FORECASTING SYSTEM IMBALANCE VOLUMES AND ANALYSIS OF UNUSUAL EVENTS IN COMPETITIVE ELECTRICITY MARKETS

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CONTENTS

ABSTRACT

The introduction of competition and deregulation in electricity markets is not a simple change. Recent events around the world have highlighted the consequences of shortcomings in the operation of electricity markets.

Markets for electrical energy thus tend to be much more complex than other commodities market. Their analysis therefore does not lend itself to simple models. The aim of this thesis is to present a feasible approach to their analysis combining classical statistics with Data Mining techniques. That is the development of effective methodologies to transform huge amounts of shapeless and unstructured data into organised and understandable information.

The England and Wales Electricity market provides the perfect framework for this thesis. The change from the centralised Pool to the New Electricity Trading Arrangements (NETA) created a wide range of challenges for all market participants, including the SO, to optimise their strategies in order to maintain or increase their revenues and profits. The changes resulted thus not only in new questions but also in the need to explore new ways to achieve their answers.

This thesis contributes not only to the analysis of NETA but also to the development of new methodologies that can be applied later in date or for the analysis of other new structured electricity markets. To achieve this, the thesis unfolds in two different directions: the modelling and forecast of the market volume, and the analysis and characterization of unusual market conditions.

DECLARATION

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other University or other institution of learning.

To my mother, my father, my abuelita

And to the one I have so near in my heart…my abuelito.

whenthherain
fallstthey
talkofma
nchestherbut
whenthe
triumphant
rainfalls
wethinkof
rainbows

(Lemn Sissay 2002)

ACKNOWLEDGEMENTS

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I would like to pay a special tribute to my family, especially to my parents, Jose Maria, my Abuelita and my Titos. Although they are not physically here with me, their support does not reduce through thousands of miles away. The power of their encouragement is directly proportional to the square of the distance according to the universal law of love.

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PUBLICATIONS

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“Market Clearing Prices in the Balancing Mechanism of England and Wales”, Daniel Kirschen and Maria Garcia, IEEE Power Engineering Society's 2004 Power Systems Conference and Exposition (PSCE'04), October 2004.

“Forecasting System Imbalance Volumes in Competitive Electricity Markets”, Maria Garcia and Daniel Kirschen, submitted to IEEE Transactions on Power Systems, (under review).

CHAPTER 1

Introduction

1.1 Liberalising electricity markets

Electrical energy is a dynamic and fundamental good. These two characteristics have marked the history of electricity markets since the establishment of the first power stations in the nineteenth century. From the initial open and brutal competition passing through regulated structures and vertically integrated monopolies, current approaches move towards liberalised markets designs. Electricity markets liberalisation combines the unbundling of vertically integrated utilities, the limitation of central and governmental control, and the introduction of competition at all levels.

The reasons behind this electricity industry reorganisation, which started in the 1980s, are not completely manifest. To explain the ground for this reform, different arguments can be presented (Stoft, 2002, Banks, 1996, Moorhouse, 1995). Among those, one should mention the economic aim of marginal cost pricing, the technological developments in generation, transmission and information technology, the drastic slowdown in the growth of demand in developed countries, and the world-wide globalization and liberalization trend.

Within the power market one must distinguish the physical structure from the architecture or design (Stoft, 2002, Hunt and Shuttleworth, 1996). The physical structure consists of three main parts: generation (producing electricity), transmission (transferring the power over the high voltage network) and distribution (delivering the power to the consumers). From a design perspective, the power market includes different submarkets such as forward markets, spot markets, transmission capacity markets and ancillary services markets. Each of these markets can be organised as a pool (centralised market), bilateral (customized contracts, brokered, and exchanges) and hybrid models. To complete the definition of the market architecture it is also necessary to include the links between the different submarkets. These linkages can be classified as implicit (i.e. transmission rights and bilateral market) or explicit (i.e. forwards and spot market prices), as well as temporal (i.e. submarkets temporal sequence) and spatial (i.e. transmission and distribution networks).

From the early attempt in Chile in 1983, several countries around the world have undertaken regulatory reforms in their electricity industry. The broadness of the liberalisation and deregulation depends not only on the industry structure and infrastructure (generation portfolio, demand requirements) but also on the economic and institutional frameworks. Many restructuring moves can be performed towards a more competitive market. Based on the models presented by Hunt et al. (Hunt and Shuttleworth, 1996), Figure 1.1 shows the double dimension of the restructuring process. The vertical axis shows the reforms dealing with ownership and management, and the horizontal axis displays the ones dealing with the market structure

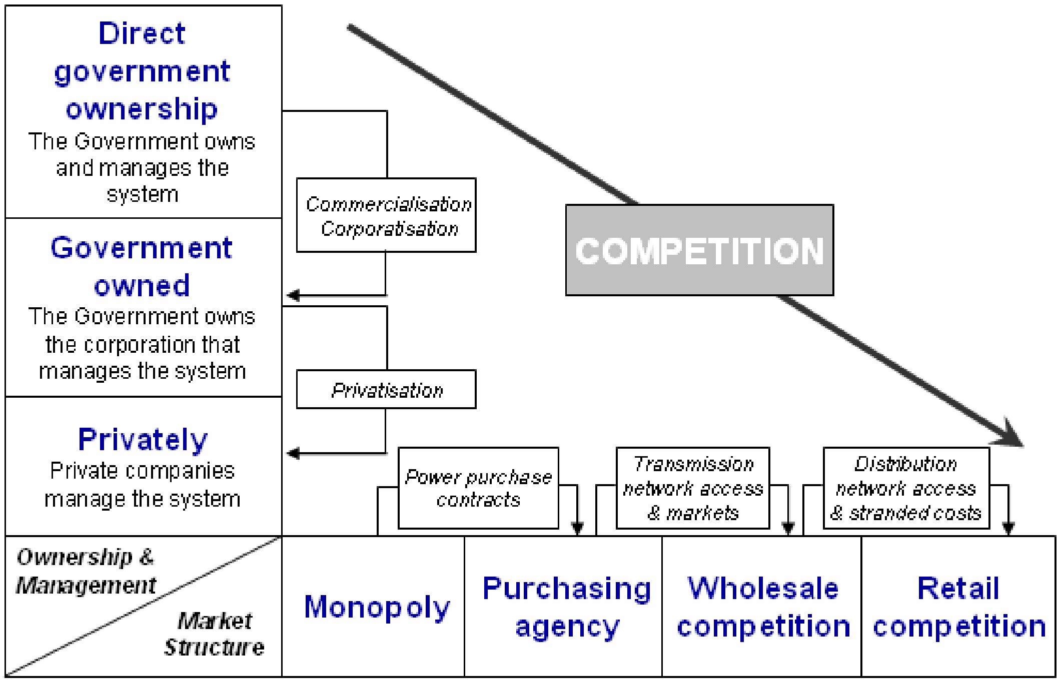


Figure 1.1 Restructuring dimensions and possibilities

Any regulatory reform involves complex changes that are introduced as an ongoing process. Policies are gradually implemented to allow people and institutions time to adjust and to allow policies to be reviewed and refined as markets grow, technology changes and competition develops. To describe the different realizations of the reforms is not the goal of this thesis, but a brief discussion on the consequences of these reforms is included.

1.2 Consequences of deregulation

Energy, and more specifically electricity, has become a key issue in development plans, not only those involved in the essential service itself represents, but also it has an impact on environmental, economic and even international policy. Regulatory reforms have an effect on different aspects of the industry, and often involve a substantial long-term commitment to change. Therefore governments need to be convinced that the changes will be worthwhile. These consequences can be part of the reform objectives but also penalties derived from the imposed structural changes. Some of the impacts of deregulation are:

- *Stranded costs.* Stranded costs can be defined as the decline in the value of electricity-generating assets due to restructuring of the industry (VanDoren, 2000, Stoft, 2002). Regulated markets allowed the capital cost of assets to be reflected in electricity rates. For example, in the US, State public utility commissions had different rules regarding those assets and also have different rules about recovering their cost. In a restructured industry, the options to deal with stranded costs of government-own utilities are wider than for private companies. In the US, some state regulators have continued to allow utilities to recover the cost of those facilities, whereas others have not.

- *Electricity prices.* Pricing is one of the main regulatory tools. In a regulated market, they allow wealth redistribution, and often cross-subsidies to take place. As presented by Pineau (Pineau, 2000), different pricing options can be defined (average cost, marginal cost, real time, time of use, Ramsey, non-linear and reliability), and each of them pursues different goals, from fixed cost recovery to energy saving promotion. Lowering electricity prices is one of the main goals of deregulation. In competitive environment, producers monitor their cost closely to all margins, and ideally offer electricity at its marginal cost. Competitive conditions also mean more complex pricing systems that can reflect reliability and time of usage conditions (Schweppe et al., 1988).

- *Risks.* In electricity markets certain risks, such as demand variations, equipment failure, and input prices are independent of the market structure. However, in a regulated and vertically integrated industry all these risks are easily covered by carrying excess capacity. Deregulation does not only accentuate the inherent market risk but also produces additional sources of risk like complex pricing structures. Nevertheless, decentralised markets are also more flexible and provide several mechanisms to deal with risk. Particulary notable among those are spot contracts, futures, and options on futures (Werner, 2002, Collins, 2002, Mohr and Unger, 1999).

- *Investments.* Investments are directly related with both system reliability and electricity prices (Hogan, 1998, Kirschen and Strbac, 2004). Before deregulation, it was the utility's responsibility, under centralised generation planning, to assure that enough generation capacity was available. In the restructured power industry, generally there is either no central planning for new generation capacity additions, or a guarantee of recovery of generation investment. On the other hand, generation companies do not have any obligation to ensure a sufficient supply of electricity. However, if there is not enough investment, capacity scarcity will occur, prices will increase, and reliability levels may decrease.

1.3 Modelling Electricity Markets

Unfortunately electricity markets modelling present several differences compared with any other traded commodity market (Pilipovic, 1998, Strickland, 2000, Ocana et al., 2001, OFGEM, 2000b, Cardell et al., 1997):

- Electricity as an energy commodity cannot be treated as a purely financial investment. Energy commodities are inputs to the production processes. This makes many of the common models unsuitable for the case of electricity, since the basic rules are quite often broken. In the electricity markets the prices offered may in some cases drop to zero or even reach negative values. This free disposal is not normally represented in the traditional models.

- Imperfect competition in electricity markets. There are strong interaction effects across different parts of the system due to the transmission constraints that limit the flow of power in an electricity network. Large participants can exercise market power by increasing their own production, lowering some prices, and exploiting the necessary feasibility constraints in the network to exclude competition from others (Alaywan et al., 2004). It is then necessary to consider a model of imperfect competition with strategic interactions in an electricity transmission network. This includes situations where a generator could exercise market power by increasing its production in order to block transmission of a disproportionate amount of competing generation. This example illustrates a possible exercise of market power that differs from the usual analysis of imperfect competition in more familiar commodity markets where a firm would just exercises market power by restricting its own production without any network restriction.

- Electricity parameters show a very high seasonality. This means a recurrence in the values and also in the volatility. These transient movements can be found in intra-month, intra-week, and intra-day values due to changes in the demand side. This creates a necessity for a forward modelling in order to look for changes in seasonality.
- Electricity cannot be stored easily. This is an extreme condition not presented by any other commodity. Storage limitation in electricity affects volatility in both forward and spot market quantities and prices: while the spot prices display a very high volatility, the forward prices volatility increases as maturity approaches.
- Energy markets are relatively young. This youth affects the historical information available on spot prices and reduces significantly the amount of present-day traded volumes. As a consequence electricity markets are still somewhat illiquid. This special characteristic makes the prices analysis more difficult.

1.4 Approaches to Electricity Markets modelling

Markets for electrical energy thus tend to be much more complex than other commodities market. Their analysis therefore does not lend itself to simple models. Such an analysis, however, is extremely important to regulatory authorities because they will want to check that the market is operating efficiently and that some parties are not taking advantage of their market power.

Market participants are also interested in analysing the market to understand the behaviour of their competitors and to optimise their bidding strategy.

Different techniques can be applied in the study of electricity markets. Each of them looks at the market from a different perspective and tries to explain specific areas of the market. The most important approaches are: financial econometric analysis, operational electricity models and data mining techniques.

1.4.1 Financial Econometric Analysis

This technique is based in the extensions of the Geometric Brownian Motion (see for example (Hunt and Shuttleworth, 1996)). The main techniques used in this approach are mean reversion, stochastic volatility and jumps. The obtained models are commonly applied in the study of spot and forward prices as well as sensitivity risk analysis for future contracts and options. One of the main difficulties of this approach is to adapt classical modelling techniques developed for purely financial markets to the complexity of the electricity market. Because many of the basic assumptions used for financial markets are not valid in electricity markets, ignoring the realities of the market could cause grave mistakes costing a great amount of money to a trading party.

1.4.2 Operational electricity models

These models combine the technical characteristics and limitations of the physical electricity system with a realistic modelling of the participants' behaviour. According to their mathematical structure the different approaches can be classified as optimization models, equilibrium models and simulation models (Ventosa et al, 2005).

1.4.2.1 Optimization models

These models focus either on the profit maximization of a single firm, or the cost minimization of the total cost of the whole system operation. Although they are formulated as a single optimization program, they capture both the operational constraints of the interested firm and the price clearing process.

In the simplest market models the firms' decisions are assumed to have no influence on the clearing price. This can be defined either in a deterministic or a stochastic manner. These approaches have been used to solve generation scheduling (Gross and Finlay, 1996) and risk management problems (Fleten et al., 1997).

Another group of optimization models are the so-called leader-in-price models. They consider the influence of the firm's production on the price by including the residual demand function (Garcia et al., 1999) when modelling the optimal output for the firm. These models have been used to solve unit commitment problems and to obtain optimal offer curves (Ventosa et al., 2005).

1.4.2.2 Equilibrium Models

These models present a wider perspective of the market operation, since they consider the competition among all the participants (Ventosa et al.,2005). These models are based on the Nash equilibrium concept (the market reaches its equilibrium when each player's strategy maximizes its profit against the strategies of its competitors). Depending on the definitions of the firm's strategy we can distinguish between Cournot equilibrium and Supply Function Equilibrium (SFE) models.

In Cournot models the firms' strategy is purely quantitative (Daughety, 1989). Hence, the representation of the firm's optimum output is a set of algebraic equations. These models have been widely used in areas such as market power analysis (oligopoly models) (Borestein and Bushnell, 1999, Borestein and Kinittel, 1995), hydrothermal coordination (Barquin et al., 2003), congestion pricing (Hogan, 1997) and risk analysis (Otero-Novas et al., 2000). The main drawback of the Cournot model is that equilibriums prices are high than what is actually observed and unrealistically sensitive to the demand representation. This arises from the fact that the firm's output is defined in terms of quantities and directly linked to the demand conditions.

SFE are more complex models where the firm's strategy is based on offer curves (quantities and prices) (Kemplerer and Meyer, 1989). Their mathematical representation relies on a set of differential equations, which limits their numerical tractability. The main areas of applications include: market power analysis (asymmetric duopoly) (Green and Newbery, 1997), electricity price estimators (Rudkevich et al., 1998) and network modelling (Ferrero et al., 1997). The main limitations of these models reside in their complex mathematical structure, which limits their ability to capture a realistic representation of the competition between participants and the system operation constraints.

1.4.2.3 Simulation models

Simulation models are an alternative to equilibrium models for the cases that require a more flexible representation. These models describe each firm's strategic decisions dynamic by a set of sequential rules; the basic building blocks are stocks that flow within a structure of information feedback loops. In this way, the firms learnt from historic information and past decisions, react to competitors' moves, and adapts to changes in the environment (Ventosa et al.,2005).

The main type of simulation model is agent-based (Bunn and Oliveira, 2001). Agent-based modelling is applicable to a wide variety of business problems. It is also known as agent-based or bottom-up simulation. In these computer simulations, software agents represent the generating firms at a power plant level; suppliers can also be included as agents in order to model the demand side of the market. Agents are programmed to develop their own bidding strategies according to their own plant characteristics and the market rules. Agent-based simulation is normally used for price and market power analysis (Bower and Bunn, 2000) and as a possible tool for forecasting the market evolution or the possible effects that regulation changes may have on the participants (Bunn and Oliveira, 2001). One of the big difficulties with these models is the need create realistic and flexible agent operation rules. The model should also capture all the possible interactions between the participants to create an accurate market environment. Too many simplifications can lead to incorrect agents' behaviour and false predictions.

1.4.3 Data mining techniques

Data mining (Figure 1.2) starts with the data, and seeks to discover novel patterns. A data mining project progresses in phases: understanding the market and the data, preparing the data, and analysing the data with the specific goals in mind. This creates an interactive process because when the patterns emerge, the initial goals may need to be redefined. As a result of this multi-step process it is possible to discover the useful patterns in the data that help understand the market drivers.

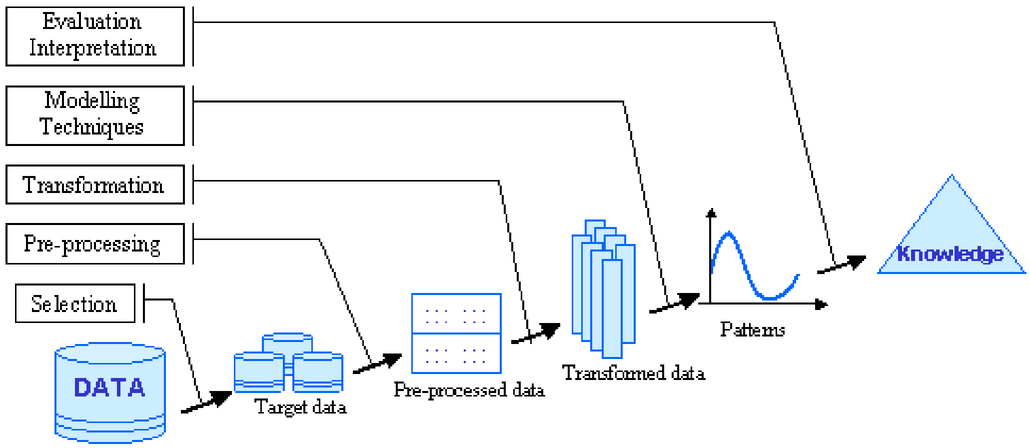


Figure 1.2 The Data Mining transformation: from raw data to knowledge

With data mining the researcher does not rely on assumptions so as to study the market behaviour but analyses the real data and extracts the actual patterns from them. Data mining differs from the methods previously described in the fact that no simplifications of the market mechanisms are needed. Therefore, the market is analysed from a realistic bottom up approach where linear, non linear and highly dimensional conditions can be modelled. One of the big difficulties of the data mining approach is to select the correct data to explore. It is thus particularly important to understand the market rules and the interactions between the different market quantities.

Data mining can be used to perform a wide variety of analysis from forecasting to a global analysis of the market drivers, or a more specific analysis of the strategies of the market participants and the possible interactions between them.

The easy access to electronic communications networks has allowed a big change in every business environments. This change is mainly driven by the recent presence of computers that has allowed a beneficial use of more and more data. Power companies are also part of this development. Data management in electricity markets is getting complicated due to two events:

- The possibility to gain access to a huge amount of operational data taken from improved communication channels. For instance, in the England and

Wales program all the different participants are required to be electronically linked and to submit their desired operation levels through these communication links; also the operation of the market on a rolling 48-half hour basis generates massive amounts of data that are now available on the internet (Garcia, 2001a).

- The worldwide deregulation of electricity markets. The introduction of competition has introduced a new challenging perspective in the market participants. A deregulated market creates for the generators a self-dispatch perspective, which requires a strategic analysis of how to run the plants in the most cost-effective mode. On the demand side, they are able now to adjust their consumption level to the most economical one (Heslop, 1997).

These two situations have resulted in the fact that the information required to make strategic decisions is hidden in complex and often badly structured databases. The analysis of these data should produce a more realistic model of the market's behaviour.

1.5 Scope of the thesis

Deregulated electricity markets are a gold mine of discovery, and the aim of this thesis is to present a feasible approach to their analysis combining classical statistics with Data Mining techniques. That is the development of effective methodologies to transform huge amounts of shapeless and unstructured data into organised and understandable information.

The framework of the thesis is the England and Wales electricity market, which is detailed described in Chapter 2. Within this broad context, the thesis focuses on two complimentary approaches for its study. The first is a modelling and forecast analysis of the market volume. The second approach is the analysis and characterization of unusual market conditions.

