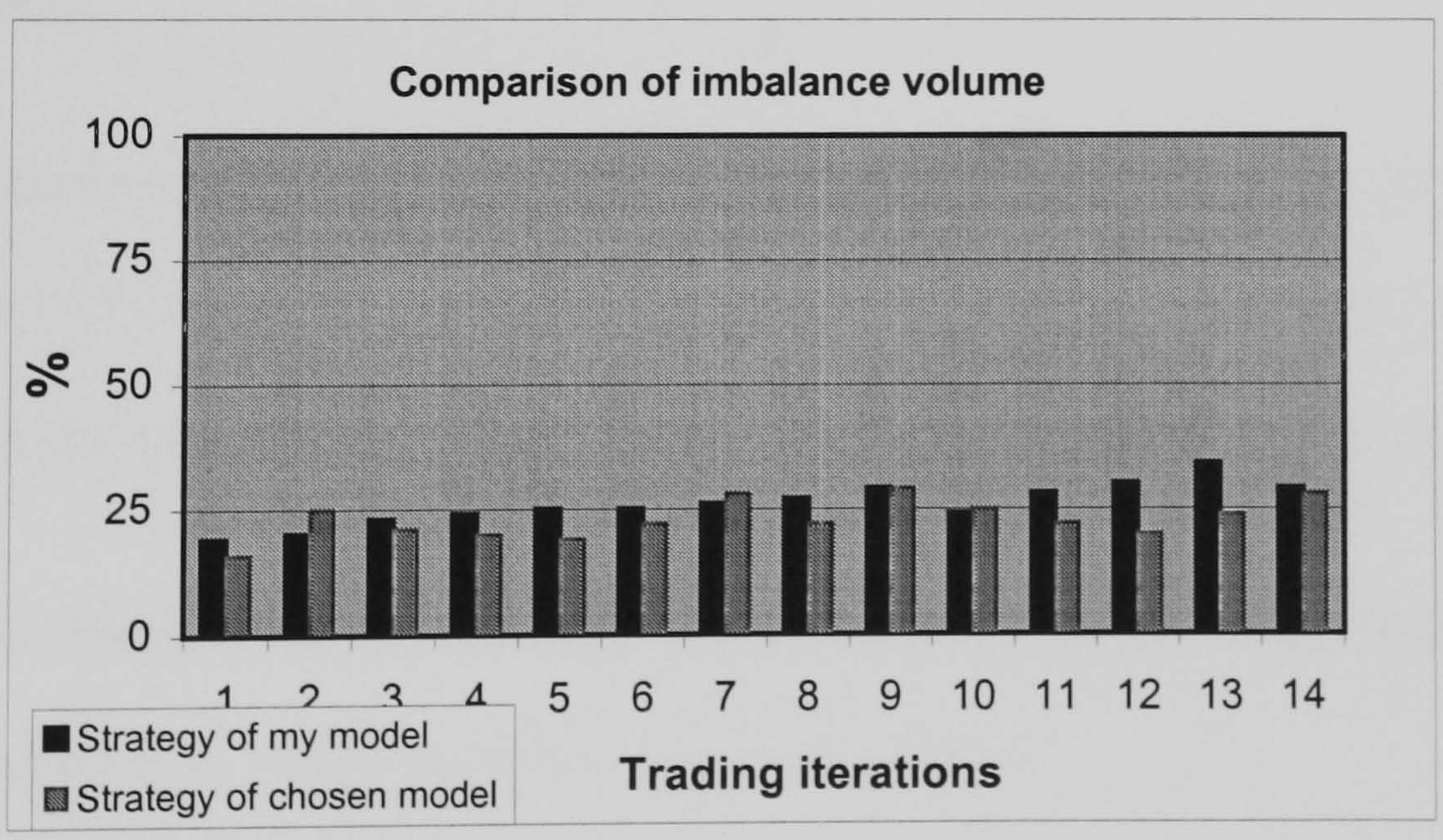

Figure 7.12: Comparison of imbalance volume for different generators in the fourth week

7.3 Summary

Based on the evaluation experiments carried out, the comparison results have revealed some significant differences between the two models and their developed trading strategies. The experimental results have drawn conclusions that the proposed model and the designed trading strategies have better performance than other related work. In contrast to those related work from the literature, the proposed market model and the trading strategy evolving method have advantages following,

1. Although the electricity trading system in the U.K. is a deregulated market with the longest history in global energy industry and has become the benchmark of worldwide electricity markets, there are few research results published for analysing such a trading market mechanism, especially involving human intelligence. Furthermore the other major work that has not been proposed by academia and industry is to study the possibility and consequence of gaming behaviours and market power on NETA. The research demonstrated in this thesis has done some pioneering work to first model the trading mechanism of this market and to study the influence of market manipulation by trader's gaming strategies.

2. The features of the designed model has made closer to the reality in power market than any other research models which had been developed before, such as
   - The number of market participants is same as the real case in NETA;
   - The market model simulates a two-side market, with demand fully incorporated, which had been achieved by others;

3. While there has been an amount of effort imposed on analysing the gaming strategies and their influences over the electricity trading market by adopting game theory, only had they solely used either noncooperative or cooperative game theory to analyse the market player's gaming behaviours. However the energy crisis in California and problems happening in other power markets have demonstrated that it is not capable of analyzing the gaming strategies practiced in power market, because market players have been using mix of both when they are making collusion among energy companies.

   One of the creative contributions presented by this research is that both of the cooperative and competitive game strategies are employed together to simulate various forms of trading strategies of different market players, which follows the reality of power market trading.

4. So far, no research work has ever studied how to make gaming binding more efficient when market participants are cooperating. In this case, a more extreme management-enforcement cooperative gaming technique, "Trigger price strategies", is introduced to enhance this strategy and has been proved to be a useful method for executing cooperative agreements among gaming generators.

5. Incorporating these problems into a decision making process requires search and optimisation techniques. Most research have tried using conventional optimization techniques to find best trading strategies. However many of the classical learning and search methodologies require the use of derivative information that usually is not available. Others are limited to one dimension only. In addition all of the classical techniques are single-peak optimisation techniques. Yet modelling these complex market behaviours and search the right trading strategies often do not

have accurate measurement of their variables and require many objectives to be met before any solution is considered adequate. These deficiencies have made most research in this field have to bring a lot of assumptions to make their algorithms work. Therefore, a search technique which can handle these problems should be:

- Be capable of handling possible non-linear interactions between various elements;
- It is able to deal with incomplete, uncertain and imprecise of information;
- Non-deterministic and posterior;
- Global optimization;
- Be able to deal with non-numerical variables.

Evolutionary Computing, a new breed of learning and search techniques that meets the requirements of this research, is chosen and well overcome these decision-making problems.