Data mining techniques are introduced in Chapter 3, which first describes their different styles, purposes and domains, and then concludes with a detailed description of the organization and stages of the data mining process.

The first contribution of this thesis is to develop a new methodology to forecast the market volume or Net Imbalance Volume (NIV), a key variable for the system operator. Forecasting in power systems is necessary because decisions cannot be implemented immediately and because they need to be evaluated for a certain period of an activity. Wang et al. (Wang and McDowall, 1994), Dash et al.(Dash et al., 1995), Bunn (Bunn, 2000), Sfetsos (Sfetsos, 2003) and Kermanshahi et al. (Kermanshahi and Iwamiya, 2002) provide overviews of the progress that has been made recently in the broad field of forecasting in power systems. The introduction of competitive electricity markets has considerably increased not only the complexity of this task but also the breadth of this field (Garcia and Kirschen, 2004):

- Forecasting is no longer an activity performed only by the system operator. All market participants must do some forecasting to operate their systems more efficient and economically, thus maximizing their profitability and controlling their exposure to risk.

- Load is no longer the only uncertain variable that must be forecasted. Market participants are interested in prices (Bastian et al., 1999, Crespo Cuaresma et al., 2004, Rodriguez and Anders, 2004, Wang et al., 2002, Nogales et al., 2002, Contreras et al., 2003) , traded volumes, and market length.

- Market variables are much more “noisy” than the system load.

- The values of these variables are driven in complex ways by many interacting factors. It is thus important to expand previous one-dimensional approaches (see for example (Crespo Cuaresma et al., 2004)) to multidimensional inputs.

- The amount of data to be considered is huge and involves not only the market clearing data but also the positions that the participants took prior to gate closure and synthetic indicators of market activity.

- Changes in market rules affect the way some variables are calculated and influence the behavior of market participants. These changes reduce the amount of historical data that can reliably be used for forecasting.

The developed forecasting methodology for NIV analysis and forecast is presented in Chapters 4 and 5. In Chapter 4, the analysis and forecast of NIV is based on one-dimensional techniques, and uses time series to first identify the "time structure" of the data and then to produce a medium term forecast (one week ahead) of this variable. This line of analysis combines both the adaptation of traditional techniques, used for forecasting the behavior of financial and other physical commodities, with the introduction of singular spectrum analysis, a recently developed technique. Chapter 5 expands the scope of the analysis to a multidimensional perspective. Other market variables are included to achieve an effective methodology for forecasting NIV in both the medium term (one week ahead) and long term (one month ahead). The first part of the chapter seeks to uncover the possible relations between NIV and the considered market variables. The relationships are analysed from a qualitative (i.e. linear, non-linear), quantitative (i.e. their statistical significance), and temporal (i.e. instantaneous, lagged) perspective. The second part of the chapter presents a forecasting methodology based on the relation between the past (seen) values of the balancing mechanism variables and the future (unseen) values of NIV. However, the relations linking the past and future values of these variables are neither simple nor linear. Data mining techniques, in particular neural networks, are shown to be able uncover these complex associations while maintaining the time structure of the analyzed series.

The second main contribution of this thesis, arising from the second approach, is to develop a methodology for the analysis of unusual events a topic seldom considered in the analysis of electricity markets. Chapter 6 proposes a new line of analysis based on the relationships between causes and effects. This chapter first introduces the prior work in the area of unusual events. Then, it covers the analysis of the unusual events trigger variables (causes) considering not only their probability of occurrence but also their duration as well as the time between events. The last part of the chapter analyses the effects that these events have on the market behaviour.

The innovation of the proposed methodology is not only the combination of one-dimensional and multidimensional techniques but also its capability to consider the simultaneous occurrences of events and the dynamic analysis of the market reaction to an event or combination of a combination of events.

The final chapter (Chapter 7) brings together the general conclusions derived from the different analyses and suggests new directions both in the line of analysis presented and for future analysis in the context of the Great Britain electricity market analysis.

CHAPTER 2

The New Electricity Trade Arrangements

2.1 Introduction

Despite electricity's unusual characteristics, new market designs try to make its trading similar to the trading in any other commodity. The design of a competitive market is based on two simple principles: a competitive and efficient energy trading, and the reliable operation of the grid. However, there is no simple recipe when designing a power market. The existing generation resources, the demand requirements as well as the segmentation and ownership of the industry must be considered to successfully define the different market architecture, mechanisms and rules.

With the establishment of the Electricity Pool in 1990, England and Wales became one of the first countries to introduce competition in the provision of electricity (Bourn, 2003, OFGEM, 1999c, OFGEM, 2000a). The Pool was a compulsory market where generators (AES and British Energy, 2001) and suppliers traded according to a set of rules (the Pool rules). It had a centralised structure in which National Grid Company (NGC), as the system operator, was responsible for scheduling, dispatching and pricing. Each day generators submitted their bids to the Pool, declaring the amount of electricity that they were willing to generate and the minimum price that they were willing to accept for this production. Using a unit commitment program, NGC ranked all the generators bids in "merit order" starting with the cheapest until there was enough generation to meet the demand plus the reserve (unconstrained schedule) while satisfying the constraints. In each period, the most expensive accepted bid determined the price for all the generated electricity.

In summary, the Pool was successful in maintaining the security of the supply, creating the half-hourly pricing structure and facilitating the entry of new generation into the market. However OFGEM and some other participants considered that it also failed on several major accounts (McClay et al., 2002, Hesmondhalgh, 2003, Bourn, 2003, Dettmer, 2002). The complexity of bidding and price setting, the relative lack of both supplier pressure and demand-side participation, and the limitation of capacity payments resulted in a situation where consumers were facing higher prices than would have been feasible otherwise.

OFGEM believed that there was no simple way to modify the Pool mechanisms so as to get more competitive and transparent prices so it was felt that new market design was needed (OFGEM, 2002, OFGEM, 2000a, OFGEM, 1999c, Neushloss and Woolf, 1999). In October 1997 a review of the electricity trading arrangements was initiated by the Minister of Science, Energy and Industry. In November 1998, the DGES published a framework document explaining how the new programme would be taken forward. This culminated in the publication of a two-volume report by OFGEM in July 1999 (OFGEM, 1999b, OFGEM, 1999a). This report explained the reasons for the replacement of the Pool with what was called "New Electricity Trade Arrangements "(NETA). NETA went live replacing the Pool on the 27th of March 2001.

2.2 Operation of the New Electricity Trade Arrangements (NETA)

The philosophy of NETA is not to dictate how the energy will be bought and sold but to provide mechanisms for almost real-time clearing and settlement of the imbalances between the contracts and the actual positions of the different parties involved in electricity trading (OFGEM, 2002, Electricity Asociation, 2002, Bourn, 2003).

The main difference between NETA and the Pool is that the new system is based and designed around bilateral trading between generators, suppliers, traders and consumers. In this way the participants can choose the way they want to trade and choose the related mechanism to do it.

NETA, like the Pool, is based on half-hourly trading periods but incorporates the following features (Stephenson and Paun, 2001, OFGEM, 2000a): forward and futures markets, short-term power exchanges, a balancing mechanism, and a settlement process. The rules that govern these last two functions are set down in the Balancing and Settlement code. Figure 2.1 describes the timeline for NETA operation and the resulting market structure.

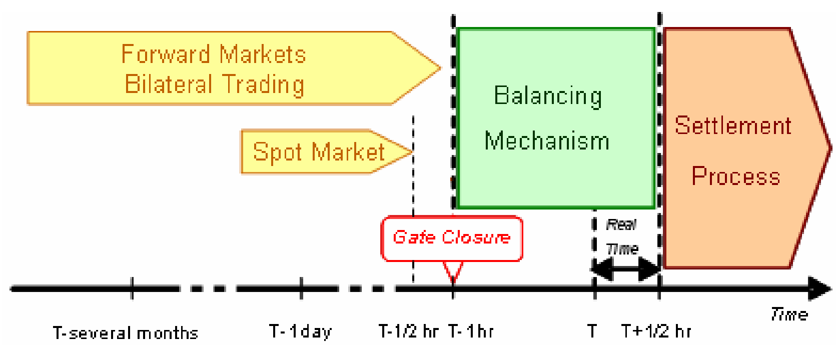


Figure 2.1 The New Electricity Trade Arrangements (NETA) Timeline

2.2.1 Forwards and futures markets

These markets are bilateral contract markets for firm delivery of electricity (Bunn and Oliveira, 2001, Stephenson and Paun, 2001, Bourn, 2003, OFGEM, 2002, Kirschen and Strbac, 2004). They operate from a year or more ahead of real time up to 24 hours ahead of real time and occasionally up to gate closure. These markets provide the opportunity for generators to enter into contracts to deliver a specified quantity of electricity on a specified date and at a specified price with suppliers and consumers. The freedom and bilateral pricing is expected to guarantee that prices better reflect generation costs (Hesmondhalgh, 2003). Bilateral trading also increases the market liquidity as traders (that do not produce or consume physical quantities of energy) also seek to enter the market (Bourn, 2003).

2.2.2 Short term power exchange

Power exchanges provide a wide variety of contracts. They can be done from months of delivery to half hourly intervals (Stephenson and Paun, 2001). Market trading includes not only over the counter trading but also electronic trading and other financial services. By trading in the spot markets participants can fine tune their contractual position reducing the risk of being exposed to real-time spot markets. These markets are open 24/7 with access available either through the internet or by leased line. In all these exchanges, offers and bids can be posted, modified or withdrawn at any point until they are accepted. Continuous trading helps participants to deal with unforeseen events and therefore gives stability to electricity prices. There are two main power exchanges in operation since the introduction of NETA: the UK Power Exchange (UKPX) and the UK Automated Power Exchange (UK APX).

Forward, future and short term are the main wholesale markets where the bulk of electricity is traded under NETA. Approximately 95% is covered in bilateral contracts, a further 1-2% is traded in power exchanges (Bourn, 2003) . The UKPX is the exchange with largest traded volume. Throughout NETA operation, theses markets have developed naturally. Their activity has significantly increased specially for forward contracts since participants try to secure their energy requirements in advance (Electricity Asociation, 2002). These non mandatory markets have not only increased NETA's liquidity but also its transparency by making future prices available from different reporters (Hesmondhalgh, 2003).

2.2.3 The Balancing mechanism

Bilateral trading operation does not continue up to real time. At gate closure, (initially 3.5 hours and, since 2 July 2002, 1.0 hour ahead of real time) bilateral trading stops and the balancing mechanism starts (OFGEM, 1999c). The Balancing Mechanism is necessary because electricity is not a simply commodity.

Under NETA, the different parties indicate to the SO the levels of output or consumption at which they want to operate. This creates the necessity of a mechanism to adjust, in real time, the levels of generation and demand. There are two main reasons for that:

- First, it is likely that the total output of generation does not match the total consumption of consumers at any given time. This can be due to the fact that the parties have not exactly predicted their real operating level; factors like the weather can affect the expected demand, also some generation may not be available due to unexpected faults.

- Second, the System operator may need to adjust the level of production and consumption away from the level the generator or the consumer wish to operate. These adjustments are due to technical reasons and to preserve the secure operation of the system (F.Li et al., 2002).

By gate closure all the different participants must notify their expected operation levels (final physical notifications) to the System Operator (SO), National Grid. They may also submit their willingness to deviate from these levels, in exchange for payment, by the mean of offers and bids (Figure 2.2). Offers indicate a willingness to increase the level of generation or to reduce the level of demand. Conversely, bids indicate a willingness to reduce the level of generation or increase the level of demand. Both bids and offers pairs have to include a bid/ offer price, expressed in £/MWh, and a quantity, expressed in MWh. Every offer and bid has to include a complementary 'undo' bid or offer; they represent the price of cancelling the offer or bid. Participants can submit up to five bid/offers pairs above the final physical notification and five below. The Offer Price and Bid Price values must increase (or remain constant) as the Bid-Offer Pair Number increases (Garcia, 2001b).

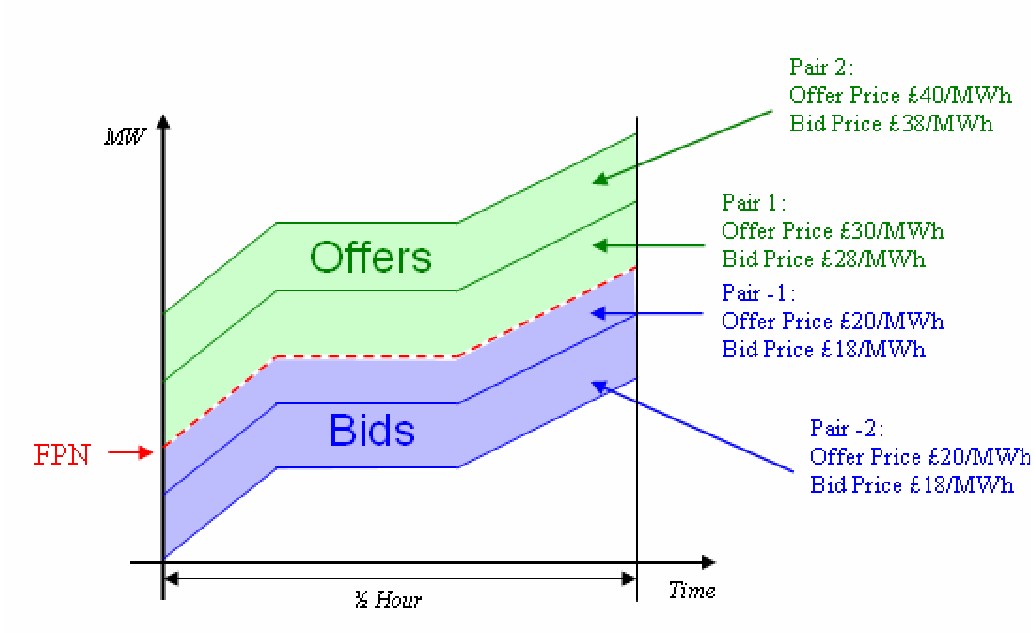


Figure 2.2 Bid and offers submission

After gate closure the SO is responsible for balancing the energy mismatch between generation and demand considering at the same time all the system physical constraints for transmission and distribution (OFGEM, 2000a, Stephenson and Paun, 2001, F.Li et al., 2002, Powell, 2001, Dettmer, 2002, Dyer et al., 2002, Clarke, 2002, National Grid Transco, 2003). This means that:

- If the system is short of generation the SO can accept offers from the generators to increase their production or accept offers from the suppliers (demand side) to reduce their consumption.
- If the system is long of generation the SO can accept bids for the generation side to reduce their output or accept bids from the demand side to increase the demand.

Trades in the balancing mechanism are visible to all market participants. In this way every participant can see its competitors bid/offers acceptances and therefore choose to adjust their bids and offers for subsequent periods.

Participants in the balancing mechanism are remunerated on a "pay as bid" basis for the volumes that they have been instructed to deliver by the SO. As presented in figure 2.3, in each Bid-Offer Acceptance the SO indicates the MW output levels at which it wishes the BM Unit to operate for certain times within the Balancing Mechanism Period.

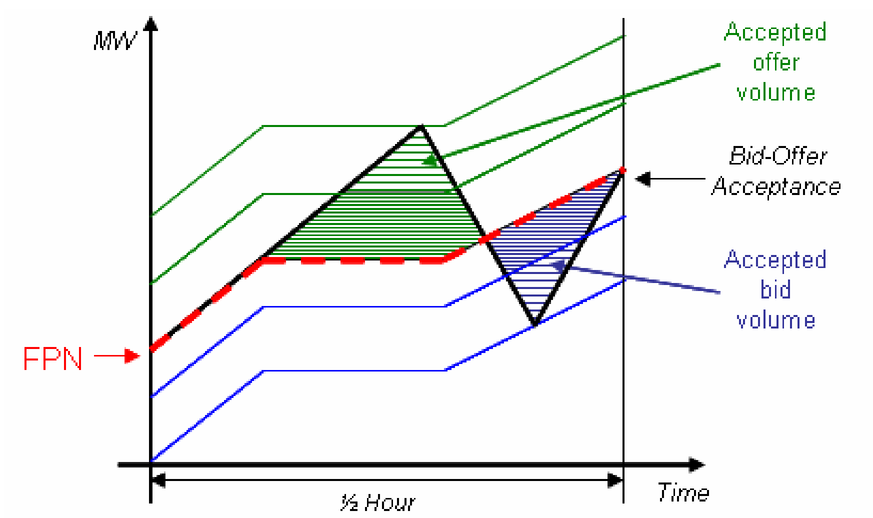


Figure 2.3 Bids and offers acceptances

The System Operator also contracts in advance (OFGEM, 2000a, National Grid Transco, 2003, National Grid Transco, 2002) (sometimes up to a year or more ahead) for some balancing services such as reserve, frequency control and voltage support. Such contracts supplements the actions that the SO does through the Balancing Mechanism and enable it to balance physically the system second by second, thereby maintaining the quality and security of supply.

2.2.4 The settlement process

After real time the settlements process starts. ELEXON, as the settlement system agent, compares the contractual positions (Final Physical Notifications (FPN) plus actions accepted through the balancing mechanism) of the participants with their real metered generation or consumption (OFGEM, 1999c). When there is a difference between these two values the participants are exposed to the imbalance settlement prices (Figure 2.4). The energy imbalance is based on a two-part cash-out regime: buyers of imbalance energy through the settlement system will pay the System Buy Price (SBP); sellers of imbalance energy will be paid the System Sell Price (SSP) (ELEXON, 2003b).

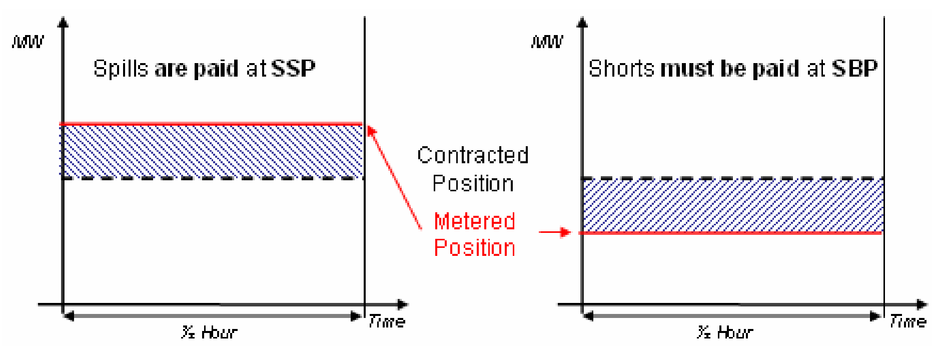


Figure 2.4 Imbalance settlement exposure

Prior to the 11th of March 2003, SBP and SSP were calculated from the balancing mechanism accepted offers and bids, respectively (OFGEM, 2000a). After that date, the dual cash out system is based on two prices: a main price and a reverse price. The main price reflects the cost of short term balancing actions, bids and offer acceptances in the balancing mechanism (ELEXON, 2003b). The reverse price (Market Index Data) is associated with the price of short term (i.e. three business days ahead of the corresponding period) energy trading in the UK-APX. The main and reverse price definitions depend on the market balance. When the market is long (i.e. the declared generation exceeds the declared demand at gate closure), SSP is the main price and it is set according its previous definition, and SBP is the reverse price and consequently is defined as the market price. When the market is short (i.e. the declared demand exceeds the declared generation at gate closure) SBP is the main price and set according to the balancing activity, and SSP is the reverse price and is set to the market price.

Figure 2.5 shows the six major classes of payments and charges included in the settlement process (ELEXON, 2004b). Five of them relate to the trading parties and arise from imbalance charges and BM cashflows derived from accepted offers and bids. The remaining one relates to the SO and represents the cost of the offers and bids that were accepted to operate the system. The sum of all these cashflows is the Total System Residual Cashflow (Cornwall, 2002). When this amount is positive, the surplus is returned to the trading parties in proportion to their metered quantities. On the other hand, when this amount is negative, the direction reverses and the deficit is recovered through charges on these parties.

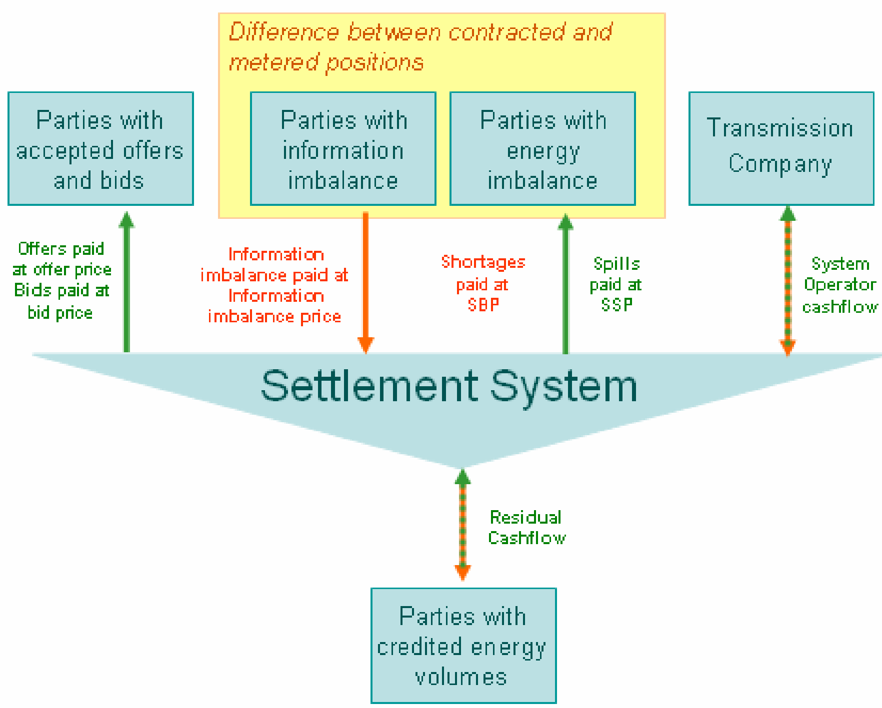


Figure 2.5 The Settlement Process cashflow (the arrows indicate the direction of payment)

2.3 Market participants and their role

2.3.1 Trading Parties

These market participants are required to sign the Balancing and Settlement Code (ELEXON, 2004d). They include:

- Parties supplying and/or generating electricity: generators, suppliers and interconnectors users. The trading entity under NETA is based on Balancing Mechanism (BM) Units. A BM unit is a plant and apparatus, which exports electricity to, or import electricity from, the transmission grid. The minimum capacity for a BM Units to be considered is 50MW (OFGEM, 2000a).

- Financial institutions trading in the electricity market without generating or supplying electricity.

2.3.2 The System Operator

As system operator, National Grid (NG) is required to operate the transmission system in an efficient, economic and coordinated manner (Stephenson and Paun, 2001, National Grid Transco, 2003). Its activities can be separated into two main roles:

- Energy balancing: the matching of generation and consumption on a minute-by-minute basis

- System balancing: ensuring that the frequency and voltage of the transmission system remain within statutory limits and handling of potential violations of transmission constraints. This may be considered to include energy trades not required simply to balance energy at the national level.

Before the introduction of NETA, NG used for these purposes a combination of ancillary services contracts and the scheduling and dispatch of generators and demand-side bidders based on the bids that they submitted to the Pool. Under NETA, a similar range of options is available, including the rescheduling of plant through the acceptance of Balancing Mechanism bids and offers and the use of options contracts for balancing services from generation and demand purchased in advance (OFGEM, 1999b, National Grid Transco, 2003, National Grid Transco, 2002).

In procuring balancing services, NG must apply the following procurement guidelines (National Grid Transco, 2002):

a) NG will purchase from the most economical sources available considering the quality, quantity and nature of the services available for purchase at that time.

b) NG will contract for balancing services on a non-discriminatory basis.

c) When there is sufficient competition in the provision of balancing services, NG must purchase the services via an appropriate competitive process.

d) When there is insufficient competition, NG will contract on a bilateral basis.

NG may buy or sell energy-related contracts forward in order to:

a) Meet its forecast requirement for balancing energy;

b) Provide options to meet possible forecast variations;

c) Reduce the total cost of balancing the system;

Analysing the role of NG over a time scale we can distinguish different stages:

- At the year-ahead stage, the activities of the System Operator (SO) will still be to plan the maintenance of the transmission system and to procure balancing services. Over these longer timescales, the SO's plans incorporate the information it receives from the major generators concerning plant availability and planned maintenance schedules (AES and British Energy, 2001).

- In the short term, meaning mainly from the day-ahead stage the SO will be responsible for:

    a) Collecting information about planned physical flows into and out of the network;

b) Performing demand forecasting and system modelling to determine whether balancing actions are required to ensure safe and secure operation of the system;

c) Dispatching such balancing actions;

d) Submitting data to the Settlement Administrator.

Balancing the transmission system has a cost, and this cost is passed first to the participants and finally to the consumers (Garcia and Kirschen, 2004). To ensure that the system is operated in the most economical way, NG is subject to incentive schemes for both internal and external costs. In this way, if NG keeps the total cost under the final target it is rewarded with a percentage of the savings. On the other hand, if the target is exceeded NG will share a percentage of the cost. Since NETA's introduction there has been one scheme for internal costs and three different incentives schemes for external costs (OFGEM, 2003). Figure 2.6 shows the last scheme, it started in April 2004 and sets a target of £415m since NETA introduction OFGEM has reduced the incentive scheme target by around £70 million (from approximately £485 million to £415 million for the current incentive scheme).

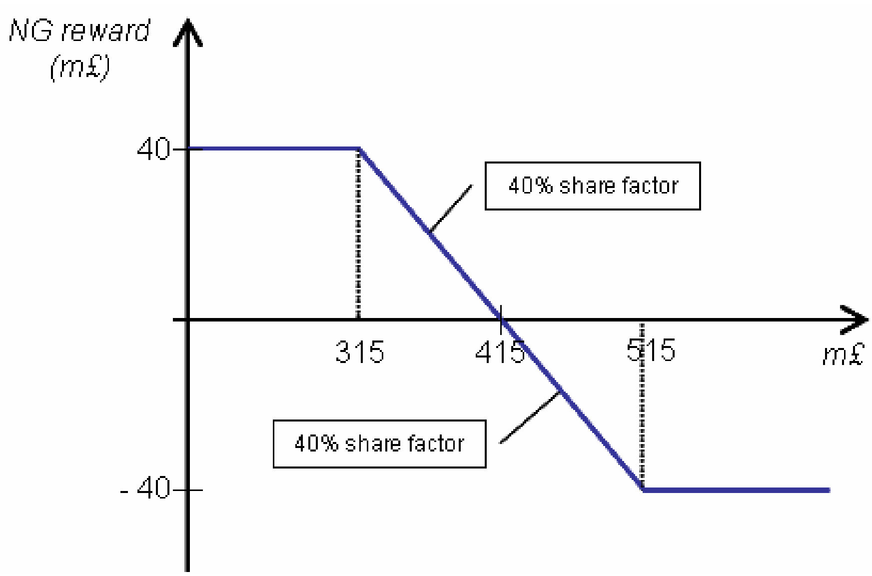


Figure 2.6 National Grid Incentive scheme

2.3.3 OFGEM

OFGEM is the Office of Gas and Electricity Markets. It is the regulator for the UK electricity markets. In its role as regulator it must both protect the consumers and promote efficient competition.

OFGEM is governed by the Gas and Electricity Markets Authority which sets OFGEM's rules of procedure.

2.3.4 ELEXON

ELEXON is the Balancing and Settlement Code (BSC) Company (an independent subsidiary company from NG) (ELEXON, 2004c). This code sets the rules and governance for the balancing and settlement process. Under NETA, generators and supply companies are obliged to sign the BSC, by doing so they take an active role in the BM and the following settlement process. Other parties may also choose to sign the code being therefore. Once they have done so, they are entitled to notify energy volumes but are then exposed to imbalance payments and charges (ELEXON, 2003a).

A very important characteristic of NETA's governance agreements is their flexibility and capability to evolve to meet new requirements (Cornwall, 2001, Bourn, 2003). Thus, any party and *Energywatch* (the consumer body) may sugest modifications to the BSC. These modifications are considered by the BSC panel, which consist of a chairman (appointed by OFGEM), industry members, a transmission company member (appointed by NG), consumer members and independent members. The final recommendations of this panel on the proposed modifications are passed to OFGEM. It is the Authority that makes the final decisions on the approval or rejection of the proposed changes.

2.4 Experience with NETA and further developments

In order to make a balanced assessment of the impact NETA has had in the UK electricity market it is necessary not only to review its achievements in the England and Wales electricity market, but also to analyse the main modifications that have led NETA to be the blueprint for the establishment of the British Electricity Trading and Transmission Arrangements (BETTA).

2.4.1 Impact of NETA

NETA has had an impact on the following areas (Stephenson and Paun, 2001, Hesmondhalgh, 2003, Dettmer, 2002, Cornwall, 2002, Powell, 2001, Cornwall, 2001, Bourn, 2003, OFGEM, 2002):

- *Market prices:* one of the main achievements attributed to NETA is its contribution to the reduction of electricity prices. After one year of NETA operation, baseload and peak prices had fallen by 20% and 27% respectively. Over-the-counter prices had fallen also by 32%. However, some authors (Cornwall, 2001, Bourn, 2003) believe that NETA should not get the whole credit for this price reduction. They believe that plant divestments and the increase in the generation capacity margin played a role that was at least as important.

Market liquidity: Forward trading has significantly increased: 98% of electricity is traded as any other commodity and only 2% is sold in the balancing mechanism. Market liquidity depends on the time scales over which electricity is traded. Short term markets appear to be less developed (1-2% of total electricity) and therefore less liquid. This is normally attributed to the lack of need of short term bilateral contracts due to the improvement of the forecasting capability of market participants.

- *Market transparency:* Electricity prices are now published by price reporters for different time scales.

- *Demand side participation:* One of the main challenges when trying to make trading of electricity similar to the trading of other commodities is the need to increase the role of the demand side. In this way, large industrial users, by providing balancing services, can help not only to balance the system but also to increase competition with the generators. “Under NETA demand side balancing services are said to be between 5% and 30% of the total (Bourn, 2003)."

- *Risk Management:* As can be seen from its structure, NETA has represented new challenges and risks for all the market participants:
    - System Operator (SO): It is a big challenge to balance the system in real time and to meet the system constraints at minimum cost. To this end the SO can opt to enter into contracts, trade in the energy market before gate closure or use the Balancing Mechanism (BM). In the BM there is a combination of compulsory generation dispatch and a voluntary part of submitting bids and offers.
    - Participants: The exposure to imbalance prices is a big risk (McClay et al., 2002). Both generation and demand need reliable and accurate notifications. The accuracy of demand forecasting has been improved from 6 to 2-3 % (Bourn, 2003). Another risk management strategy adopted by generators is the use of part-loaded plants. This allows them not only to avoid the exposure to imbalance prices, in the case of plant failures and forecasting errors, but also to take the opportunities the BM can offer. While this approach is financially beneficial for the market participants, it is also considered as one of the most technically and economically inefficient aspects of NETA.

2.4.2 NETA Modifications

The BSC provides a clear framework for modifications and improvements. In the light of NETA experience, the rules have been changed several times. After over three years of its operation a total of 174 proposals for modifications have been submitted. Out of these 84 have been approved (ILEX, 2002). Several modifications groups have been established to assess specific areas or issues.

The reduction of the gate closure from 3.5 to 1 hour, implemented on the 12th of July 2002, was considered a major modification in the general market design due to the operational changes that it caused (ELEXON, 2002a).

The big spread between SBP and SSP as well as the strong volatility of SBP have been the cause for some of the most important changes in NETA. Pricing modifications arose almost as soon as NETA went live. The goal of these changes was to reduce the punitive nature of the dual cash out system while keeping the incentive on participants to remain in balance.

As early as May 2001 the first modification (P10) (ELEXON, 2001c) was approved to reduce the high spikes of SBP. It resulted in the removal of bids and offers acceptances below a certain threshold (1 MWh) from the imbalance price calculation.

On August 2001 proposal P18 introduced the concept of Continuous Acceptance Duration Limit to distinguish between system and energy balancing action (ELEXON, 2001b). This modification was aimed to reduce the spread between SBP and SSP by eliminating the cost associated with system balancing actions (frequency control) from the imbalance prices calculation since they should reflect the cost of long term energy balancing actions. This modification resulted in the exclusion from the imbalance prices determination of acceptances with duration of less than fifteen minutes.

Dual energy pricing has been a widely debated topic and reached its more intense moment throughout the spring and summer of 2002 when two parallel modifications proposals were submitted, each supporting different definitions and calculations of imbalance prices. The first of these (P74) (Campbell Carr, 2002, ELEXON, 2002b) considered the introduction of a single imbalance price that would be defined over the market length. This proposal was rejected and instead the more conservative approach (P78) was approved. This proposal, as described in section 2.2.4, introduces a market price and keeps the dual pricing cash out established with a main price and a reverse price.

The implementation of P78 has clearly reduced the risk for market participants and its effects can not only be seen in the prices behaviour but also in the market length.

Since April 2001 imbalance prices definitions have thus been significantly modified. However this cannot be considered a closed topic and further modifications to the definition of SBP and SSP may be implemented in the future.

2.4.3 The BETTA project

The next step in the evolution of NETA is the introduction in April 2005 of the British Electricity Trading and Transmission Arrangements (BETTA). BETTA will join the trading arrangements for England, Wales and Scotland, creating for the first time a British-wide wholesale electricity market (Ofgem, , Bourn, 2003, ELEXON, 2004a, OFGEM and DTI, 2005).

BETTA is meant to have a high impact on the use of the transmission system. Under NETA Scottish generators willing to participate in the England and Wales market must also acquire a share of the interconnector capacity. BETTA will change this situation and transfer the current NETA arrangements to Scotland, resulting in significant changes for the Scottish generators and consumers.

The current BSC will also evolve into the Great Britain Balancing and Settlement Code. NG will be the provider of connection and use of the Great Britain transmission system.

CHAPTER 3

Introduction to Data Mining Techniques

"To model or not to model is not the question
We all model when expressing causal relationships

To simulate or not to simulate is not the question
We all simulate when explaining the cause of a problem.

To quantify or not to quantify is not the question
We all quantify when making relative comparisons, judgements and choices.

The real question is then ***how*** *to model,* ***how*** *to simulate and* ***how*** *to quantify". (Unknown)*

3.1 Introduction to Data Mining

Data mining derives its name from the similarities between searching for valuable business information in a large database and mining a mountain for a small amount of valuable mineral.

Data mining techniques began when business data was first stored on computers and are the result of a long process of research and product development. This evolution has continued with improvements in data access, and the incorporation of technologies that allow users to retrieve and analyse data in real time (Han and Kamber, 2001). Many organizations have realized that the knowledge contained in their huge databases is the key to the support of various organizational decisions. Within the masses of data lies hidden information of strategic importance.

Data mining differs from other research method in that it is intended to work on data without starting from a particular hypothesis, assumption or even a particular question. Essentially, it reverses the scientific method (Figure 3.1), starting from data and moving towards hypotheses instead of following the traditional order (Berry Michael and Linoff, 2000):

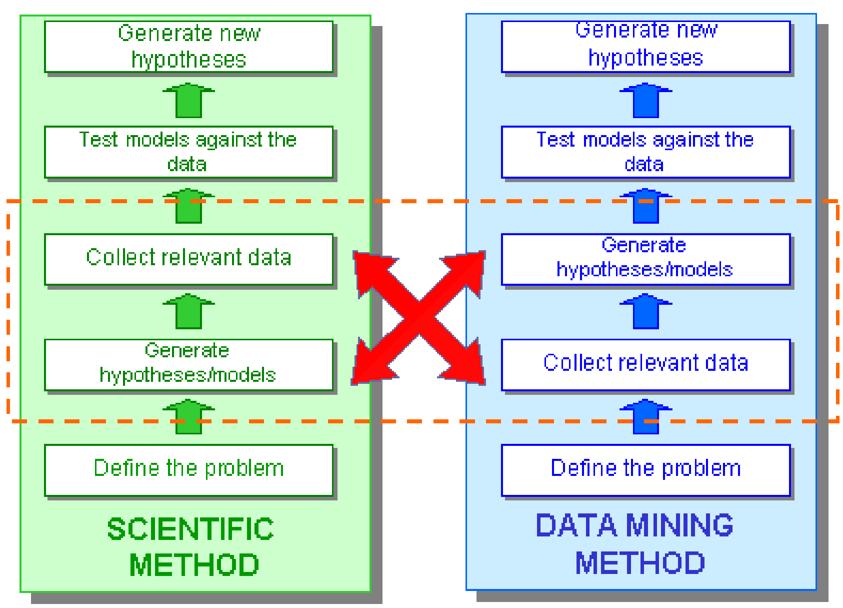


Figure 3.1 Scientific vs .Data Mining methodology

3.2 Data Mining Models

Data mining techniques can create a wide range of models. These can be classified depending on the aim (direct or indirect) and the characteristics of the model (static or continuous learning models) (Wehenkel, 1997, Han and Kamber, 2001, Kantardzic, 2002, Berry Michael and Linoff, 2000).

3.2.1 Aims of data mining

Learning from data is a process that comes in two different flavours: directed (supervised) and undirected (unsupervised) data mining.

Directed or supervised data mining directs the model towards a particular goal, which can be either to predict, to estimate, to classify or to characterize the behaviour of a variable. In other words, in supervised data mining, the model defines the effect that one set of observations, called inputs, has on another set of observations, called outputs. The variables under investigation can be divided into two groups: the targeted or dependent variables (one or more), and the explanatory variables.

Undirected or unsupervised data mining is nearer to the exploratory spirit of data mining, since there are no targeted variables. Instead, the goal is to discover the structure in the data as a whole. In unsupervised learning models all variables are treated in the same way. There is thus no distinction between explanatory and dependent variables.

The dividing line between supervised learning and unsupervised learning is basically set by the aim of the analysis, since the same tools can be used both for direct and undirected modelling. With unsupervised learning it is possible to create larger and more complex models than with supervised learning. This is because in supervised learning the aim is to find the connection between two sets of observations (input and output). In the cases where this causal relation between observations is complex, unsupervised learning can help to bridge the causal gap.

3.2.2 Static and continuously learning models

According to the dynamic characteristics of the problem the data mining models can be either static or continuously learning (Kantardzic, 2002).

Static models are used to discover relationships that are drawn from historical data. In this way, the model produces its final answer in a fixed form, and it is not updated with new values. If any further investigation is needed new data need to be collected.

Continuously learning models work in dynamic conditions. These are autonomous models with a number of primary internal set points that are externally specified. The system is self adaptive in evaluating incoming data and adjusting in real time its internal structure according to past experiences. When using a continuous learning model, it is possible that giving the same input at different times, the corresponding outputs may well be totally different, depending on what other data the model has been exposed to in the interim.

3.3 Data Mining Tasks

All data mining task involve extracting meaningful new information from the data (Kantardzic, 2002, Pyle, 1999, Cabena, 1998, Berry Michael and Linoff, 2000). The primary tasks of data mining are:

- *Classification:* the aim is to train a function that assigns newly presented objects into one of several predefined classes

- *Prediction:* the objective is to determine the future behaviour or the estimated future value for an unknown dependent variable given some input data.

- *Dependency Modelling* consists in finding a model which describes significant dependencies between variables. Dependency models explain both the structural relation between variables (often graphically) and the strength of this dependency using a numerical scale.

- *Clustering:* the goal of clustering is to identify the clusters, which can be considered as classes. Whereas in the classification problem the class (goal attribute) is given as input to the algorithm, the clustering algorithm must detect the classes by itself, creating the clusters of the dataset elements.

- *Summarization:* it is a descriptive task that involves methods for finding a compact description for a subset of data.

- *Change and deviation detection:* the aim is to discover the most significant changes in the data set.

3.4 Data Mining Domains

The development of data mining techniques has led to the identification of different domains. Data mining methods are applicable basically to any problem that involves the use of new information; this extends through areas so disperse as web mining, text mining or data scoring (Hand et al., 2001). These domains try to group sets of problems with similar characteristics in their temporal or spatial component. Although similar models are used in different areas, the parameters signification and definition varies accordingly.

The domains that best fit the characteristics of NETA data are (Roddick John et al., 2001):

- *Temporal data mining* deals with the analysis of events ordered by one or more dimensions of time. Multiple time dimensions can happen when referring to events according to different time-lines (for example day of the year, day of the week…). There are two important analysis areas in temporal data:
    - Time series analysis is focussed on the discovery of similar patterns within the same time line sequence or among different time line sequences.
    - Causal relations analysis directs the discovery of causal relationships among events that may be ordered in time and may be causally related.
- *Spatial data mining* is the branch of data mining that deals with spatial (location) data. It handles very well numerical data and usually comes up with realistic models of spatial phenomena. The major disadvantage of this approach is the assumption of statistical independence among the spatially distributed data.