6. In previous related work that adopted Evolutionary Computing as the search and learning technique, Evolutionary Computing has been used as only fundamental method to develop trading strategies. This fact made the evolvement of market player's strategy start from random, which had no sense to reality of power markets. In our study, Evolutionary Computing is used as a search, learning and optimization technique to assist game theory to discover the optimal strategies.

Although this research work has made some creative work and achievements, there are still some deficiencies existing in this model and developed method, which could be improved in future work:

1. In this research, Genetic Algorithms are introduced to search and optimize market players' trading strategies. Limited range of GA operators have been used in this research.

2. Currently the simulated NETA market model does not take transmission constraints and losses into account when market trading is carried out for simplicity reason. These lack of physical features of power system made this model less feasible.

3. The current model omits some endogenous power system variables, including start-up costs and no-load costs, and does not consider the vertical generators who own both power generation and transmission obligations.

In general, the developed market model and the designed trading strategies is capable of providing a better simulation platform to analyse the dynamic and decision making behaviour of the UK electricity trading system, and of developing an effective tool of predicting the impact of the gaming strategy and market power on such a circumstance like NETA.

8. Conclusions and Future Work

8.1 Conclusions

This research is motivated by the market collapse events occurring in California in year 2001, for which no effective system models existed to predict and take prompt action from. An effective model appeared to be difficult to establish, due to human involvement in the trading system and gaming strategies practised. It is hence hard to qualify using conventional modelling and data fitting techniques.

This work has attempted the application of Game Theory to the modelling and application of Evolutionary Algorithms to evolve a game theory based model. The aims are to model the market structure and trading behaviours in the New Electricity Trading Arrangements and to analyse and predict the possibility and consequence of gaming behaviours and market power on NETA. The work has led to the following achievements.

- An effective NETA system model has been established, using a hybrid method of game theory and evolutionary computation. The model is capable of reproducing NETA market mechanism, which has not been achieved before.

- Compared with existing models, a more sophisticated and more realistic two-sided transaction mechanism with demand fully incorporated is anommodated in this new model, which has not been achieved successfully in this research field so far.

- By utilizing game theory, the gaming strategies of power generation firms are well simulated and the market manipulation and strategic trading behaviours made by market players can hence be analysed. Further, the impact of such market performance on NETA has been found out.

- Another creative contribution in this research is that, the cooperative strategy which is being more frequently employed by electricity firms in global markets, can now be modeled, simulated, and explored fro analysis and prediction.

- "Trigger price strategies" is introduced to enhance this research and has been proved to be a useful method for executing cooperative agreements among gaming generators.

- Evolutionary Computation based methods are developed to search for trading strategies against many uncertainties and incommensurable objectives.

In summary, this research has successfully addressed problems identified in the Introduction. The research has shown that the model designed and methodologies developed are a useful decision-support tool for developing competent strategies and decision-making for the NETA system.

8.2 Future Work

The work presented in this thesis could be extended in a number of directions:

- In Chapter 5, Genetic Algorithms are introduced to search and optimize market players' trading strategies. Limited range of GA operators have been used in this research. For instance, Tournament selection is chosen as the only selection method to pick up parents. Research could be performed to employ more selection, crossover and mutation techniques, and find the suitability of different functions for this task. Therefore research into this would be fruitful. It would also be interesting to compare these techniques for improving the algorithms' power.

- It has been recognized that most of the generation based ancillary services such as spinning reserves and AGC provision, are playing more important roles in power markets. In some electricity markets such as NETA and Spain, serious strategic behaviour by power suppliers has been observed in some ancillary services markets. There have exhibited extreme price volatility in these markets. Further attempts to extend the research interests to go through the influence of market player's gaming trading strategy on these concerned market would be reasonable. Similarly, it would also be attractive to cover the reactive power provision field.

  Optimal Power Flow that is able to gain reliable, analytical and experimental insight of power system could be employed as a main technique to solve these problems out.

- Currently the simulated NETA market model does not take transmission constraints and losses into account when market trading is carried out for simplicity reason. These physical features of power system would be covered by a more realistic market model in future work.

- Another direction of future research work would be a deeper theoretical and experimental study. The current model omits some endogenous power system variables, including start-up costs and no-load costs, and does not consider the vertical generators who own both power generation and transmission obligations. This model could be improved by considering more if data are available.

References:

[1] Hamilton, M.M. and Greg Schneider, Price Caps Have Questionable Record, *Washington Post,* May 31, 2001.

[2] Investigation Report by the California Public Utilities Commission, California Energy Commission, 2002.

[3] The new electricity trading arrangements, Office of Gas and Electricity Markets, London, U.K. [Online]. Available from: <http://www.ofgem.gov.uk/docs/reta3.pdf> [July 1999].

[4] Hesmondhalgh, S. Is NETA the Blueprint for Wholesale Electricity Trading Arrangements of the Future? *IEEE Transactions on Power Systems*, 13(1): 548-554, May 2003.

[5] Introduction to the UK PX market, [Online]. Available from: <http://www.ukpx.com > [August 2002].

[6] John, M. Broder. *British Energy's crisis*, The Electricity Association, U.K., 26 September, 2002.

[7] Ferrero, R.W., Rivera, J.F. and Shahidehpour, S.M. Application of Games with Incomplete Information for Pricing Electricity in Deregulated Power Pools. *IEEE Transactions on Power Systems*, 13(1): 184-189, February 1998.

[8] Yu, Z. A Strategic Coalition Gaming Model with Spatial Formulation for Electricity Markets. *IEEE Power Engineering Review*, pp. 42-45. February 2001.

[9] Wen, F.S., David, A.K. Oligopoly Electricity Market Production under Incomplete Information. *IEEE Power Engineering Review*, pp. 58-61. April 2001.

[10] Li, G., Yokoyama, R., and Chen, L. Negotiation Models for Electricity Pricing in a Partially Deregulated Electricity Market. In *Proceedings of the Power Engineering Society Summer Meeting*, 16-20 July 2000. IEEE vol.4: 2223 – 2228.

[11] Krishna, V., and Ramesh, VC. Intelligent Agents for Negotiations in Market Games, Part 1: Model, and Part 2: Application. *IEEE Transactions on Power Systems*, 13(3): 1103-1108, August 1998.

[12] Song, H. and Liu, C. Optimal Electricity Supply Bidding by Markov Decision Process. *IEEE Transactions on Power System*, 15(2): 618-624, May 2000.

[13] Dyer, J.R.; Williams, T.G. and Dunnett, R.M. Economic Dispatch Ddvice for the NETA Balancing Mechanism. In *Proceedings of the Fifth International Conference for Power System Management and Control*, April 2002. London.

[14] St Clair, R. Load management technology-future challenges, Electricity Trading (Ref. No. 2000/038). IEE Seminar, pp.5/1-5/4. March 2000.

[15] McClay, C. and Litchev, P. Risk management issues for distributed generation. *In the Proceedings of Power Engineering Society Winter Meeting*, 2002. IEEE, vol. 1.

[16] Bathurst, G.N., Weatherill, J. and Strbac, G. Trading wind generation in short term energy markets. *IEEE Transactions on Power Systems*, 17(3): 782-789, Aug 2002.

[17] Balancing Mechanism Reporting System. Office of Gas and Electricity Markets, London, U.K. [Online]. Available from: <http://www.bmreports.com/bwx_reporting.htm> [September 2000].

[18] NGC incentives under NETA. Office of Gas and Electricity Markets, London, U.K. [Online]. Available from: <http://www.ofgem.gov.uk/docs/ngcfeb.pdf> [April 2000].

[19] Settlement administration agent user requirements specification. Office of Gas and Electricity Markets, London, U.K. [Online]. Available from: <http://www.ofgem.gov.uk/elarch/retadocs/mitbpm08.pdf> [March 2000].

[20] Stephenson, P. and Paun, M. Electricity market trading. *Power Engineering Journal*, December 2001, vol. 15:277-288.

[21] Decker, C. and Keyworth, T. *Competition Law and Commodity Markets: The Case of Wholesale Electricity*. Regulatory Policy Institute, Oxford, 2002.

[22] Mielczarski, W., Michalik, G. and Widjaja, M. Bidding strategies in electricity markets. In *Proceedings of the 1999 IEEE PES Power Industry Computer Applications Conference (PICA'99)*, 1999, pp.71-76.

[23] Exelby, M.J. and Lucas, N.J.D. Competition in the UK market for electricity generating capacity and game-theory analysis. *Energy Policy*, 21(4:348-354,) 1993.

[24] Ferrero, RW., Shahidehpour, S.M. and Ramesh, V.C. Transaction analysis in deregulated power systems using game theory. *IEEE Transactions on Power Systems,* 12(3): 1340-1347. 1997.

[25] Singh, Hao, H. S. and Papalexopoulos, A. Power auctions and network constraints. In *Proceedings of the Thirtieth Hawaii International Conference on System Sciences,* 1997. vol.5:608-614.

[26] David, A.K. Competitive bidding in electricity supply. In *IEE Proceedings: Generation, Transmission and Distribution,* 1993, 140(5): 421-426.

[27] Gross, G. and Finlay, D.J. Optimal bidding strategies in competitive electricity markets. In *Proceedings of 12th Power Systems Computation Conference (PSCC'96),* Dresden, August 19-23, 1996, pp.815-823.

[28] Lamont, J.W. and Rajan, S. Strategic bidding in an energy brokerage. *IEEE Transactions on Power Systems,* 1997, 12(4): 1729-1733.

[29] Visudhiphan, P. and Ilic, M.D. Dynamic games-based modeling of electricity markets. In *Proceedings of IEEE Power Engineering Society 1999 Winter Meeting,* 1999, vol.11, pp. 274-281.

[30] Beny, G.A., Hobbs, B.F., Meroney, W.A., O"eil R.P. and RStewart, W. Analyzing strategic bidding behavior in transmission networks. In *IEEE Tutorial on Game Theory Applications in Electric Power Market*, IEEE Engineering Society, 1999, pp.7-32.

[31] Song, H.L. Liu, C.C. and Lawarree, J. Decision making of an electricity suppliers bid in a spot market. In *Proceedings of IEEE Power Engineering Society 1999 Sumner Meeting,* 1999, vol.1, pp.692-696.

[32] Song, H.L. and Liu, C.C. Future aspects of modem heuristic heuristics applications to power systems. In *Proceedings of IEEE Power Engineering Society 2000 Winter Meeting,* Singapore, Jan. 2000.

[33] Hao, S. A study of basic bidding strategy in clearing pricing auctions. In *Proceedings of the 1999 IEEE PES Power Industry Computer Applications Conference (pICA'99),* 1999, pp.55-60.

[34] Richter, C.W. and Sheble, G.B. Genetic algorithm evolution of utility bidding strategies for the competitive marketplace. *IEEE Transactions on Power Systems,* 1998, 13(1):256-261.

[35] Li, C.A., Svoboda, A.J., Guan, X.H. and Singh, H. Revenue adequate bidding strategies in competitive electricity markets. *IEEE Transactions on Power Systems,* 1999, 14(2):492-497.

[36] Zhang, D.Y., Wang, Y.J. and Luh, P.B. Optimization based bidding strategies in the deregulated market. In *Proceedings of the 1999 IEEEPES Power Industry Computer Applications Conference (PICA '99),* 1999, pp.63-68.

[37] David, A.K. and Wen, F.S. Building optimal bidding strategies for competitive power suppliers. Accepted for publication in *Proceedings of VII Symposium of Specialists in Electric Operational and Expansion Planning (VII SEPOPE),* Brazil, May 23-38, 2000.

[38] Wilson, R. *Activity rules for a power exchange.* Power Conference, University of Califonia Energy Institute, Berkeley, March 1997.

[39] Sakk and Rzimmerman. Power system bidding tournament for a deregulated environment. In *Proceedings of the Thirtieth Hawaii International Conference on System Sciences,* 1997, pp:681-686.

[40] Strbac, G. and Kirschen, D. Assessing the competitiveness of demand-side bidding. *IEEE Transactions on Power Systems,* 1999, 14(1):120-125.

[41] Weber, J.D. and Overbye, T.J., "A two-level optimization problem for analysis of market bidding strategies. *Proceedings of IEEE Power Engineering Society 1999 Summer Meeting,* 1999, vol.5, pp.681-686.

[42] Wen, F.S. and David, A.K. *Optimal bidding strategies for power suppliers and large consumers.* Working paper, Hong Kong Polytechnic University, 2002.

[43] Wolak, F., Nordhaus, R. and Shapiro, C. *Preliminary report on the operation of*

the ancillary services markets of the California independent system operator (ISO). August 19, 1998.

[44] Liu, Y., Alaywan, Z., Rothleder, M., Liu, S. and Assadian, M. A rational buyer's algorithm used for ancillary service procurement. In *Proceedings of IEEE Power Engineering Society 2000 Winter Meeting,* Singapore, January 2000.

[45] Bierman, H. S. and Fernandez, L. *Game theory with economic applications.* NewYork, 1998.

[46] Li, Y. *Neural and Evolutionary Computing IV,* Lecture Notes, 1996.University of Glasgow, UK.

[47] Owen, G. *Game Theory,* 3rd ed. Academic Press, London, 1995.