- *Spatio-Temporal Data mining*: this branch combines both of the characteristics specified above. Two main streams can be identified depending on how the dimensions are embedded: the first one incorporate temporal observation into spatial systems, and the second one incorporates space into temporal data mining systems.

3.5 The Data Mining Process

Data mining is only one of the necessary steps in the data exploration process. Many models have been developed to serve as schemes for how to organize the process of gathering data, analysing data, disseminating results, implementing results, and monitoring improvements. All of these models are concerned with the process of how to integrate data mining methodology into the process of transforming data into information. The different approaches to the problem are driven and adapted to the environment where they are going to be used (i.e. manufacturing, technical activities...).

One of the most popular methodologies is the CRISP (CRoss-Industry Standard Process for data mining) model. It was proposed in the mid-90s by a European association of companies as a standard process model for data mining. According to this model the data exploration process can be summarised in six different phases (SPSS, 2000) (figure 3.2):

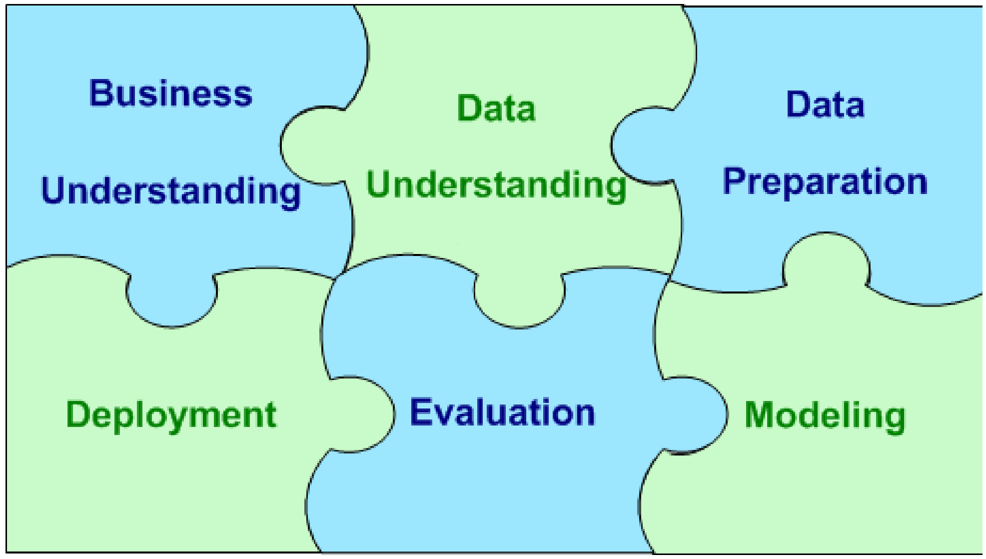


Figure 3.2 The data mining process

Business understanding: the initial phase is focused on the project objectives and requirements. The main outcome from this stage will be the identification of the problems that need to be solved.

Data understanding: this phase starts with collecting the data and continues with the necessary tasks to get familiar with the data in order to understand their meaning and explore different aspects such as the quality of the data or possible hypotheses to detect a priory hidden information.

Data preparation is one of the most important parts of the process and also one of the phases that require the most time to be completed (approximately 60% of the total time of the process). The old saying "garbage-in-garbage-out" is particularly applicable to the typical data mining projects where large data sets collected via some automatic methods serve as input to the analysis. Preparing the data also prepares the miner for the analysis phase. Different tasks are involved in order to transform the raw data into the final data set that will be used by the modelling tools. The tasks involved in this phase are: data selection, data cleaning, data construction, data integration and data formatting.

Modelling: Various modelling techniques are applied in this phase and the corresponding parameters are adjusted to their optimal values. Normally more than one modelling techniques is applied to the same data mining problem and this requires different data formats and data preparations.

Evaluation: Once the model or models have been developed, it is necessary to review the steps executed to construct the model in order to confirm that it meets the business objectives. It also includes the revision for any important part that may not have been sufficiently considered in the modelling process.

Deployment: The creation of a model is not normally the end of the process. The complexity of the deployment phase depends on the project requirements and can vary from a project report (PhD thesis) to a real time specification of the data mining process across the enterprise (web-pages personalization).

The phases are not necessarily completed in a sequential order. It is often necessary to move back and forth between them. The outcome of each phase determines which will be the next step to follow.

The process is cyclical and it is often remarked in this method that the outputs of a data mining process can always be used as inputs in new and more business-focused data mining processes.

CHAPTER 4

The Net Imbalance Volume:

One-dimensional analysis

4.1 Introduction

4.1.1 The Net Imbalance Volume as the System Imbalance Volume

As described in Chapter 2, one of National Grid's responsibilities is to keep the system in balance. Keeping the system in balance has a cost that is ultimately passed on to the consumers. To keep this cost under control, the regulator and the system operator (National Grid) agree each year on an annual target cost. If the system operator manages to operate the system for less than this target cost, it is rewarded by being allowed to retain part of the difference. On the other hand, if it exceeds the target, it must pay part of the excess. This scheme gives the system operator a strong incentive to minimize the balancing cost. Being able to forecast accurately the amount of balancing energy that it will need to buy or sell during each half-hourly market period helps the system operator meet this goal. Instead of accepting some of the bids and offers that are made by market participants in the balancing mechanism, the system operator also has the option to buy or sell energy in the forward market. If the cost of the required balancing actions usually decreases with the lead time with which they are performed, advance trading in the forward market could save a significant amount of money as long as the forecast is sufficiently accurate. If the forecast is incorrect, the system operator might indeed have to compensate for excessive trades it made in the forward market by buying or selling more energy in the balancing mechanism.

The system operator is thus very interested in analyzing and forecasting the Net Imbalance Volume (NIV), which is defined (equation 4.1) as the algebraic sum of the imbalances of all the individual market participants. This variable represents the system imbalance volume or the total energy that it must trade in the forward market or through the balancing mechanism.

$$NIV = \sum Accepted\ Offers + \sum Accepted\ bids + Interconnector\ trades + SO\ trades \qquad (4.1)$$

4.1.2 Aims and structure of the analysis

NIV's one dimensional analysis is based on a time series analysis. One of the main and common characteristics of all the balancing mechanism quantities is their structure as series variables. This variable structure implies that each of them includes an embedded two-dimensional structure: the explicit variable and a time variable (displacement variable) that introduces an implicit distribution of the way the quantities are organized.

Time series analysis provides a systematic approach to explore the dependence among the observed values in the sequence of time.

The main objective of NIV's time series analysis is to extract the information carried in the ordering of the NIV values:

- Identify NIV's "within variable" time interaction. This involves the identification of NIV time structure (trend and seasonal components decomposition) and;
- Forecast future values of NIV based only on its previous values

To achieve this double objective two domains are considered:

- The time domain: it is a record of what happens to a variable as a function of time. It is based on the assumption that the correlation in adjacent values is best explained in terms of a regression of the current value and past values.
- Frequency domain: it sees time domain as a linear superposition of sine and cosine waves of different periods.

These two ways of looking at NIV are interchangeable; that is, no information is lost in changing from one domain to another.

These two double objectives and domains are discussed in the two main sections of this chapter: NIV's structural analysis and NIV's one-dimensional forecasting. The former analyses the structure and components of the series, and the later shows how to predict NIV's future values combining different time series techniques. Each of these sections is presented accordingly to the CRIPS data mining methodology (see section 3.5). Therefore for each section, the first part describes the initial objectives, then the data selection and preparation processes are introduced followed by a description of the different modelling tools and techniques. The sections finish with the results and the conclusions that can be derived from analysis of these results.

4.2 NIV data structure analysis

4.2.1 Objectives

This is a descriptive analysis. While for non-time dependent variable a descriptive analysis mainly deals with the summary statistics of the data (i.e. mean and variance) in time series analysis the case is totally different. Moreover, as stated by (Chatfield, 2003) in some cases these basic statistics can be highly misleading and do not have their usual properties. Thus, this analysis focuses on understanding the typical time-series effects of NIV, which include:

- To describe the time structure of NIV in order to detect and separate (if applicable) its different components: trend, seasonality and noise.
- To describe the characteristics of the series itself in order to identify the most suitable forecasting method.

4.2.2 Data Selection and preparation

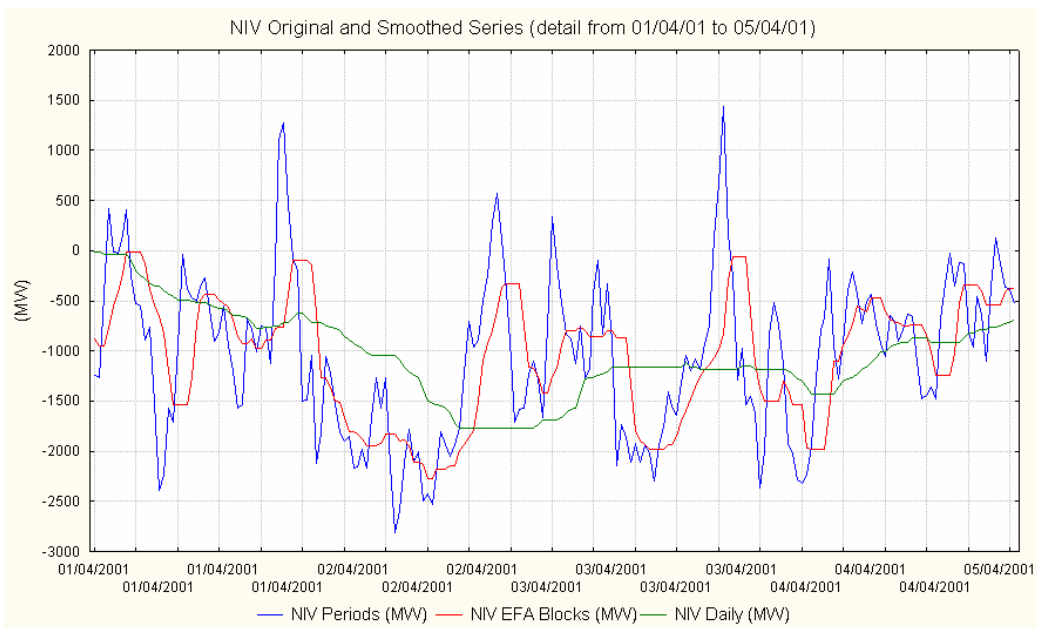
The NIV data analysed covers the period from 1/04/01 to 30/05/02, with a half-hour resolution (i.e.48 daily observations).

As for any time series analysis, the data preparation process must achieve two objectives: to transform the data into a form that exposes better the information to the modelling tool and to preserve the nature of the pattern that already exists.

The first stage of the data preparation is a smoothing or filtering process. Different techniques can be used for this purpose such as moving averages, exponential weighted averages, 4253H filter, and moving medians. The first three techniques are based on the calculation of means of consecutive values, and differ mainly in the distribution of the weight that past observations have on the final smoothed value. A detailed description of these methods can be found in (StatSoft, 2004). Smoothing moving medians is the selected filtering technique for this analysis. The median value of a number of successive observations centred in the middle of the moving window is calculated. This value reflects the central tendency of the selected window in such a way that it is uninfluenced by extreme values. In this analysis two different windows lengths were considered (8 and 48 periods) giving two series representing respectively the NIV moving median in EFA blocks and the NIV moving median on a daily basis (Figure 4.1).

Time	23:00	23:30	00:00	00:30	...	02:30	03:00	...	06:30	07:00	...	10:30	11:00	...	14:30	15:00	...	18:30	19:00	...	22:30	23:00	23:30
Periods	47	48	1	2		6	7	..	14	15	...	22	23	...	30	31	...	38	39	...	46	47	48
EFA Blocks	1						2			3			4			5			6			1	
Day	D-1		D																				

4.1 (a) Time frame for periods, EFA Blocks and Daily values



4.1 (b) Detail of NIV Original and smoothed series using EFA Blocks and Daily medians

Figure 4.1 Smoothing process

The next stage in the process is to apply different transformation processes over each of the obtained series. The aim of these transformations is to normalise the values, remove the trend, and adjust the variance. Depending on the series structure different transformation techniques should be considered. The existing literature on time series (Chatfield, 2003, Peña et al., 2000, Montgomery Douglas and Johnson Lynwood, 1976, Pankratz, 1983, Brockwell and Davis, 1996, Brillinger, 2001) presents a wide range of techniques including logarithm and squared roots transformations of the original series (Box-Cox transformation). However these techniques are highly recommended for the cases where the variance or the seasonal components of the series increases proportionally with the mean. Figure 4.2 shows the relation between NIV's mean and its standard deviation. The lack of linearity between NIV's mean and variance rules out this type of transformations. Thus the techniques used for NIV's transformation are:

- Mean subtracting: each value in the series is transformed using equation 4.2; where *M* is the overall mean for the untransformed series.

$$Y = x - M \tag{4.2}$$

- Standardization (Normalization): each value in the series is standardized: according to equation 4.3; where *M* and *SD* are the overall mean and standard deviation for the untransformed series.

$$Y = \frac{x - M}{SD} \tag{4.3}$$

- Linear trend subtraction: the values in the series are transformed to remove the trend over time. In equation 4.4, *t* refers to the observation's position within the series (i.e. case number) and *a* and *b* are constants that are calculated from the data.

$$Y = x - (a + b \cdot t) \tag{4.4}$$

- Autocorrelation correction: the values in the series are transformed to remove an autocorrelation of a particular lag. Equation 4.5 shows how this is done for the case the lag is one and the parameters *a* and *b* are constants estimated from the data.

$$Y = x - (a + b \cdot x_{lag}) \tag{4.5}$$

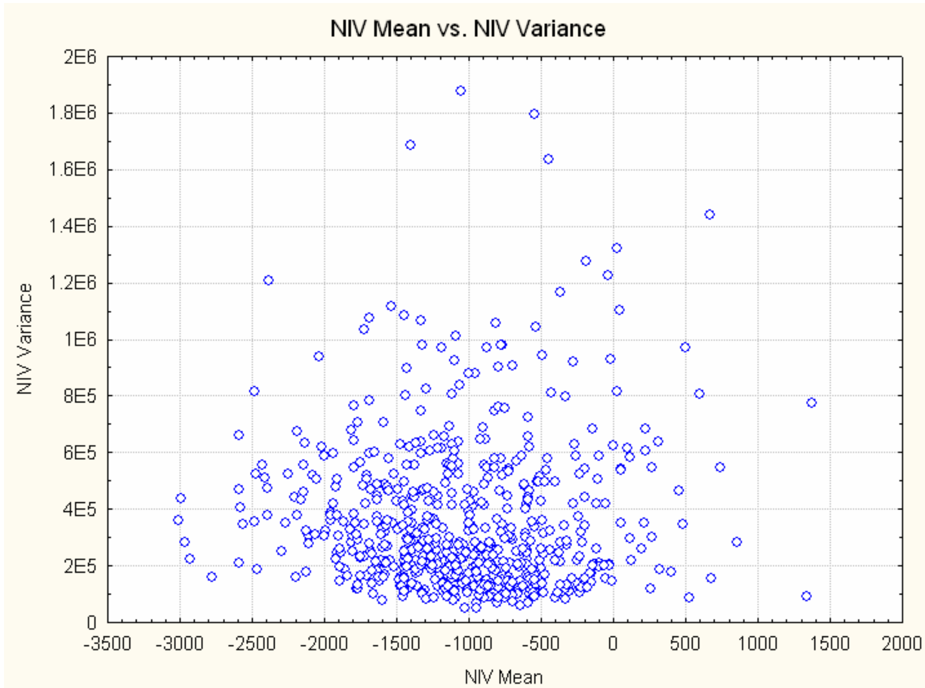


Figure 4.2 NIV's mean vs. variance scatterplot

As a result of the transformation process, eight different series where obtained. Figure 4.3 shows the different transformed series for both EFA blocks (Figure 4.3.a) and daily resolution (Figure 4.3.b). In both figures, the original NIV smoothed series is represented in blue, the transformed series are presented in red (subtracted mean), green (linear trend subtracted), grey (standardised series, y-right axis) and pink (autocorrelation correction). The similarities between the subtracted mean and the linear trend correction show how NIV's linear trend is mainly driven by its mean. The autocorrelation corrected series is NIV's low frequency filter and captures its noisy behaviour at higher frequencies. These processed series are the different inputs for the modelling process.

Different statistical tests have been applied to check the sanity of the transformed data. These tests include: main statistical characteristics (mean, standard deviation, maximum and minimum values), values distribution and normality checks. The tests performed all yielded the answer that the transformed data has no errors and that the integrity of the data is maintained after the transformations.

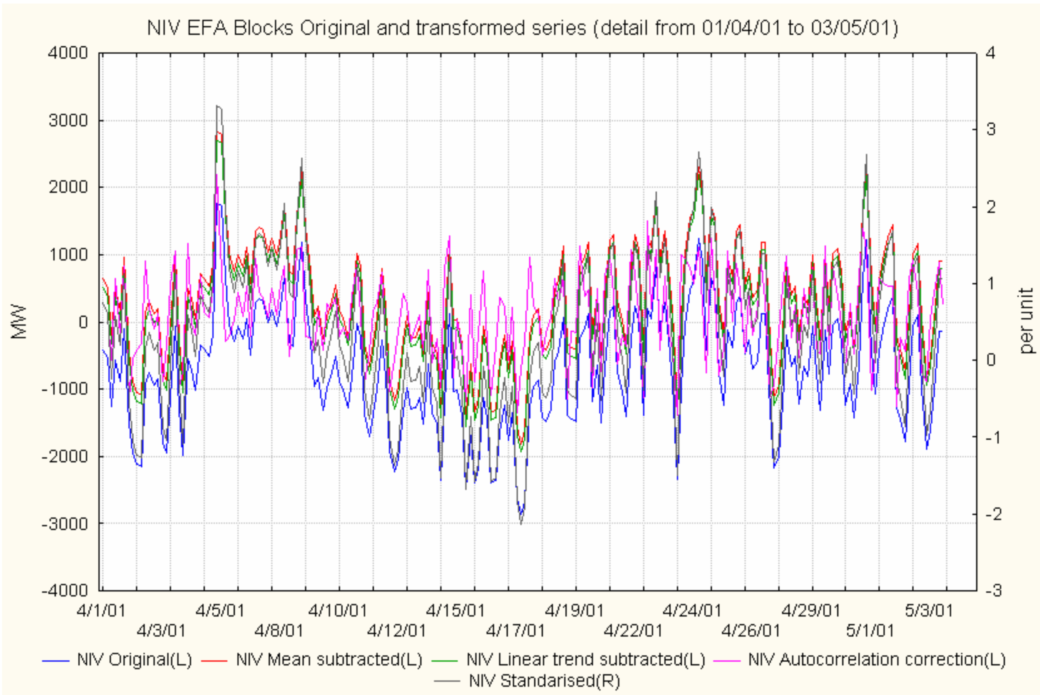


Figure 4.3 (a) NIV EFA Blocks series transformations

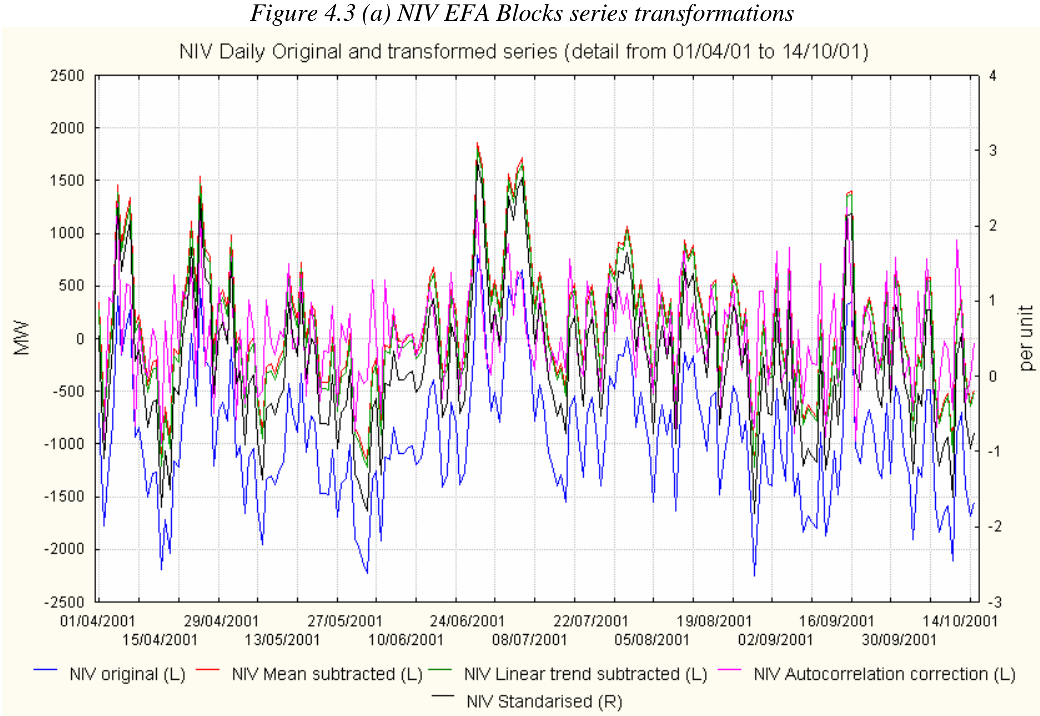


Figure 4.3(b) NIV Daily series transformations

Figure 4.3 NIV series transformations

4.2.3 Modelling tools

In order to describe and understand the data structure different techniques have been used in the analysis. In most cases these modelling tools provide complementary results, however some of them were used to verify and check from different angles the coherence of the results obtained for NIV's series characteristics.