[48] Osborne, M. and Rubinstein, A. A Course in Game Theory. MIT Press, 1995.

[49] KC Tan and Y Li, Grey-box model identification via evolutionary computing, Control Engineering Practice (An IFAC Journal), 10(7), 673-684, July 2002.

[50] Darwin, C. *On the origin of Species by Means of Natural Selection or the Preservation of Favored Races in the Struggle for Life.* London, Murray. 1859.

[51] Frieberg, R.M. A learning machine: part I. *IBM Journal of Research and Development,* 1958, 2(1):2-13.

[52] Fogel, L.J., Owens, A.J., and Walsh, M.J. *Artificial Intelligence Through Simulated Evolution.* 1966, John Wiley, New York.

[53] Holland, J.H. Adaptation in Natural and Artificial Systems. 1975, University of Michigan Press, Ann Arbor.

[54] Bienert, P., Rechenberg, I., and Schwefel, H.-P. *Messung kleiner Wandschubspannungen bei turbulenten Grenzschichten in Ablosenahe.* Technical Report of the Hermann Fottinger-Institute for Fluid Dynamics, Wi 8/45, Technical University of Beilin, 1966.

[55] Goldberg, D. E. *Genetic Algorithems in search, optimization & Machine Learning.* Addison-Wesley, New York, 1989.

[56] Li, Y., Ng, K.C., Murray-Smith, D.J., Gray, G.J., and Sharman, K.C. Genetic algorithm automated approach to the design of sliding mode control systems. *International Journal of Control*, 1996, 63(4):721-739.

[57] Li, Y., and Ng, K.C. A uniform approach to model-based fuzzy control system design and structural optimisation. *Genetic Algorithms and Soft Computing*, F. Herrera and J.L. Verdegay, Physica-Verlag Series on Studies in FUZZINESS, 1996, vol.8:129-151.

[58] The review of the first year of NETA. Office of Gas and Electricity Markets, London, U.K. July 2002.

[59] International Energy Agency, World Energy Outlook, 2005.

[60] Heap, S. P. *Game theory*. Oxford University Press, 1995.

[61] Friedman, J.W. *Game theory with economic applications*. Oxford University Press, 1996.

[62] McClay, C. The impact of NETA imbalance prices on contracting strategies for generation and demand. In *Proceedings of Fifth International Conference on Power System Management and Control*, 2002. pp:13-18.

[63] The Balancing Mechanism Reporting System (BMRS). [Online]. Available from: <http://www.bmreports.com> .

[64] The new electricity trading arrangements, Ofgem DTI conclusions document. Office of Gas and Electricity Markets/DTI, London, U.K. [Online]. Available from: <http://www.ofgem.gov.uk/docs/netaoct.pdf> [Oct 1999].

Appendices

Tools to Analyse Trading Competition and Strategies

1 Introduction

As described in Chapter 2, there exists no electricity market that is perfectly competitive in the world. Market participants in the electricity market develop gaming strategies in order to maximize their own profits. The electricity generators (main sellers) are neither competitive price-takers who have no control over price, nor monopolistic price-setters who are the single decision makers. Market Clearing Price (MCP), market share allocation and then individual profit are results of the interactions among individual market participants, as individual decision makers. Each market participant has to determine and evaluate its strategic behaviours based on a great deal of uncertainty and risk.

Game theory is a discipline that is concerned with how individuals make decisions when they are aware that their actions affect each other and when each individual takes this into account. It is the interaction among individual decision makers, all of who are behaving purposefully, and whose decisions have implications for other people that make strategic decisions different from other decisions [45].

Necessarily gaming strategies need to be explored and evaluated. Incorporating these problems into a decision making process requires some search and optimisation techniques. Many of the classical learning and search methodologies require the use of derivative information that usually is not available. Others are limited to one dimension only. In addition all of the classical techniques are single-peak optimisation techniques [46]. Therefore Evolutionary Computing, a new breed of learning and search techniques that are non-deterministic and a suitable solution to search the global optimum, is chosen to solve this decision-making problem.

This chapter deals with the two evolving tools that are being employed in this project, namely game theory and Evolutionary Computing (EC). The first part provides background and application of developing strategic behaviours on electricity markets through Game Theory. EAs is discussed in the second part.

2 Game Theory

Game theory is a discipline that is used to analyze problems of conflict among interacting decision makers. It may be considered as a generalization of decision theory to include multiple players or decision makers. Game theory can be classified into two areas: cooperative and non-cooperative, in which the distinction relates to whether agreements made between trading participants are binding. Cooperative game theory assumes that such agreements are binding, whereas non-cooperative game theory does not.

2.1 Noncooperative Game Theory

So far there are much more research contribution of using non-cooperative game theory on electricity market research and developing gaming strategies. Noncooperative games can be zero-sum games or nonzero-sum games. In zero-sum games, the gains of one player equal the losses of the other player. In nonzero-sum games, the gains of one player do not equal the losses of the other player. The solution for nonzero-sum games was first formulated by John Nash, and the Nash equilibrium is now a universally used game theory methodology on the research of electricity trading strategy.

Noncooperative games can be described using two kinds for formats. The first format is the normal or strategic form, and the second is the extensive form. In the strategic form, one deals with a set of players, a set of choices or strategies available to the players, and a set of payoffs corresponding to these strategies. The payoff for a given player depends not only on the strategy chosen by that player but also on the strategies chosen by the other players. Additionally, it is assumed that the rules of the game, the strategies available to the players, and the payoffs are common knowledge. Each player is assumed to act rationally to maximize its profit.

As introduced above, the Nash Equilibrium is the most widely used noncooperative game theory among then. The formal definition of his concept is given below [47]: Suppose there are N players in a game, X_i is the set of possible strategies for player i, and $v_i(s_1, \ldots s_N)$. A Nash Equilibrium is a strategy profile $\{s_i^*, \ldots s_{Ni}^*\}$ such that each strategy s_i^* is an element of X_i and maximizes the function $f_i(x) = v_i(s_i^*, s_{i-1}^*, x, s_{i+1}^*, \ldots s_{Ni}^*\}$ among the elements of X_i. That is, at a Nash Equilibrium, each player's equilibrium strategy is a best response to the belief that other players will adopt their Nash Equilibrium strategies. In Nash Equilibrium it is assumed that the rules of the game, the strategies available to the players, and the payoffs are common knowledge, which does not reflect the real cases in power markets.