The applied modelling techniques are now described.

4.2.3.1 Autocorrelation and partial correlation analysis

Any correlation analysis measures how values of one variable change as values of another variable change. Autocorrelation describes how well one observation from a series correlates with others from the same series at different times. The distance between observations is the lag.

Like the correlation coefficient for two different variables, the autocorrelation coefficient for a lag k is defined as:

$$r_k = \frac{\sum_{t=1}^{N-k}(x_t - \bar{x}) \cdot (x_{t+k} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2} \tag{4.6}$$

Where $\bar{x}$ is the overall mean and N is the total number of observations.

The seasonal patterns of the data can be observed via correlograms. A correlogram (or an autocorrelogram) displays graphically and numerically the serial correlation coefficients (and their corresponding standard error) for consecutive lags in a determined range of lags. For the case of daily moving medians the considered range of lags is 1-30 in order to detect intra-week and intra month seasonality. For the case of EFA blocks data, the range of lags extends from 1 to 42 to detect intraday and intraweek seasonality.

The partial autocorrelation is an extension of the autocorrelation function that clarifies the existence of seasonal effects by removing the effect of the correlation of the intermediate elements within a specific lag (e.g.. the partial correlation coefficient of order two measures the excess correlation between observations two steps apart not accounted by the correlation at lag 1).

4.2.3.2 Singular Spectrum (Fourier) Analysis

This method can be seen as a mathematical prism that scatters the information of the series into its components parts. The purpose of the analysis is to detect the seasonal and cyclical components by decomposing the series into its sinusoidal (sine and cosine) waveforms. The analysis can be easily modelled as a multiple regression problem of the form:

$$\mathrm{x}_{\mathrm{t}} = a_0 + \sum_{k=1}^{q} a_k \cdot \cos(\lambda_k \cdot t) + b_k \cdot \sin(\lambda_k \cdot t) \tag{4.7}$$

In this equation λ is the frequency expressed in terms of radians per unit of time. The cosine parameters a_k and sine parameters b_k are regression coefficients that define the degree to which the respective functions are correlated with the data. Overall there are q different sine and cosine functions; if there are N data points in the series, then there will be $N/2+1$ cosine functions and $N/2-1$ sine functions. In other words, there will be as many different sinusoidal waves as there are data points.

To fit sine and cosine functions of different lengths to the data the explicit formulae requires solving a large number (N^2) of complex multiplication which results in a very time consuming process. This computational problem is usually approached using the Fast Fourier Transform (FFT). This algorithm developed in the mid-60's reduces significantly the time required as well as improves the accuracy of the results. For a detailed description of the procedure see (Chatfield, 2003).

The spectrum created by the Fourier decomposition can be analysed depending on the three main characteristics of a sinusoidal wave: frequency, phase and amplitude. In this way the spectral analysis of NIV shows which are the important components of the series and its periodicity (length of the waveforms).

4.2.3.3 Caterpillar decomposition

This technique is also known as ‘singular-spectrum analysis’ (SSA). SSA is a very new method of time series analysis and its theory is based on multiple geometry rather than classical statistics. It is a model-free exploratory technique and can be used both for series decomposition and forecasting purposes (see section 4.3).

The method transforms the one-dimensional series into a multidimensional problem. In this way, the original series is decomposed in independent time series such as a changing trend, oscillatory components and an unstructured noise, which are all additive components.

A simple SSA consists of four steps (Golyandina et al., 2001):

- Construction of the trajectory matrix. Considering the time series F ($F=(f_0,f_1,\ldots,f_{N-1})$) of length N, and L the integer that defines the window length. Setting $K= N-L+1$ and defining the L-lagged vectors X_j (equation 4.8) and the trajectory matrix **X** (equation 4.9)

$$X_j = (f_{j-1},\ldots,f_{j+L-2})^T, \quad 1 \le \mathrm{j} \le \mathrm{K} \tag{4.8}$$

$$\mathbf{X} = (f_{i+j-2})_{i,j+1}^{L,K} = \begin{pmatrix} f_0 & f_1 & f_2 & \cdots & f_{K-1} \\ f_1 & f_2 & f_3 & \cdots & f_K \\ f_2 & f_3 & f_4 & \cdots & f_{K+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{L-1} & f_L & f_{L+1} & \cdots & f_{N-1} \end{pmatrix} = \left[\mathrm{X}_1 : \ldots : \mathrm{X}_\mathrm{K}\right] \tag{4.9}$$

- Singular value decomposition of the matrix **X**. By calculating eigenvalues and eigenvectors of the matrix S ($S=XX^T$ of size L x L), we obtain L singular values. These are the square roots of the eigenvalues of the matrix S and the corresponding right and left singular vectors. We thus obtain a decomposition of **X** as a sum of rank one matrices $\mathbf{X_i}$ for $i=1\ldots.d$, with d ($d\leq L$) the number of nonzero singular values of **X**

- Grouping. The indexes $I= \{1, \ldots ,d\}$ are split into several groups $I_1,\ldots,I_m$. The matrixes $\mathbf{X_i}$ are added within each group. Equation 4.10 shows the result of this step, which is the reconstruction of the trajectory matrix:

$$\mathbf{X} = \sum_{\mathbf{k}=\mathbf{1}}^{m} \mathbf{X}_{\mathbf{I_k}} \tag{4.10}$$

Where $\mathbf{X}_{\mathbf{I_k}} = \sum_{i \in I_k} \mathbf{X}_i$

- Series reconstruction. The last step consists in the averaging over the diagonals of the matrices $\mathbf{X_{Ik}}$. This diagonalization transforms each matrix of the grouped decomposition (4.10) into a new series of length N. Thus the original series is decomposed in the form:

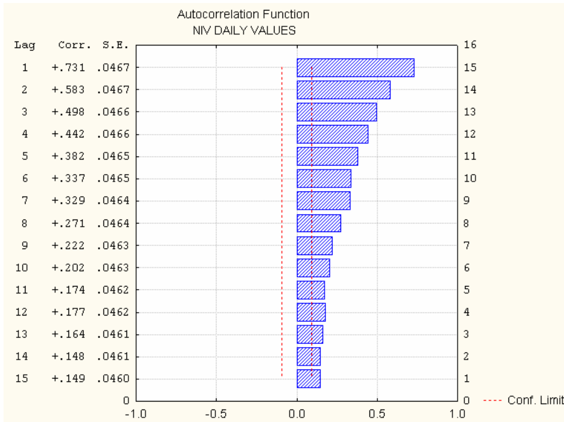
$$f_n = \sum_{k=1}^{m} f_n^{(k)}, \quad n = 0,\ldots,N-1 \tag{4.11}$$

The SSA is a non parametric model that generates a decomposition with additive components that are both independent and identifiable (trend, oscillatory or noisy component). The choice of the window length and the way of grouping the matrices X_i depends on the characteristics of the original series and the purpose of the analysis.

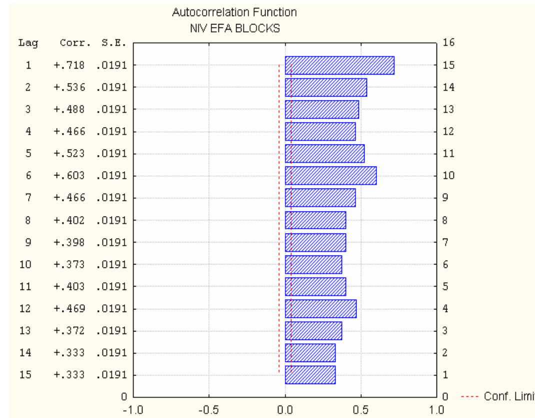
4.2.4 Numerical results

4.2.4.1 Autocorrelation and partial correlation analysis

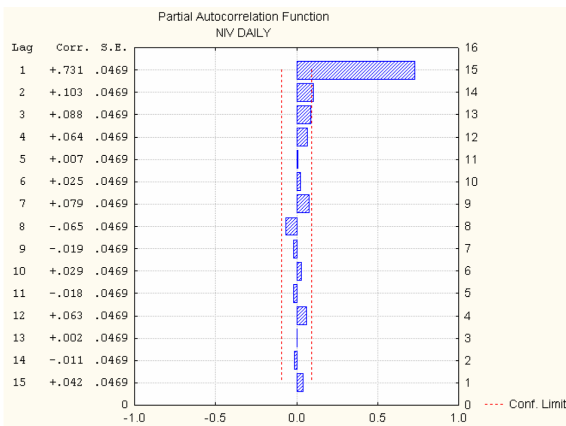
Figure 4.4 shows the autocorrelation and partial correlation values for NIV daily and EFA blocks for the period from 1/04/01 to 30/05/02. To help visualization, only 15 lags have been included.



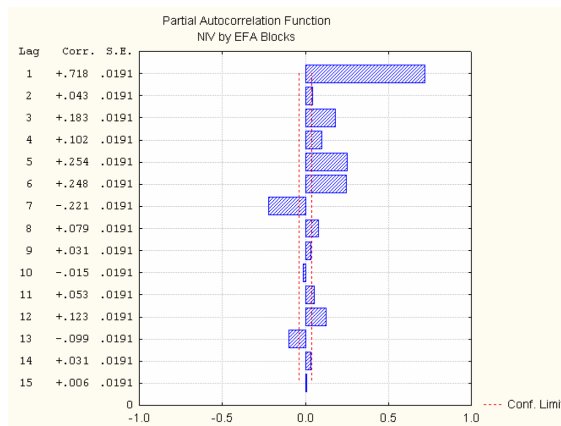
4.4 (a) Autocorrelation coefficients for NIV daily smoothed series



4.4 (b) Autocorrelation coefficients for NIV EFA blocks smoothed series



4.4 (c)Partial autocorrelation coefficients for NIV daily smoothed series



4.4 (d)Partial autocorrelation coefficients for NIV EFA blocks smoothed series

Figure 4.4 Autocorrelagrams for NIV daily and EFA blocks smoothed series

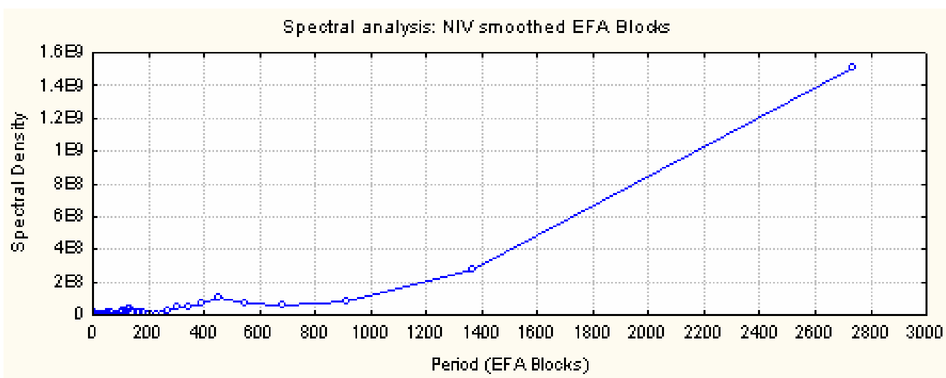
The results in Figures 4.4 (a) and (b) show respectively for the daily and the EFA block smoothed series, a high correlation with the previous lag (lag 1) and a gradually decreasing correlation as the lag increases. The intraday seasonality is also appreciated in Figure 4.4(b) for the EFA blocks series. From the second to the fourth lag, the correlation coefficients gradually decrease and then in for the fifth the correlation value starts increasing reaching a local maximum in the sixth lag.

Figures 4.4 (c) and (d) show the results for the partial autocorrelation. They present a clearer picture of the previous results because the correlation factors within the lag window have been removed for different values of the lag. In both figures, the most significant partial autocorrelation correspond to lag of 1 (i.e. the previous observation). Note that the partial autocorrelation and the autocorrelation values are the same for a lag of 1. The partial correlation for higher lags is non significant.

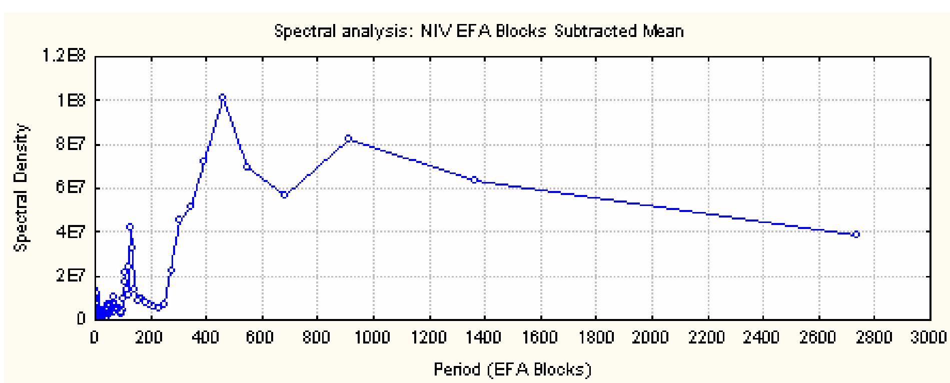
4.2.4.2 Singular Spectrum (Fourier) Analysis

This method is applied over the different daily and EFA blocks of the original series and the transformed series described in section 4.2.2.

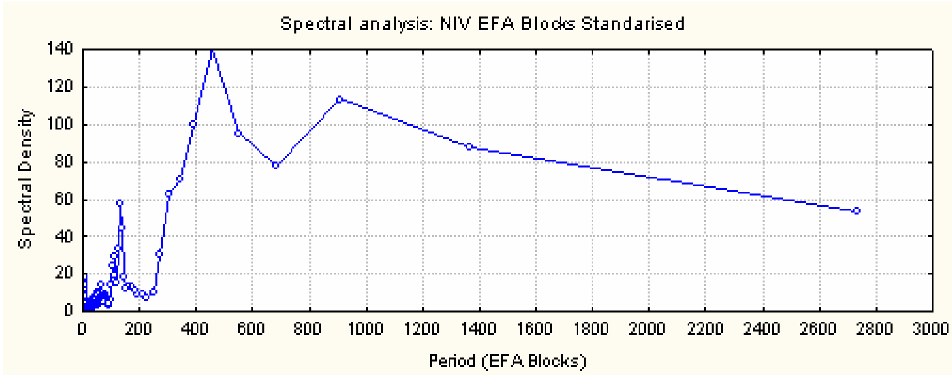
Figures 4.5 and 4.6 show the spectral density (y axis) for the corresponding frequencies (x axis in number of cycles per unit), for the different series.



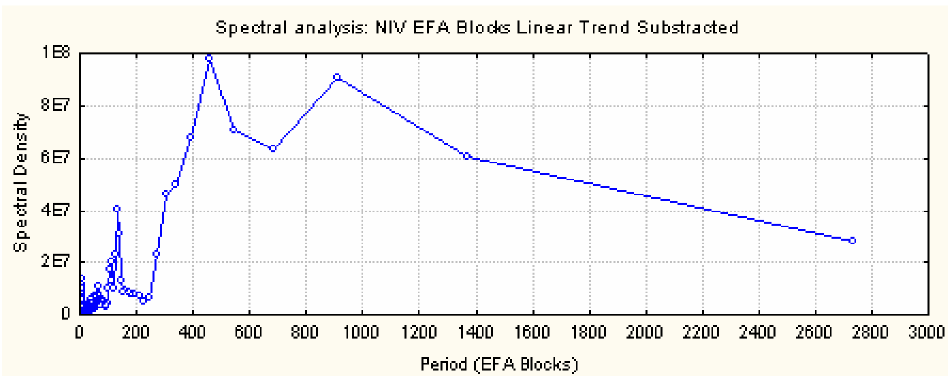
4.5 (a) Spectral analysis for the original NIV EFA blocks smoothed series



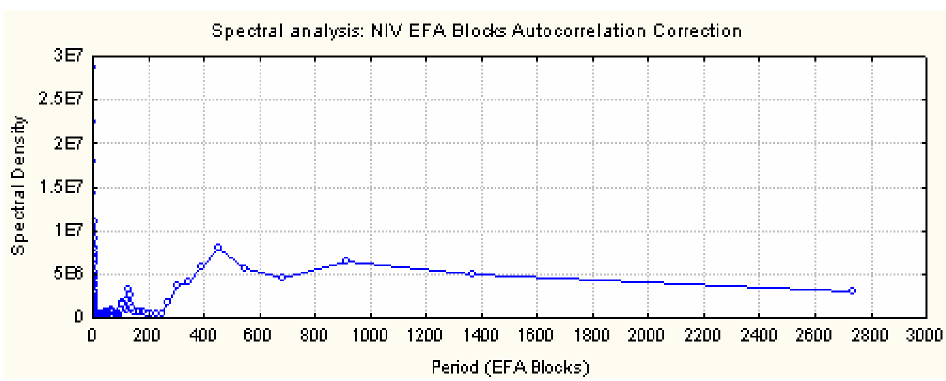
4.5 (b) Spectral analysis for NIV EFA blocks subtracted mean series



4.5 (c) Spectral analysis for NIV EFA blocks standardized series

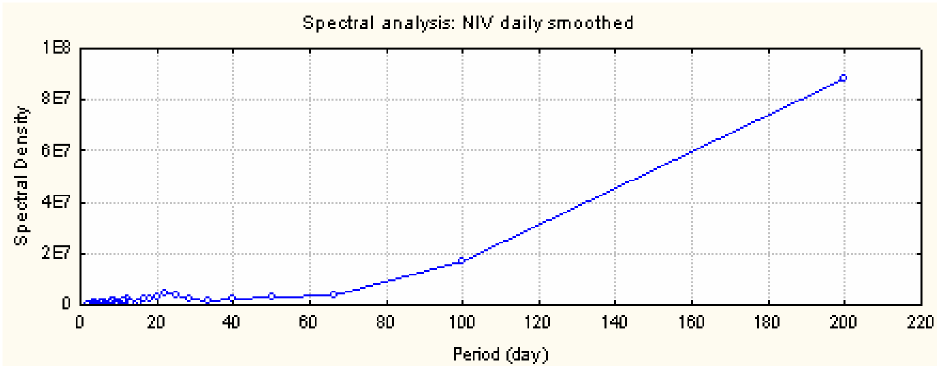


4.5 (d) Spectral analysis for NIV EFA blocks subtracted linear trend series

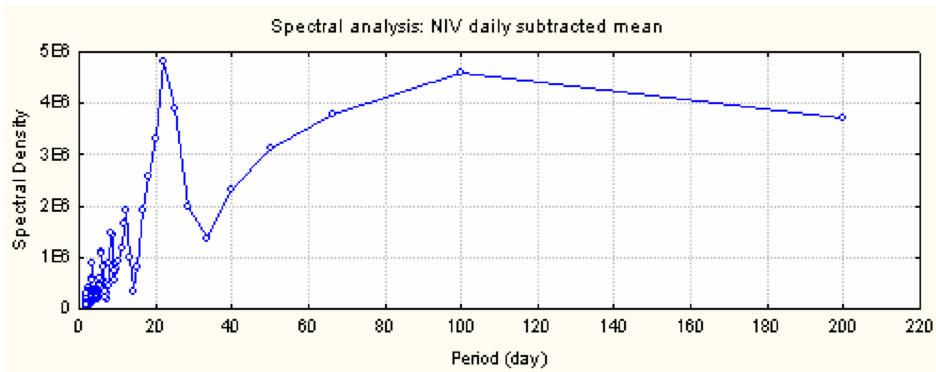


4.5 (e) Spectral analysis for NIV EFA blocks autocorrelation corrected series

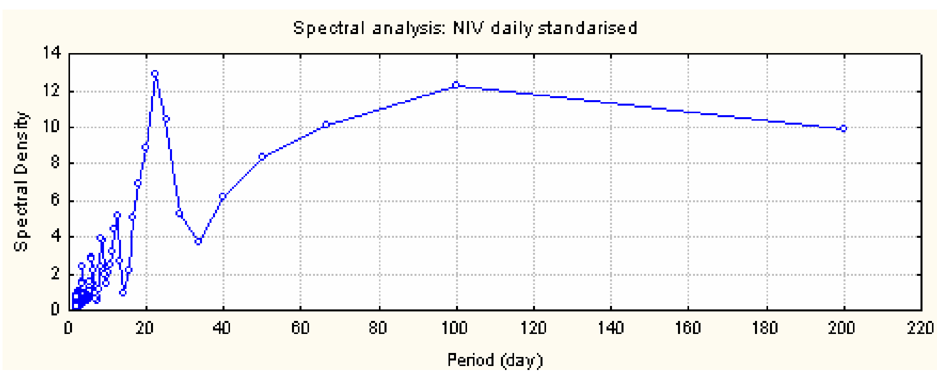
Figure 4.5 Spectral Analysis for NIV's series in EFA blocks resolution



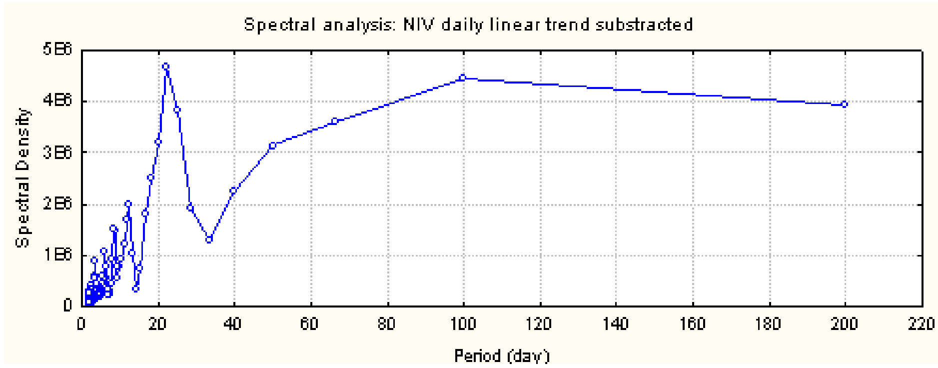
4.6 (a) Spectral analysis for the original NIV daily smoothed series



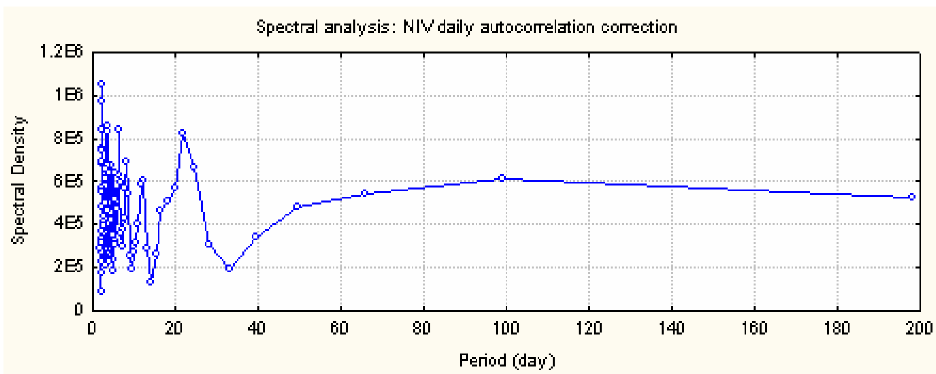
4.6 (b) Spectral analysis for NIV daily subtracted mean series



4.6 (c) Spectral analysis for NIV daily standardized series



4.6 (d) Spectral analysis for NIV daily subtracted linear trend series



4.6 (e) Spectral analysis for NIV daily autocorrelation corrected series

Figure 4.6 Spectral Analysis for NIV's series in daily resolution

The results in Figures 4.5 (a) and 4.6 (a) show that for the non transformed smoothed series the spectral density presents a clear maximum for a cycle of 200 days, which can be attributed to the strong effect of the trend. These results are also consistent with the previous autocorrelation results shown in figure 4.4 where the previous lag showed the highest autocorrelation. This serial dependency is corrected and removed with the series transformations. In this way, the transformed series spectral density (figures 4.5 and 4.6 (b) to (d)) show significant peaks for cycles of 21 (3 weeks) and 100 days. Despite these results are consistent for all the analysed series in daily and EFA blocks resolution, they do not correspond to any physical seasonality.

For the autocorrelation corrected series, there are a significant number of high frequency components (Figures 4.5 (d) and 4.6(d)) with a significant spectral density that are closely related with NIV's noisy component.

When evaluating a smaller selection of cases it is possible to detect weekly and daily cyclical components. However these results are quite unstable and keep on changing for the different sections of data analysed.

4.2.4.3 Caterpillar decomposition

The analysis is performed in two different stages over the daily moving median values of NIV (Figure 4.6):

- In the first stage all the data from 01/05/2001 to 30/06/2002 are considered
- The results for the series decomposition show a big change in the behaviour of the data starting in November 2001. Different events occurred during the end of the year 2001 that made the market extremely long. Among these events, one should note in particular the Enron collapse that increased market uncertainty and mild weather conditions. To discard these external effects over the market length, a new data set is analysed. This corresponds to the period from 01/01/2002 to 30/06/2002.

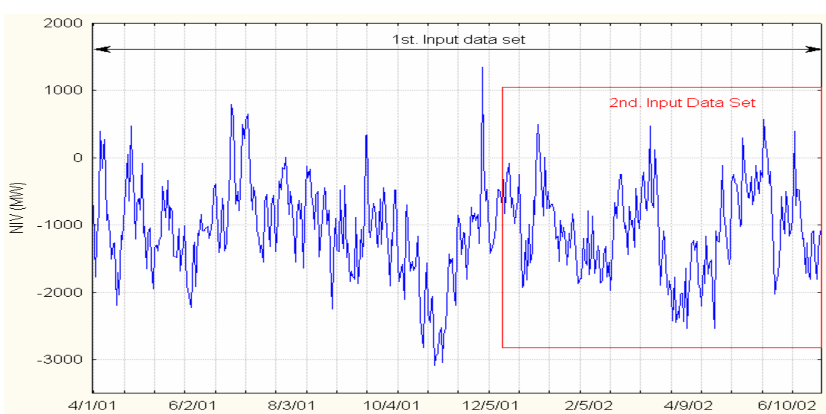


Figure 4.7 NIV (MW) from 1/04/01 to 30/06/02

Figure 4.8 presents the decomposition for the second input data. In all the graphs, the NIV values in MW are plotted along the y-axis. Each of these graphs represents the corresponding series for each of the eigenvalues calculated from the original series.

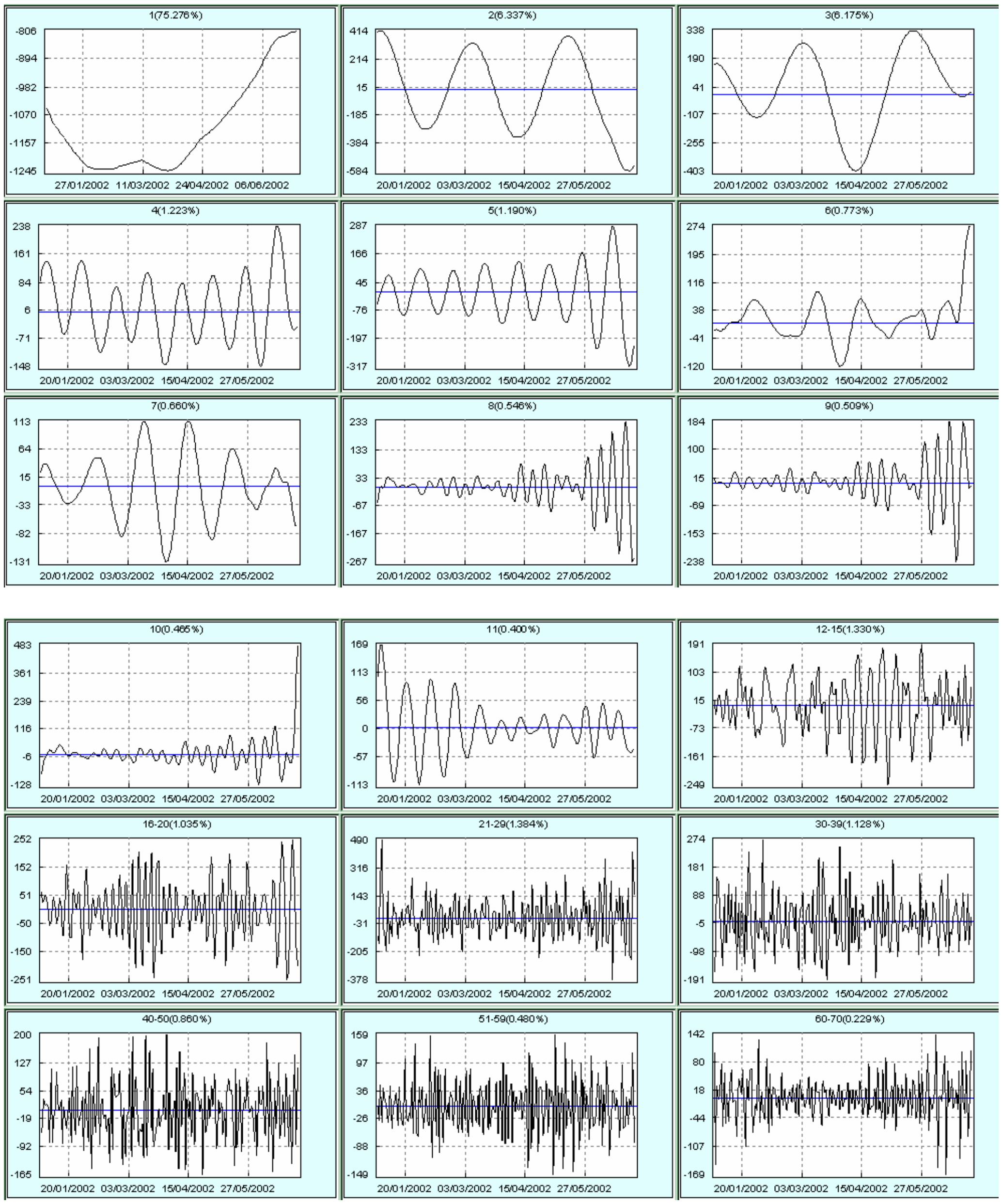
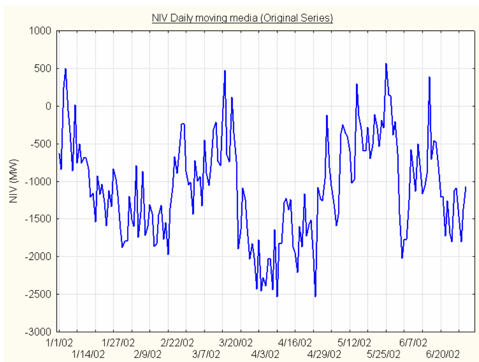
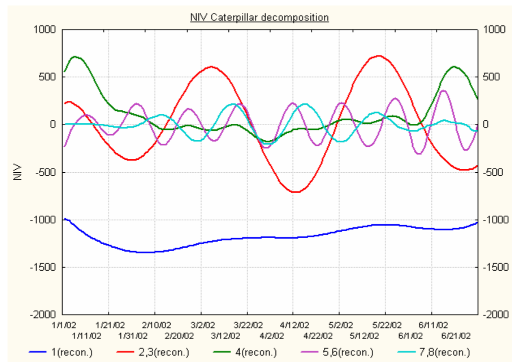


Figure 4.8 NIV Caterpillar decomposition

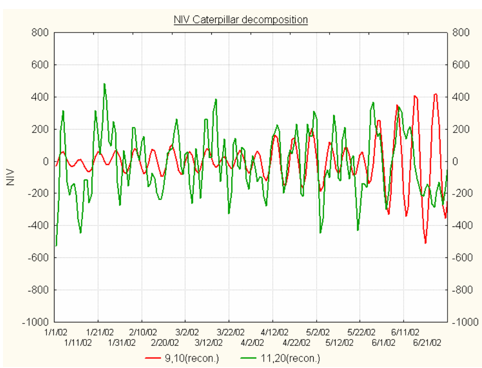
In order to reduce the number of series component to be considered. These components were grouped manually based on their behaviour, their weight on the overall value of the series and the correlation values between the different series. Figure 4.9 shows the results for the series reconstruction.



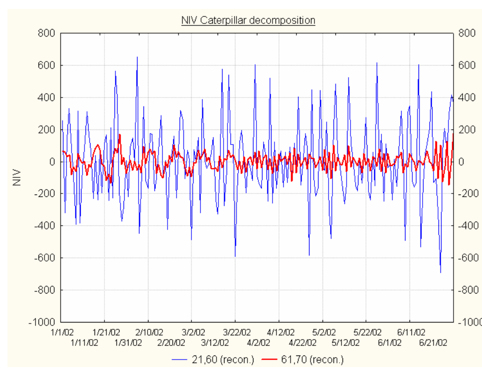
Original Series



Reconstructed Series [1],[2-3],[4],[5-6],[7]



Reconstructed Series [9-10],[11 to 20]



Reconstructed Series [21 to 60], [61 to 70]

Figure 4.9 NIV original smoothed and reconstructed series

Table 4.1 shows a brief statistical analysis of the original NIV and each of the reconstructed series. Figure 4.10 shows the contribution in percentage to the total value of NIV of each component.

Table 4.1 Statistics for NIV original and reconstructed series:

	MEAN	STD.DV.	MIN	MAX
NIV	-1077.79	663.59	-2536.6	569.7
1	-1175.61	94.90	-1346.9	-983.5
2,3	-0.93	421.29	-715.2	721.4
4	109.95	232.43	-177.7	709.4
5,6	-0.90	163.88	-310.6	360.8
7,8	-0.05	101.71	-209.5	215.7
9,10	-2.11	137.20	-509.3	413.6
11,20	-13.10	193.28	-525.5	481.9
21,60	4.67	257.40	-696.2	649.3
61,70	0.89	58.31	-147.1	176.3

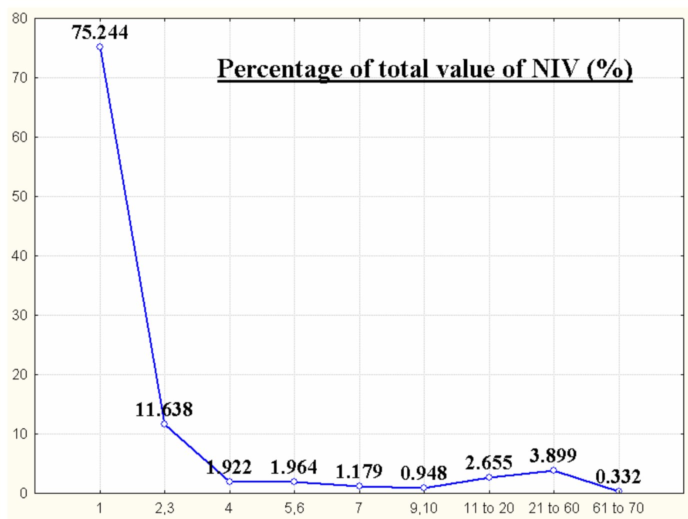


Figure 4.10 Contribution of the reconstructed series to the original NIV series

In order to analyse the time structure of the reconstructed series, autocorrelation and spectrum analysis are combined. These results show the following characteristics for NIV's caterpillar decomposition:

- The trend is determined by eigenvalues 1 and 4, which comprise a 77.166% share of the decomposition.
- Seasonal components:
  - Eigenvalues 2 and 3 make up a strong cyclical trimester and monthly component. Together, they represent a 10% share of the total value.

- Eigenvalues 5 and 6 make up a strong cyclical component with a 20-day period. They have a 2% share of the total value.
- Eigenvalues 7 and 8 make up a strong cyclical weekly component and a decreasing monthly cyclical component. They have a 1% share to the total value.
- Eigenvalues 9 and 11 make up present a strong cyclical weekly component. They have approximately a 1% share of the total value.
- Eigenvalues 12 to 40: present strong intraweek and daily variation with approximated 4% share to the total value.

- The noise is driven by eigenvalues 40 to 70 with a total contribution of less than 5% of the decomposition.

4.2.5 Conclusions

From the results obtained in the autocorrelation and partial correlation analysis it is observed that the NIV series exhibits the behaviour of a random walk model where its value is mostly similar to the previous observation plus a random shock.

The singular spectrum analysis shows consistent mathematical results for the analysis of the different transformed series. However these results just demonstrate a seasonal component (i.e. daily variation) known a priory and the noisy behaviour of NIV.

The caterpillar methodology confirms the results of the autocorrelation and Fourier decomposition since it does not detect any strong seasonal components with stable amplitude. However it can be used as a filter to reduce the effect of noise on NIV.

4.3 NIV one dimensional forecasting

4.3.1 Objectives

Forecasting is a common exercise in different science domains. It is the process of predicting an uncertain output variable given a set of input data that normally correspond to past values of either the output variable (one-dimensional forecasting) or other related input variables (multidimensional forecasting). Assuming that $\boldsymbol{f}$ is the unknown function that relates the current value of y_t with the input data, three types of forecasting methods can be used:

Subjective forecasting: these methods also called implicit, informal, or experience based use subjective knowledge and information. They transform objective and subjective inputs into forecast using techniques that range from extrapolation to the more refined Delphi methodology (Weeby and O'Connor, 1996).

One-dimensional forecasting: $y_t=\boldsymbol{f}(y_{t-1},y_{t-2},\ldots,y_{t-k})$, where y_{t-i} corresponds to the i^{th} lagged value of the series for i Є (1,k).

Multidimensional forecasting: $y_t=\boldsymbol{f}(y_{t-1},y_{t-2},\ldots,y_{t-k}, u_{t-1},u_{t-2},\ldots,u_{t-k},\ldots,v_{t-1},v_{t-2},\ldots,v_{t-k})$,where y_{t-i} , u_{t-i} and v_{t-i} correspond to the different variables i^{th} lagged values of the series for i Є (1,k).

In this chapter one-dimensional techniques are used to forecast NIV. The accuracy of different methods is compared and the effect of the amount of seen data on the quality of the forecast is analysed.

Throughout this chapter, $Y_N(k)$ refers the forecast of y_{N+k} made at time $t=N$ for k steps ahead.

4.3.2 Data selection

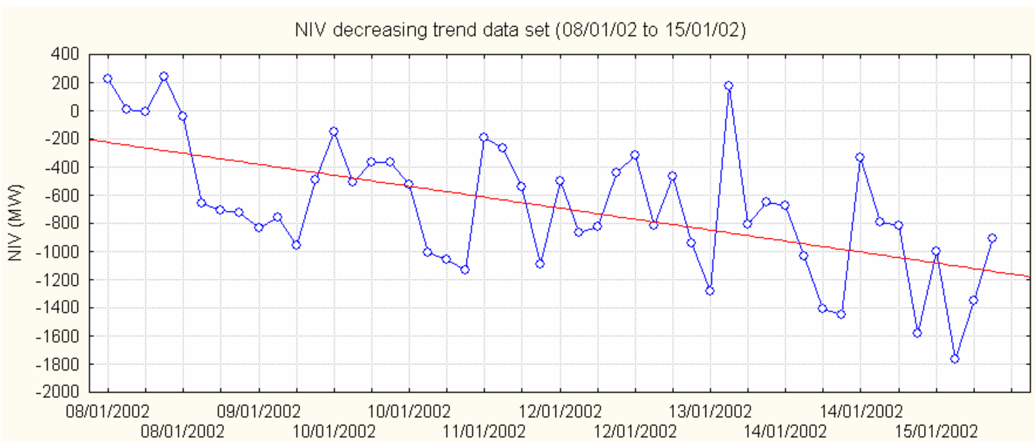
The analysis is based on NIV values smoothed in EFA blocks resolution. The data is organised in “seen” and “unseen” blocks:

<u>Unseen data:</u>

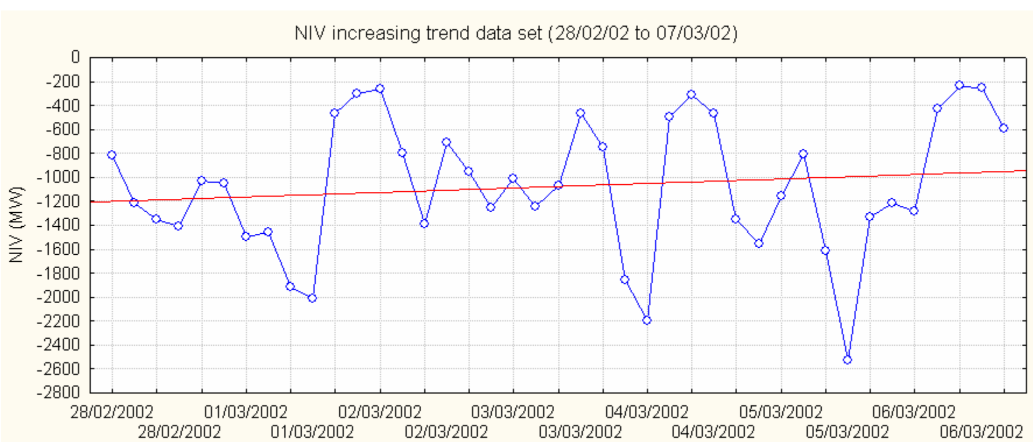
The unseen data sets correspond to a one-week period in EFA blocks observations (42 unseen points).