Finite nonzero-sum games are also called bimatrix games, given the notation used to represent the payoffs in the game. A bimatrix game consists of two players, each of whom has a finite number of actions called pure strategies. When player 1 chooses pure strategy i and player 2 chooses pure strategy j, their payoffs or gains are represented by a_{ij}, and b_{ij}, respectively. A mixed strategy for player 1 is a vector x whose i-th component represents the probability of choosing pure strategy i. Thus $x_i \geq 0$ and $\Sigma\, x_i = 1$. A mixed strategy for player 2 is defined analogously. If x and y are a pair of mixed strategies for players 1 and 2, their expected gains are $x'Ay$ and $x'By$, respectively. A pair of mixed strategies (x^*, y^*) is said to be a Nash equilibrium if

$$(x^*)'Ay^* \geq x'Ay^* \; \forall\, x \geq 0,\; \Sigma\, x_i = 1$$

and

$$(x^*)'By^* \geq (x^*)'By^* \; \forall\, y \geq 0,\; \Sigma\, y_i = 1$$

In other words, (x^*, y^*) is a Nash equilibrium if neither player can gain by unilaterally changing its strategy.

A particularly interesting special case of a Nash equilibrium is a Nash equilibrium in pure strategies, i.e., one in which the probability of choosing a particular strategy is 1 for each player.

Noncooperative games are the foundation for some of the standard models in oligopoly. The study of oligopoly models is essential to study market power.

2.1.1 Cournot Duopoly

A Cournot model [48] involves a duopoly game in which two firms produce an identical product and must decide how much to produce without knowing the output decision of the other. For convenience, assume that each firm's cost is 0. Assume that x_1 and x_2, represent the output decisions of each firm. The market price is represented by $p(x_1 + x_2)$, where $p(x)$ is the inverse demand curve. The profits or payoffs for each firm are $\lambda_1 = p(x_1 + x_2)$. The strategy of each firm is to choose x_i in order to maximize its profit without knowing the decision of the other firm.

2.1.2 Bertrand Duopoly

Under a Bertrand model, each firm must choose the price at which it is willing to produce. Ignoring bounds on output, we can assume that the lower priced firm will capture market share and that both firms will have equal outputs at equal price. If $x(p)$ represents the market demand function, the payoff or profit of firm 1 can be represented as

$$\lambda_1(p_1, p_2) = \begin{cases} p_1\, x(p_1), & \text{if } p_1 < p_2 \\ p_1\, x(p_1)/2, & \text{if } p_1 = p_2 \\ 0, & \text{if } p_1 > p_2 \end{cases}$$

Bertrand game has a structure similar to the problem of simple prisoner's dilemma [57]. If both players cooperate, they can both charge the monopoly price. However, each player has an incentive to reduce its price slightly and capture market share, even though it knows that both players will be worse off if they both cut price.

2.1.3 Market Power Mitigation

Market power can be defined as the ability of a market participant to raise prices above the competitive level by restricting output or restricting new entrants. Horizontal market power is often associated with a single firm or a few firms controlling a large part of the supply.

Although generation divestiture has been used as a remedy for this problem in the electric power industry, it is not always a viable option. In such instances, financial contracts such as contracts for differences (CfD) can be used to accomplish what might be termed as virtual divestiture. Game theory can be used to study the effects of CfDs on bidding incentives. The purpose of a CfD is to insulate the supplier against the temporal price variations in the market. Once counter party in the CfD agrees to pay the other the difference between the contract price and the prevailing market or pool price.

A CfD can be either two-way or one-way. A two-way CfD is similar to a financial futures contract and is defined in terms of a strike price (£/MWh), and a quantity (MWh). For the defined quantity, the seller pays the buyer if the pool price rises above the strike price, and the buyer pays the seller if the pool price falls below the strike price. A one-way CfD is similar to a financial option contract and also includes an option fee in addition to the strike price and contract quantity. Under a one way contract, difference payments are made only if the pool price rises above the strike price.

The effect of a CfD is to fix or bound the revenue for a generator. In the extreme, where the entire output of a generator is contracted under a CfD, the generator's revenue will be completely insulated from market price variations, and, consequently, the generator should have no incentive to raise prices. Ideally, one would like to contract just the appropriate fraction of output required to mitigate market power.

To illustrate how CfDs can eliminate incentives to raise prices, we will set up a simple Cournot model with two generators (A and B) and one load. Each of the generators has an incremental cost of £10/MWh and a maximum output of 75 MW. The strategic decision for the generators is to choose a level of output that maximizes their profits.

The price is set by the demand curve. We will assume that each generator chooses between two levels of output, a high output of 75 MW and a low output of 20 MW, as shown in Table 1.

Table A.1: Output decisions of A and B

Output (MW)		Generator B High	Generator B Low
Generator A	High	75 75	75 20
Generator A	Low	20 75	20 20

Table A.2: Prices corresponding to output decisions

Pirce (£/MW)		Generator B High	Generator B Low
Generator A	High	40	45
Generator A	Low	45	150

Table A.3. Profits without CfD

Profit (£)		Generator B High	Generator B Low	
Generator A	High	2250	2625	A's profit
		2250	700	B's profit
Generator A	Low	700	2800	A's profit
		2625	2800	B's profit

Table A.4. Profits with CfD for 30MW

Profit (£)		Generator B High	Generator B Low	
Generator A	High	2250	2475	A's profit
		2250	550	B's profit
	Low	700	-500	A's profit
		2475	-500	B's profit

Table A.5. Profits with CfD for 10MW

Profit (£)		Generator B High	Generator B Low	
Generator A	High	2250	2575	A's profit
		2250	650	B's profit
	Low	650	1700	A's profit
		2575	1700	B's profit

The low output may be interpreted as withholding of capacity with a motivation to increase prices. If prices increase sufficiently, the generator can make a higher profit at the low output. There are four possible cases to consider, depending on the decision of each generator. The prices corresponding to these cases are shown in Table 3.2. Table 3.3 shows a Nash equilibrium for the case when both generators choose low levels of output to maximize their profits. However, if a CfD is applied to 30 MW of the generators output, the Nash equilibrium changes, as shown in Table 3.4. The strike price in the CfD is assumed to equal the competitive price of £40/MWh. In this case, profits are maximized at the competitive price corresponding to the high output by each generator. Similarly, Table 3.5 shows the profits if a CfD is applied to 10 MW of the output.

2.2 Cooperative Game Theory

Cooperative game theory, which is quite different from noncooperative game theory, used to be generally applied to solve allocation problems. The various solutions proposed for cooperative games could be interpreted as alternative solutions to an allocation problem. The energy crisis in California and problems happening in other power markets, where more collusion and price tricks among energy companies reveal have emerged, have motivated research interests in adopting cooperative game theory to study coalition gaming strategies. The key ideas involve the concept of coalitions or groups that are formed to benefit from economies of scale.

For instance, equity arguments call for solutions that allocate costs to coalitions in a manner that guarantees that all coalition members are at least as well off as they would be if they were not a part of the coalition. This is sometimes called the stand-alone test. Solutions that exactly allocate the total costs and satisfy the stand-alone test, are called core solutions. Alternative solution concepts such as the Shapley Value are also possible.