In this analysis, two different forecast starting points (corresponding to an increasing and a decreasing trend periods) have been selected (Figure 4.11):

- From 28/02/02 to 07/03/02: this period corresponds to an increasing trend
- From 08/01/02 to 15/01/02: this period corresponds to a decreasing trend



NIV decreasing trend data set



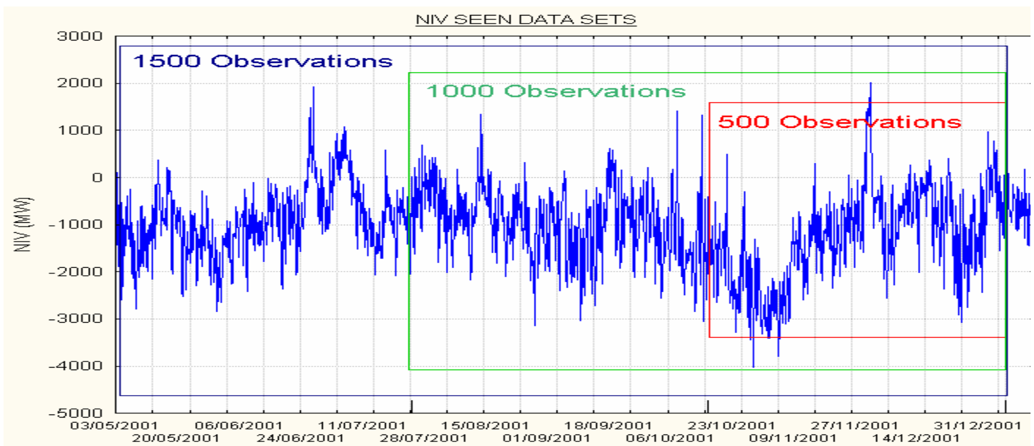
NIV increasing trend data set

Figure 4.11 NIV unseen data sets

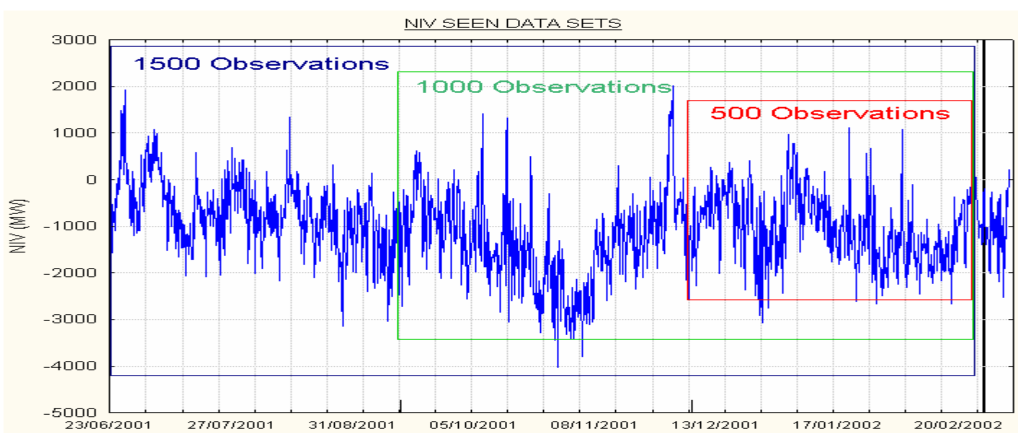
<u>Seen data:</u>

The seen data are used by the different techniques to create the forecasting bases. From each starting point three different sets of seen data have been created (Figure 4.12):

- Case 1: 500 observations from the starting forecast point
- Case 2: 1000 observations from the starting forecast point
- Case 3: 1500 observations from the starting forecast point



Seen data sets for decreasing trend forecasting period



Seen data sets for increasing trend forecasting period

Figure 4.12 NIV seen data sets

4.3.3 Modelling techniques

Different techniques are applied over the created seen data sets to compare the methods performance when forecasting NIV.

4.3.3.1 Autoregressive Integrated Moving Average (ARIMA)

The autoregressive integrated moving average (ARIMA) is usually known as the Box-Jenkins approach. In 1970 Box and Jenkins built a general forecasting method with the assumption that time series (after transformations and differencing) arise from a stationary autoregressive moving average process.

An autoregressive process is one where each observation is made up of a random error component (random shock, ε) and a linear combination of prior observations (equation 4.12):

$$y_t = \xi + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \varepsilon \qquad (4.12)$$

Where ξ is a constant and ϕ_1, ϕ_2 are the autoregressive model parameters.

A moving average process is one where each observation is made up of a random error component (random shock ε) and a linear combination of prior random shocks (equation 4.13):

$$y_t = \mu + \varepsilon + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots \qquad (4.13)$$

Where μ is a constant and θ_1, θ_2 are the moving average model parameters.

Combining 4.12 and 4.13, an *autoregressive moving average model* with **p** autoregressive terms and **q** moving average terms is defined as:

$$y_t = \gamma + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \qquad (4.14)$$

The Box-Jenkins model explicitly includes differentiation. This is used to stabilize a time series until it meets the series stationarity requirement (i.e. constant mean, standard deviation, and autocovariance).

In brief, the main stages of the ARIMA modelling are:

- Model identification: The ARIMA model is defined by three types of parameters: the autoregressive parameters (*p*), the number of differencing passes (*d*), and moving average parameters (*q*). The plot of the data and autocorrelogram are examined to determine the necessary level of differencing (*d*). The series is differentiated until the correlograms converge fast to zero. The parameters p and q are not usually greater than 2 but their determination is not straightforward. In this case we followed the practical recommendations suggested by Pankratz (Pankratz, 1983)

- Estimation: at the next step the autoregressive and moving average coefficients, are estimated using function minimization procedures (Chatfield, 2003, Brillinger, 2001, Shumway Robert and Stoffer David, 2000), so that the sum of the squared residuals is minimized.

- Forecasting: new values of the series are calculated using the estimates of the parameters from the previous stage. Since the estimation process is performed on transformed (differenced) data before the forecasts are generated, the series needs to be integrated (integration is the inverse of differencing) so that the forecasts are expressed in values compatible with the input data. This automatic integration represents the letter *I* in the ARIMA methodology.

4.3.3.2 Exponential smoothing

This technique differs from ARIMA and other polynomial extrapolations in the influence that past observations have on the forecast.

Given a series $y_1, y_{2,\ldots,} y_N$, the forecast for y_{N+1} can be computed as a weighted sum of past observations:

$$Y_N(k) = w_0 y_N + w_1 y_{N-1} + w_2 y_{N-2} + \ldots = \sum_{j=0}^{N-1} w_j y_{N-j} \qquad (4.15)$$

Where the coefficients w_j are the weights, $\sum_{j=0}^{N-1} w_j = 1$ and $w_0 \geq \ldots \geq w_N$. In this way recent observations have more weight than observations from further in the past. If the weights decrease exponentially (i.e geometrically, with a constant ratio for every unit increase in the lag) one gets:

$$w_j = \alpha(1-\alpha)^j \quad \text{for } 0 \leq \alpha \leq 1 \qquad (4.16)$$

The value of α (the smoothing constant) depends on the characteristics of the time series. The smaller its value the more the forecast depends on past observations. If α =1 the forecast is equal to the most recent observation. Substituting (4.16) in equation (4.15) gives:

$$\begin{aligned} Y_N(k) &= \alpha\sum_{j=0}^{N-1}(1-\alpha)^j y_{N-j} = \alpha y_N + (1-\alpha)\left[\alpha\sum_{j=1}^{N-1}(1-\alpha)^{j-1} y_{N-j}\right] = \\ &= \alpha y_N + (1-\alpha)Y_{N-1}(k) \end{aligned} \qquad (4.17)$$

Equation (4.17) can be used to calculate the forecast recursively.

Exponential smoothing can also be generalised to deal with series that include trend and seasonal variations. The general idea is that forecasts are not only computed from consecutive previous observations (as in simple exponential smoothing), but an independent (smoothed) trend and seasonal component are added. The trend and/or the seasonal component can then be modelled as linear, exponential, damped or omitted completely.

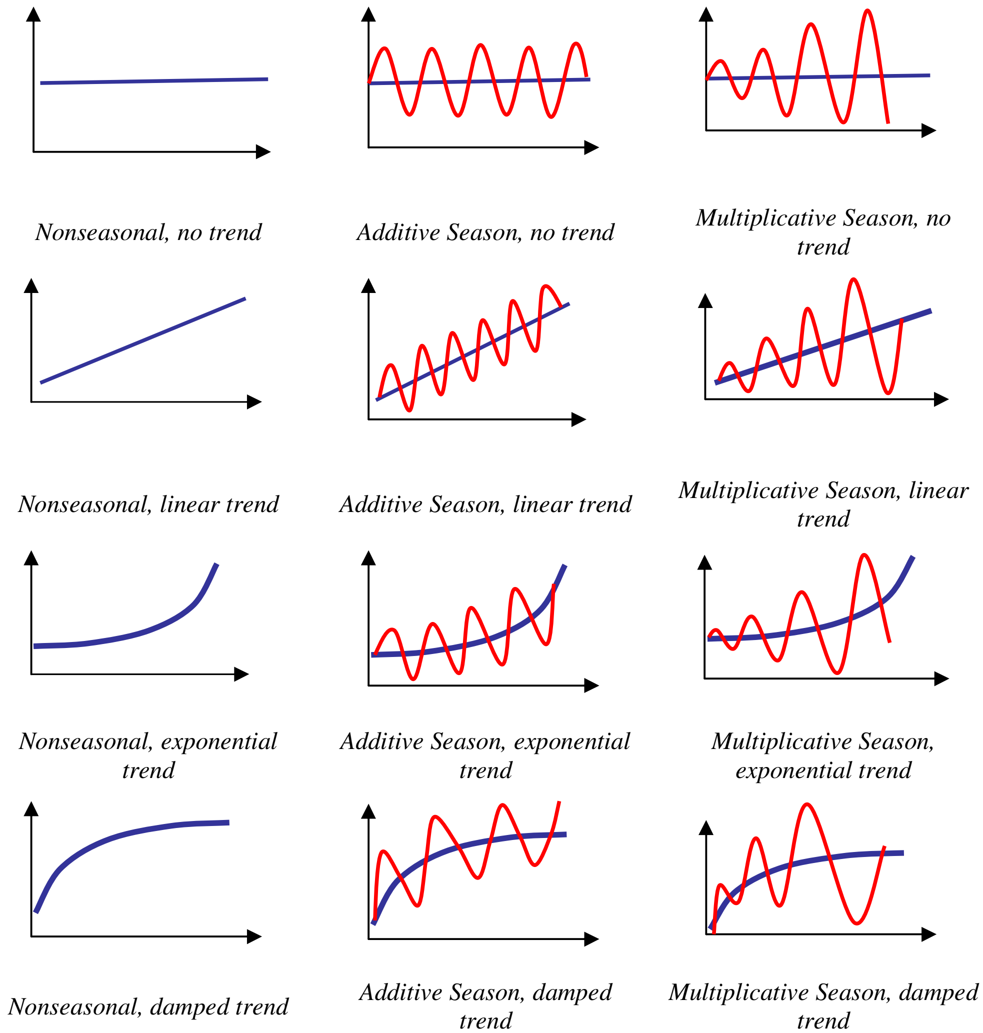


Figure 4.13 Exponential Forecasting Models

4.3.3.3 Caterpillar

The Caterpillar decomposition allows both the extraction of the components and the development of the corresponding linear recurrent formula. In this way it is possible to forecast some periodic components or the trend ignoring noise and all oscillatory components.

Consider the series the series $Y_N=Y_N^{(1)}+ Y_N^{(2)}$. If $Y_N^{(2)}$ can be considered as noise, the problem is to forecast the series $Y_N^{(1)}$ in the presence of this noise.

This implies not only the need of a window of length L that allows the series separability (see equation 4.11), but also that the series Y_N can be forecasted using a linear recurrent formula of the form:

$$Y_N(k) = w_1 y_{N-1} + w_2 y_{N-2} + \ldots + w_d y_{N-d} \qquad (4.18)$$

In this way, $Y_{N+1}(k)$ which is the extension of the known data $y_1, \ldots y_N$, is constructed. In turn, extrapolation to k points forward is reduced to the application of k times of the prediction procedure for one point. The basic idea of the computation of the point $Y_{N+1}(1)$ is the following:

Consider the sequence $y_1, \ldots y_N$ and construct a sample in the form of the trajectory matrix **X**. From all the vectors that form the matrix **S,** a leading sample of r vectors $V_1, V_{2,\ldots,} Vr$ is chosen as a basis of **S**. In this way the main components of the series are filtered from its noise and unwanted oscillatory terms. The resulting parametric equation of the sample is:

$$\mathrm{S(P)} = \sum_{i=1}^{r} p_i \mathrm{V}_i \qquad (4.19)$$

Where the set of parameters p_i corresponds to the value S(P) which is a column of L (L = window length) elements. In this case the set of parameters $P^k = (p_1^k, p_2^k, \cdots, p_r^k)$ corresponds to the k-th, (k=1,2,…n) column of the trajectory matrix **X.** Therefore:

$$\begin{aligned} &\mathbf{X}^1 = S(P^1) \\ &\mathbf{X}^2 = S(P^2) \\ &\ldots \\ &\mathbf{X}^N = S(P^N) \end{aligned}$$

To predict the value of $Y_{N+1}(1)$ it is necessary to find the $(N+1)$ column X^{N+1} which also fits the parameters $P^{N+1} = (p_1^{N+1}, p_2^{N+1}, \cdots, p_r^{N+1})$ Using the data $y_1, \ldots y_N$ these parameters can be obtained using equation 4.19, and the predicting column is written as:

$$\mathbf{X}^{N+1} = S(P^{N+1}) \qquad (4.20)$$

Thus, this methodology first relies on a vector forecasting and then returns to the time series representation. The SSA algorithm must therefore be repeated for each new forecasted point. For an in depth explanation and full matricial development refer to (Golyandina et al., 2001). Further examples of the application of this technique can be found in (Loskutov et al., 2000, Ghil and Allen, 2002, Loskutov and Istomin, 2001)

4.3.4 Post-analytical techniques

Each of the methods previously described generates both a forecasting base and forecasted values. Different post-analysis are performed on each of the obtained values:

- Forecasting base: Sanity checks are performed over the data analysing the statistical characteristics of the obtained values. This includes the calculation of statistical parameters (i.e. maximum, minimum, mean, standard deviation) and normality checks.
- Forecasted values: This analysis involves the calculation of different error measurements. These error values have been used to compare the results obtained with the different methods. The errors used are :
  - Maximum absolute error (*maxae*): the absolute value of largest difference between a forecasted value and an actual value (obtained from the unseen data):

    $$Maxae = Max\left|(Y_{j_{actual}} - Y_{j_{forecasted}})_{j=1}^{N}\right| \tag{4.21}$$

  - Mean absolute error (*mae*): the average magnitude of difference between a forecasted value and an actual value from the unseen data:

    $$Mae = \frac{1}{N}\sum_{j=1}^{N}\left|Y_{j_{actual}} - Y_{j_{forecasted}}\right| \tag{4.22}$$

  - Root mean squared error (*rmse*): the error magnitude. It is defined as the square root of the squares of the sum of the differences between the actual and the forecasted values. It penalises very large deviations in the forecast:

$$Rmse = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(Y_{j_{actual}} - Y_{j_{forecasted}})^2} \tag{4.23}$$

- Mean error (Bias): the average value of the difference between the actual and the forecasted values. It can have positive or negative values to reflect the average position of the forecasted results (higher/lower) over the real ones.

$$Bias = \frac{1}{N}\sum_{j=1}^{N}\left(Y_{j_{actual}} - Y_{j_{forecasted}}\right) \tag{4.24}$$

- Percentage of signs correct: the percentage of times that the signs of the forecasted and the actual values are the equal.

$$\%sign = 100 \cdot \frac{1}{N}\sum_{j=1}^{N} s(Y_{j_{actual}}, Y_{j_{forecasted}}) \tag{4.25}$$

Where:

$$s(Y_{j_{actual}}, Y_{j_{forecasted}}) = \begin{cases} 1 & (Y_{j_{actual}} < 0 \text{ and } Y_{j_{forecasted}} < 0) \\ 1 & (Y_{j_{actual}} > 0 \text{ and } Y_{j_{forecasted}} > 0) \\ 1 & (Y_{j_{actual}} = 0 \text{ and } Y_{j_{forecasted}} = 0) \\ 0 & \text{otherwise} \end{cases}$$

4.3.5 Numerical results

4.3.5.1 Increasing trend NIV forecasting period

As described in section 4.3.2, three different cases are considered which include respectively 500, 1000 and 1500 observations in the seen data set. Figures 4.14, 4.15 and 4.16 present for each case the last values of the forecasting bases and the predicted values obtained with the different methodologies. The corresponding errors for each forecast are given in Tables 4.2, 4.3 and 4.4.