The emphasis in cooperative game theory is on solutions that are equitable. In contrast, noncooperative game theory helps us study efficient solutions under new market designs. Just as we study the stability of an engineering system, we can study how efficient a market design might be by using game theory.

2.3 Application of Game Theory in Analyzing Trading Strategies in Power Markets

Solely using either noncooperative or cooperative game theory is not capable of analyzing the gaming strategies practiced in power market, because market players have been using mix of both to manipulate the market prices to maximize their profits.

The gaming strategies studied here is often called supergame. The word is intended to suggest a sequence of games, finite or infinite in number, played by a fixed set of players. Particularly, the strategies employed in electricity market is in semiextensice form, means that the simultaneous moves of the market players are modeled as game in strategic form. Thus, there is a succession of points in time (t = 0, 1, 2, . . .). At each point each player makes a choice. The simultaneous choices at one such time are represented within a game in strategic form and the supergame is the sequence of these games.

The interaction among the market players in power market could be simply represented by a modified famous game theory game, a repeated prisoners' dilemma, which is presented as following.

Table 3.6: A prisoners' dilemma game

B \ A	Confess	Not confess
Confess	5,5	15,0
Not confess	0,15	10,10

A certain strategy added to improve the traditional repeated prisoners' dilemma, which represents the real strategy that gaming market players employ to enhance their binding agreement, is called trigger strategy. It is a strategy under which a player uses two single-shot actions, s_i* and s_i^c. The player will begin by choosing s_i* and will have in mind some action combination s*. If all players $j \in N$ choose s_j* in each iteration of the game, them player i continues to choose s_i*; however, if any player j ever deviates from s_j* then, as soon as that deviation is detected by player i she switches to choosing s_i^c and continues to choose s_i^c in all future iterations, no matter what choices are made by others. When s^c is an equilibrium of the game (such as confess, confess in the repeated prisoners' dilemma), yields a large payoff to each player than does, the strategy combination is a perfect equilibrium.

Modelling these complex market behaviours and search the right trading strategies often do not have accurate measurement of their variables and require many objectives to be met before any solution is considered adequate. Therefore, a search technique which is able to handle this inaccuracy more effectively is needed.

3 Evolutionary Computing

3.1 Introduction

The limitations of classical optimisation techniques were explained earlier. Classical techniques are single-peak numerical optimisation techniques. This works well for reaching the optimum of a local peak but for problems that are multi-modal, this optimum will most likely not be the global optimum [49]. Optimisation of real-life solutions must often satisfy more than one objective and may have constraints imposed on the search, including non-numerical parameters.

Newer optimisation techniques are non-deterministic, by adding a degree of randomness and probability to the search for solutions. The search techniques is mostly a posterior, are widely adopted in machine learning. These encourage the search position to escape a local peak in the hope of finding higher peaks.

Evolution is ubiquitous natural force that has shaped all life on the Earth for approximately 3.2 billion years. For several thousand years, humanity has also utilised artificial selection to shape domesticated plant an animal species. In the past few decades, however, science has learned that the general principles at work in natural evolution can also be applied to a completely artificial environment. In particular, within Computer Science, the filed of automated machine learning has adopted algorithms based on the mechanisms exploited by natural evolution.

Darwin [50] first proposed that there are four essential requirements for the process of evolution to occur:

- Reproduction of some individuals within a population.
- A degree of variation that affects probability of survival.
- Heritable characteristics, that is, similar individuals arise from similar parents.
- Finite resources, which drive competition and fitness selection.

The consequence of these processes is the gradual adaptation of the individuals in a population to the specific ecological niche they occupy. This can therefore be viewed as a form of long-term learning by a population, on the characteristics suited to their particular environment.

The term Evolutionary Computing (EC) refers to the study of the foundations and applications of certain heuristic techniques based on the principles of natural evolution. In spite of this fact, these techniques are traditionally classified into three main categories, namely, Genetic Algorithms (GAs), Evolution Strategies (ESs) and Evolutionary Programming (EP). This classification is based on some details and historical development facts rather than major functioning differences. In fact, their biological basis is essentially the same.

It is particularly useful to consider the history of evolution within computing as it covers much of the timeframe of computing itself. Some of the earliest work can be traced back to [51], who introduced the idea of an evolutionary algorithm approach for automatic programming. Later significant development included the creation of EP by [52]. [53] founded the initial work on GAs at the University of Michigan. Parallel work was also initiated by [54] in ESs. However, the major barrier to the early adoption of evolutionary algorithm in the computing domain came from opposition within the computing science community itself. That was often based on the incorrect belief that such algorithms, with probabilistic processed as a core mechanism, would not be amenable to produce functional code. The second barrier was the problem that contemporary computing technology in software, and particularly hardware, in the early 1970s was barely capable of generating useful results in acceptable time scales (i.e., less than a few weeks). This problem added to the belief that such methods, while theoretically interesting, would never be capable for practical applications.

Now Evolutionary Computing is frequently used as a generic term that incorporates GA, ES, EP and their variants. The origin of EA was an attempt to mimic some of the processes taking place in natural evolution. Although the details of biological evolution are not completely comprehended (even nowadays), there exist some points supported by strong experimental evidences:

- Evolution is a process operation over chromosomes rather than over organisms. The former are organic tools encoding the structure of living being, i.e. a creature is 'built' decoding a set of chromosomes.

- Natural selection is the mechanism that relates chromosomes with the efficiency of the entity they represent, thus allowing those efficient organisms that are well-adapted to the environment to reproduce more often than those which are not.

- The evolutionary process takes place during the reproducing stage. There exists a large number of reproductive mechanisms in the Nature. Most common ones are mutation (that causes the chromosomes of offspring to be different to those of the parents) and recombination (that combines the chromosomes of the parents to produce the offspring).

All EAs have two prominent features which distinguish themselves from other search algorithms. Firstly, they are all population-based. Secondly, there are communication and information exchanges among individuals in a population. Such communication and information exchanges are the results of selection and/or recombination in EAs.

The Genetic Algorithms (GA) is a representative of this new breed of search, machine learning and optimisation techniques that are non-deterministic and a posterior. GA employs coding and hence deals with non-numerical variables. An organism's genetic code is its position in solution space while its survival in its environment and its number of offspring indicates probabilistically the degree to which it meets its objectives. Evolutionary algorithms are powerful techniques in the search for global optimal solutions, but they usually require to evaluate objective functions many times. These objective functions may, in a real problem, be difficult or time-consuming to evaluate. Hence the less evaluations the better.

3.2 Fundamentals of Genetic Algorithms

3.2.1 The Working Mechanism

Genetic algorithms [46] [55] that represent a paradigm of evolutionary computation, is a general-purpose global search method for solving complex problems. Based on Darwinian's survival-of-the-fittest, GAs work by repeatedly modifying a population of artificial structures through the application of selection, crossover, and mutation operators. A GA's fitness function measures the quality of a particular solution.

The following sequence is a common starting point for most GAs:

1. Create generated population of N chromosomes, each of some length m bits.
2. Test each chromosome (i.e. a possible task solution) within the problem space and assign a measure of fitness $f(x)$.
3. Selection phase: Select a pair of chromosomes from the population with probability based on their fitness.

4. Apply a set of genetic operators to the two parent chromosomes: With some crossover probability p_c, apply crossover at some randomly selected point along each chromosome.
5. Apply mutation to each new chromosome with a probability p_m.
6. Place the new chromosomes in the new population.
7. Replace the old population with the new population.
8. Test if target termination criteria is met, such as a specific best fitness value; else repeat from stage 2.

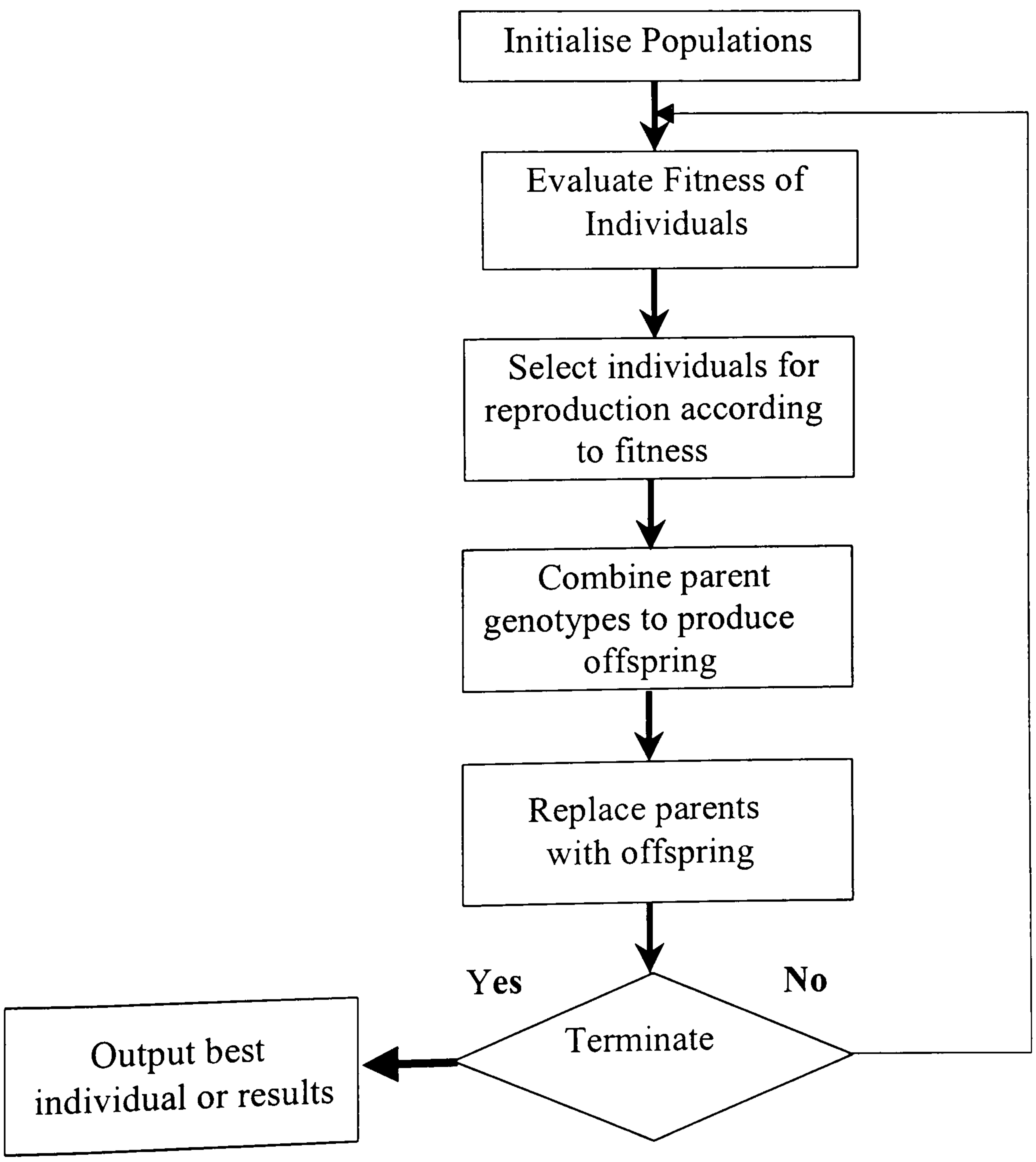

Figure A.1: GA sequence of operations

Each loop of the sequence, illustrated in Figure 3.1, is termed a generation. The central concept of the GA is the chromosome, which is the encoding of information in a string of symbols. These strings can be manipulated by a set of genetic operators. Using the process of fitness proportional selection, the chromosome strings, which encode a potential solution the specific task or function, evolve toward an improved solution.

3.2.2 Technical Details

1 Encoding

The user should select a "reasonable" (i.e., not one bit quantity) or the smallest possible coding alphabet that permits a natural expression of the problem. The basic coding methods are outlined below [46].

- Integer coding;
- Real coding;
- Logarithmic coding;
- Byte coding;
- One-Integer-One-Parameter coding;

The advantage of coding is that logic values or decisions, e.g., those concerning whether to have a particular component in a design, and logic operators can be encoded ina chromosome and this included in the search. This makes the search and optimisation more versatile and complete and may lead to novel creation or inventions.

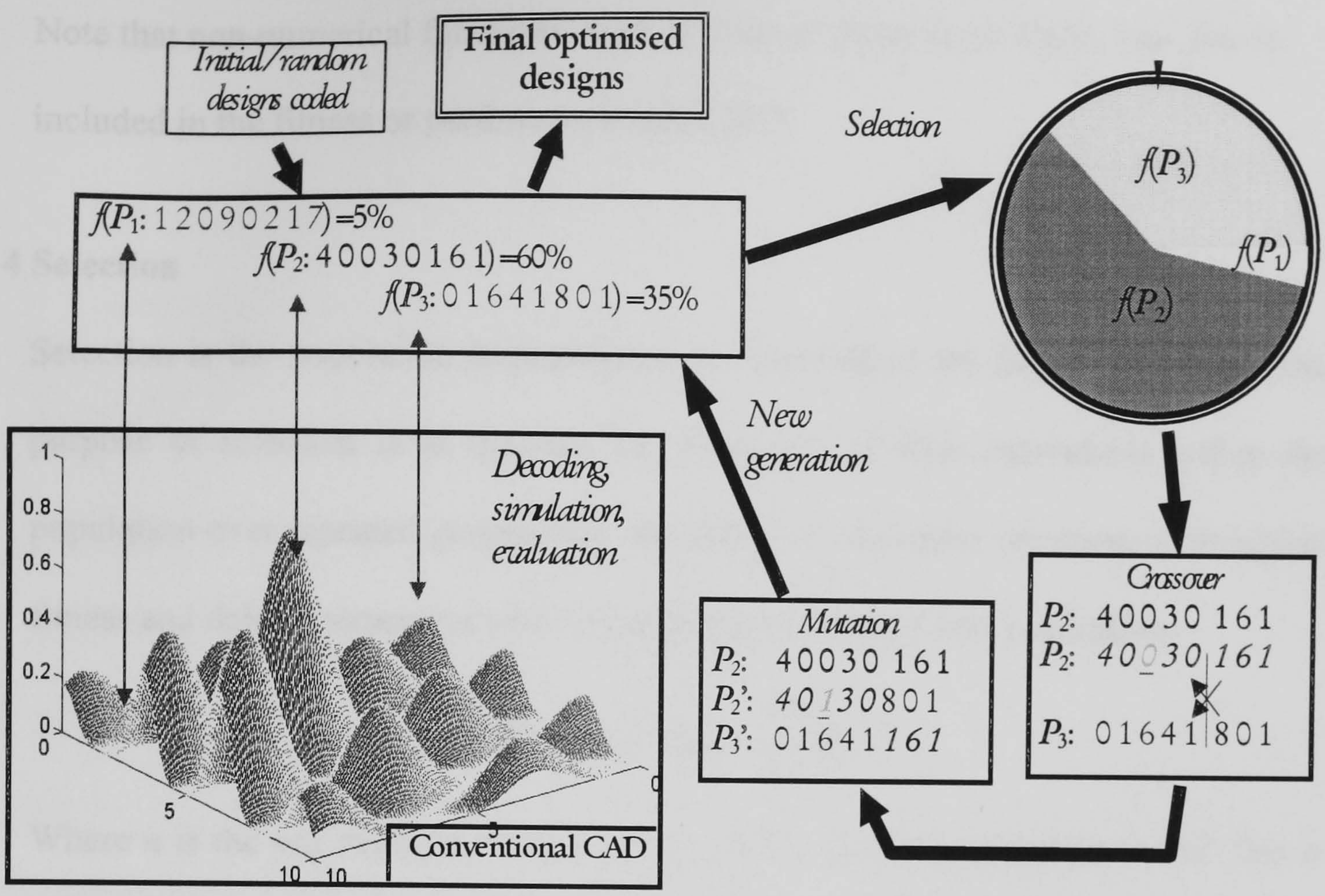

Figure A.2: Genetic Algorithm – Working principles and standard operators [46]

2 Initial population

This needs to be large and mainly random when string lengths are large. However, known or a-priori parameter sets and those that the user would like to start with should be included for a faster convergence or for further improvement [56].

3 Objectives and fitness

In GA, optimisation error is usually measured by the sum of absolute errors (l_1 norm) between the actual and the simulated output of the system, as given by:

$$e(\boldsymbol{P}_i) = \sum_{j=1}^{N} | y_j - \hat{y}_j |$$

where N is the total number of data of simulation steps. Clearly, the fitness or performance can also be measured by an l_2 or l_∞ norm, as they and l_1 are finitely bounded with one another.

Note that non-numerical functions, such as rules or fuzzy logic terms, can also be included in the fitness or performance index [57].

4 Selection

Selection is the population improvement or "survival of the fittest" operator. The purpose of selection is to increase the frequency of fitter individuals within the population over repeated generations. Basically, it duplicates structures with higher fitness and deletes structures with lower fitness to create a new population.

$$P_{select}(n) = f(n) / \sum_{K=1}^{prop} f(k)$$

Where n is the nth string, p = total number of strings in the population, and $f(n)$ is the fitness of the nth string. The selected individuals are then copied into the next generation using the set of genetic operators, normally composed of mutation and crossover. However there is always a pressure between exploiting the population through selection and exploring the search space via crossover and mutation. Excessive selection will lead to fit but suboptimal individuals taking over the population before a target solution is found. It is then difficult for the population to recover sufficient diversity to explore the remaining search space. If the selection pressure is too weak, however the rate of evolution will fail to converge on a useful solution.

The current adopted selection mechanisms are addressed as following:

- Roulette-Wheel selection;
- Ranked roulette wheel;
- Ranking selection;
- Tournament selection;

- Elitist selection;
- Proportionate selection;
- Fuzzy selection;
- Boltzmann tournament selection;
- Steady-State selection.

5 Crossover

Crossover, when combined with selection, results in good components of good structures combining to yield even better structures. It works by selecting two parent individuals from the population with a fitness-dependent probability, and swapping sections of each individuals chromosome. The offspring are the results of cutting and splicing the parent at various crossover points.

6 Mutation

Mutation is a mechanism where a randomly selected gene within the chromosomes id replaced with an alternative allele. Mutation creates new structures that are similar to current structures. A common perspective is that mutation is primarily a secondary operator and acts to replace or regenerate bits or genes lost during the crossover process. At best mutation can help move a chromosome away from local optima by injecting new genes into the population of chromosomes. With a small pre-specified probability, mutation randomly alters each component of each structure. When used sparingly with reproduction and crossover, it is an insurance policy against premature loss of important information.

7 Stopping criteria

- Stop after finding a known maximum (or minimum) (based on some specification) or after finding a better solution than an existing/known one.
- Stop after a certain period of time. Ofter, stop after a given number of generations have been evolved, e.g, 100 generations.
- Stop when there is no improvement in the maximum (or minimum) value in the generation or when the average is close to the maximum (or minimum).

3.2.3 Advantages of Genetic Algorithms

Compared with natural evolution, the emulated process is more efficient, controllable and yet more flexible for artificial optimisation. All these methods are probabilistic in nature and exhibit global search capability, thus making them attractive for almost all areas of human activity. Genetic Algorithms accommodate all the facts of soft computing and other attractive features, namely,

1 Overcoming all drawbacks of conventional optimisation techniques;

2 Domain constraints, performance measures with dynamics and the number of independent and co-dependent elements;

3 Robustness;

4 Possible non-linear interactions between various elements;

5 Incomplete, uncertain and imprecise of information;

6 Adaptive capabilities;

7 Providing multiple optimal solutions; and

8 Inherent parallelism.