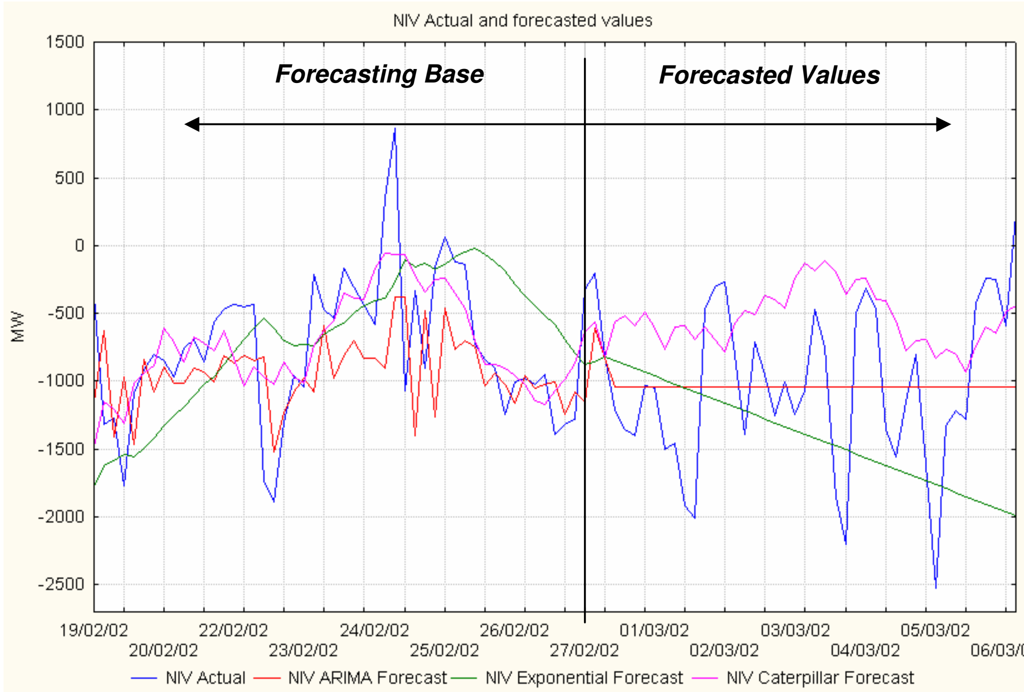


Figure 4.14 NIV Forecasting base and forecasted results for 500 cases in the seen data set

Table 4.2 Forecasted Errors for NIV increasing trend and 500 cases in the seen data set:

	ARIMA	EXPONENTIAL SMOOTHING	CATERPILLAR
Maximum Error (MW)	825.64	1667.00	637.80
Mean Absolute Error (MW)	444.01	574.80	524.94
Root mean squared error (MW)	552.61	687.439	777.65
Mean Error (MW)	-43.88	252.910	-524.30
% of signs	100	100	100

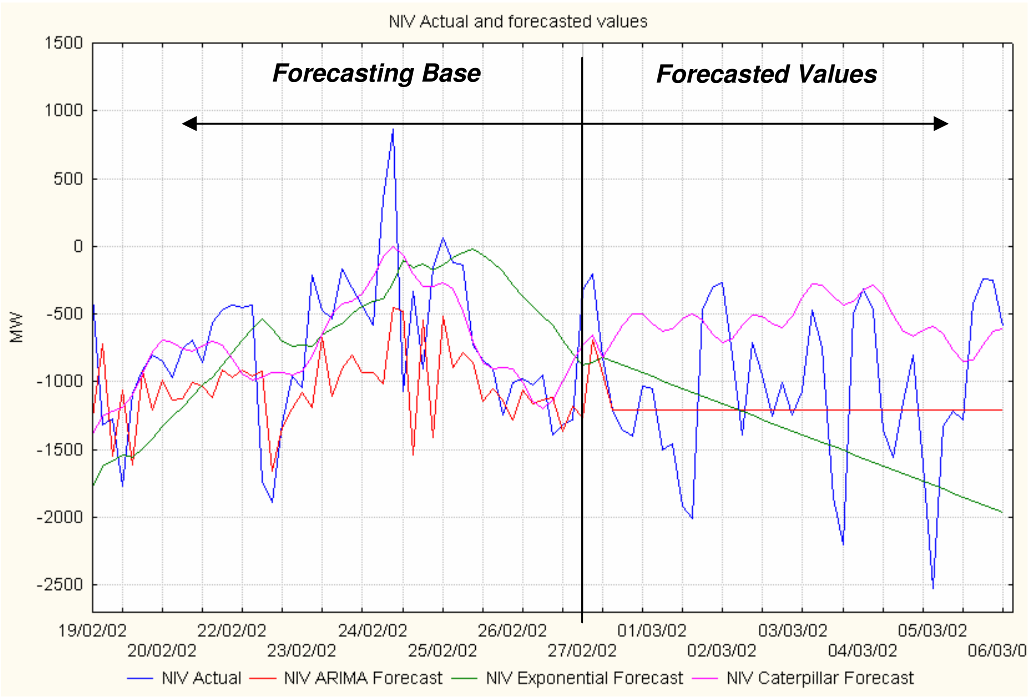


Figure 4.15 NIV Forecasting base and forecasted results for 1000 cases in the seen data set

Table 4.3 Forecasted Errors for NIV increasing trend and 1000 cases in the seen data set:

	ARIMA	EXPONENTIAL SMOOTHING	CATERPILLAR
Maximum Error (MW)	973.67	1684.75	622.47
Mean Absolute Error (MW)	453.99	600.62	492.37
Root mean squared error (MW)	573.51	726.35	770.12
Mean Error (MW)	140	286.21	-481.61
% of signs	100	100	100

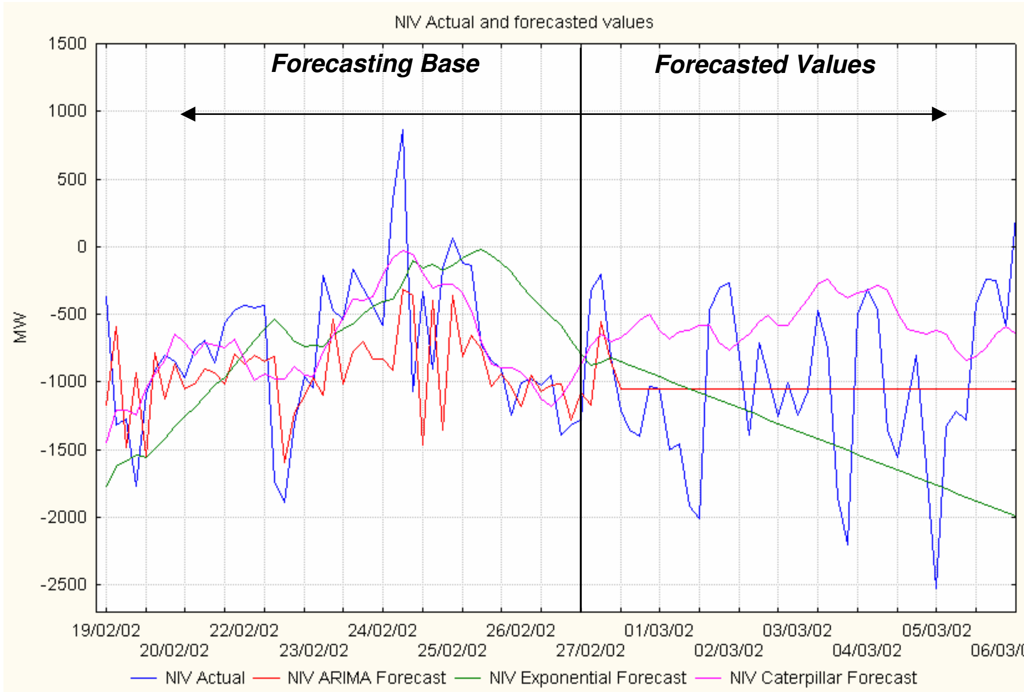


Figure 4.16 NIV Forecasting base and forecasted results for 1500 cases in the seen data set

Table 4.4 Forecasted Errors for NIV increasing trend and 1500 cases in the seen data set:

	ARIMA	EXPONENTIAL SMOOTHING	CATERPILLAR
Maximum Error (MW)	850	1110.95	623.65
Mean Absolute Error (MW)	450.69	533.10	513.05
Root mean squared error (MW)	558.46	657.68	763.94
Mean Error (MW)	-12.39	-179.04	-476
% of signs	100	100	100

For the increasing trend data set, Figures 4.14 to 4.16 present NIV's actual value (in blue) and the results for the different applied forecasting techniques. The output of the forecasting techniques includes both the modelling of the seen data (forecasting base) and the forecasted solutions. For all the considered cases, it can be noticed that the modelling of the seen data is closer to NIV's behaviour than the forecasting of the unseen data. The forecasted solutions quickly converge to a constant value (ARIMA) or to a constant slope (exponential smoothing) only the caterpillar method is capable of forecasting some oscillatory behaviour. The comparison of these figures also shows how the increase in the forecasting base does not improve the outputs but it rather smoothes them.

4.3.5.2 Decreasing trend NIV forecasting period

Similarly to the increasing trend period, three different cases are considered which include respectively 500, 1000 and 1500 observations in the seen data set. Figures 4.16, 4.17 and 4.18 each present for each case the last values of the forecasting bases and the predicted values obtained with the different methodologies. The corresponding errors for each forecast are given in Tables 4.3, 4.4 and 4.5.

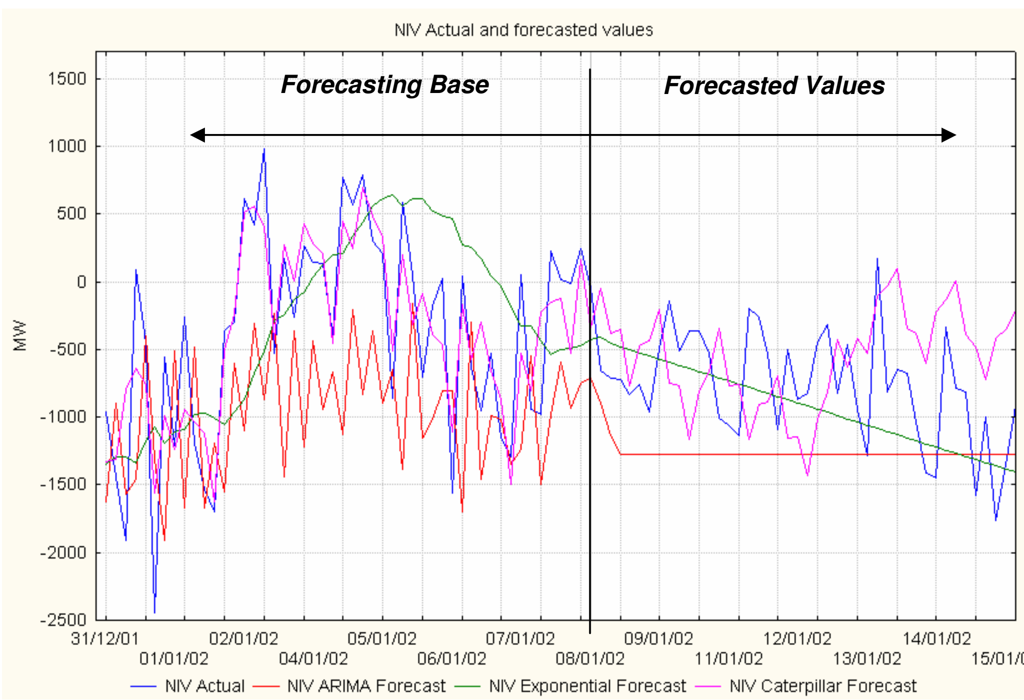


Figure 4.17 NIV Forecasting base and forecasted results for 500 cases in the seen data set

Table 4.5 Forecasted Errors for NIV decreasing trend and 500 cases in the seen data set:

	ARIMA	EXPONENTIAL SMOOTHING	CATERPILLAR
Maximum Error (MW)	1443.41	1254.33	975.29
Mean Absolute Error (MW)	573.66	359.28	496.45
Root mean squared error (MW)	658.22	425.84	562.32
Mean Error (MW)	542.99	173.20	-131.99
% of signs	95.24	95.25	92.86

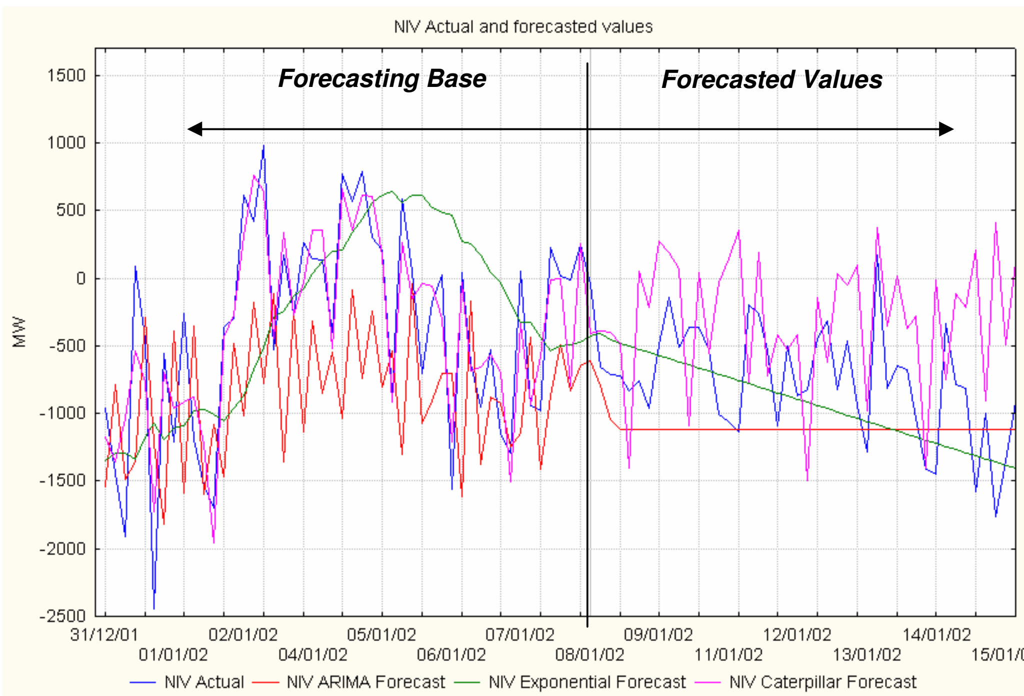


Figure 4.18 NIV Forecasting base and forecasted results for 1000 cases in the seen data set

Table 4.6 Forecasted Errors for NIV decreasing trend and 1000 cases in the seen data set:

	ARIMA	EXPONENTIAL SMOOTHING	CATERPILLAR
Maximum Error (MW)	1290.44	1254.33	724.37
Mean Absolute Error (MW)	459.92	360.31	596.51
Root mean squared error (MW)	545.57	425.33	755.03
Mean Error (MW)	370.68	159.79	-416.92
% of signs	95.35	95.35	69.77

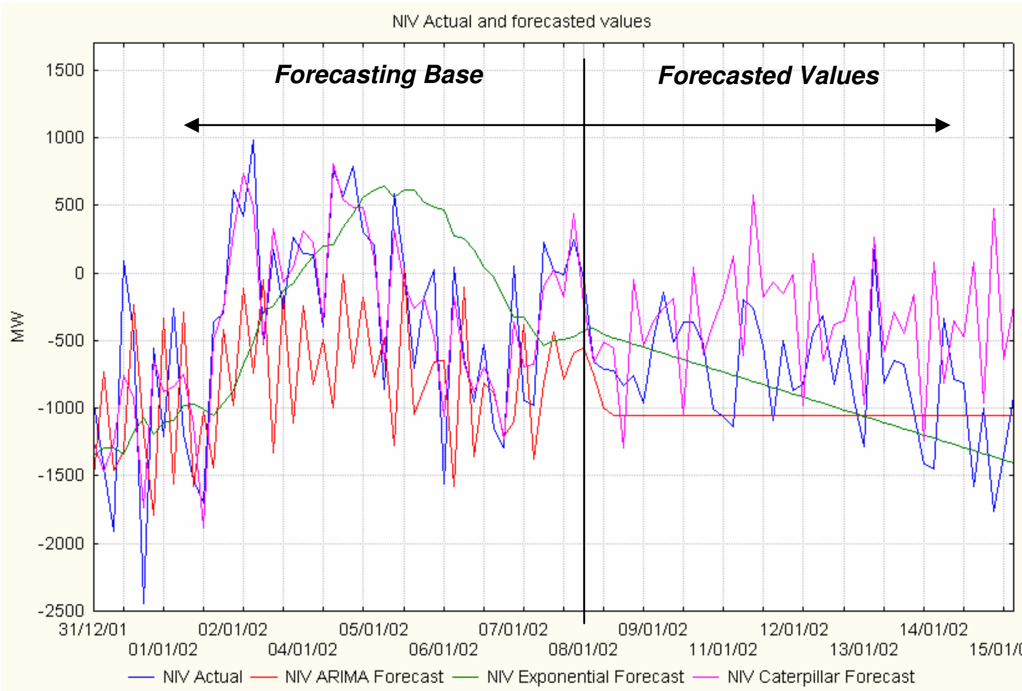


Figure 4.19 NIV Forecasting base and forecasted results for 1500 cases in the seen data set

Table 4.7 Forecasted Errors for NIV decreasing trend and 1500 cases in the seen data set:

	ARIMA	EXPONENTIAL SMOOTHING	CATERPILLAR
Maximum Error (MW)	1222.27	1254.33	694.99
Mean Absolute Error (MW)	415.20	360.31	518.05
Root mean squared error (MW)	503.31	425.33	696.07
Mean Error (MW)	304.49	159.79	-381.83
% of signs	95.35	95.35	83.72

For the decreasing trend data set, Figures 4.17 to 4.19 present NIV's actual value (in blue) and the results for the different applied forecasting techniques. The output of the forecasting techniques includes both the modelling of the seen data (forecasting base) and the forecasted solutions. As in section 4.3.5.1, it can be noticed that the modelling of the seen data is closer to NIV's behaviour than the forecasting of the unseen data. The forecasted solutions quickly converge to a constant value (ARIMA) or to a constant slope (exponential smoothing) only the caterpillar method is capable of forecasting some oscillatory behaviour. The comparison of these figures also shows how the increase in the forecasting base does not have any noticeable effect on the ARIMA and the exponential solutions. However, the Caterpillar results are pricklier as the number of cases in the forecasting bases increases.

4.3.6 Conclusions

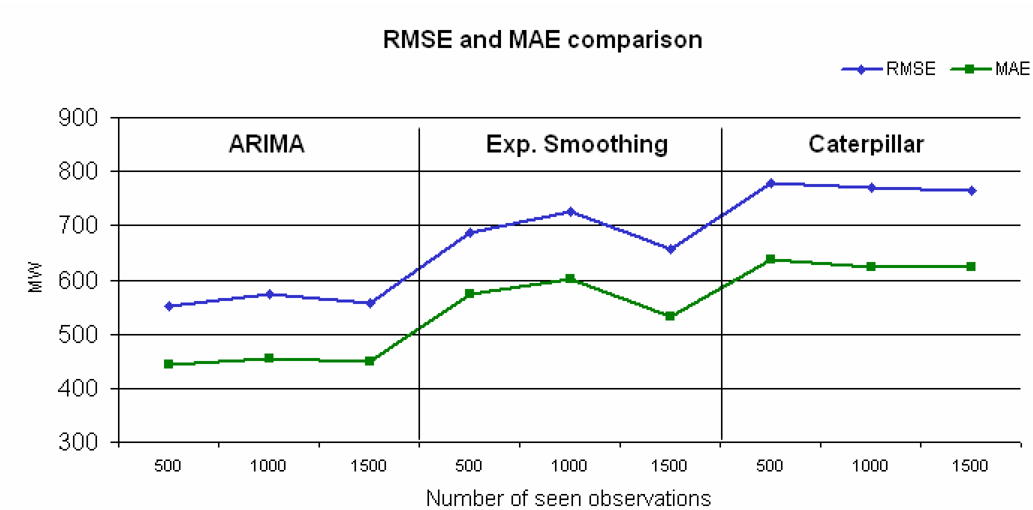
The presented methods do not provide a good accuracy in their forecast. Moreover, the characteristics of their results do not reflect NIV actual behaviour. Forecasted solutions converge quickly to a constant value (ARIMA) or to a constant slope (Exponential Smoothing). Only the Caterpillar forecasting method is capable of predicting an oscillatory behaviour.

The obtained error measurements do not show any consistent advantage of one method over the others.

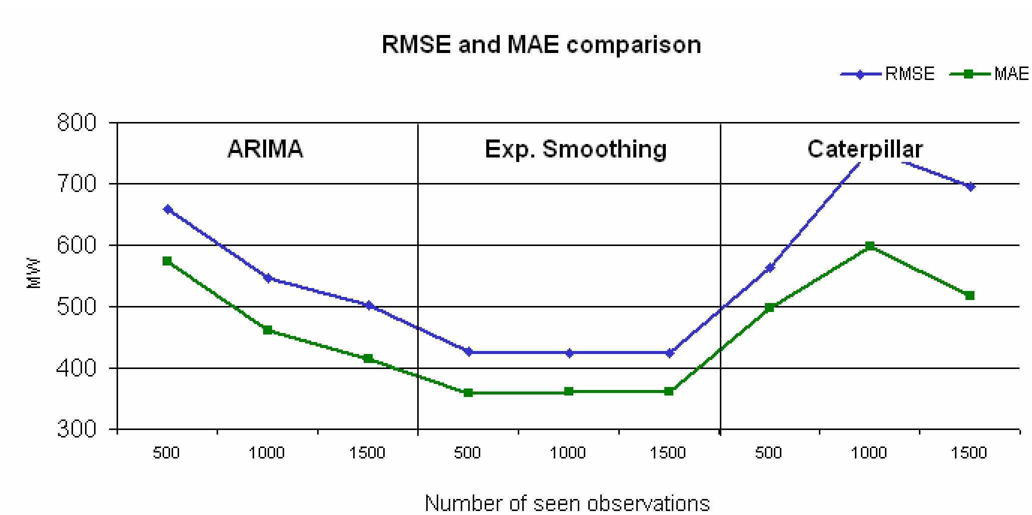
The number of observations included in the seen data has different effects for each case and for each method:

- Considering the patterns of the forecast:
    - Exponential and ARIMA: it only affects the permanent value or the final slope.
    - Caterpillar: increasing the number of observations affects the series decomposition and the reconstruction on which the forecast is based. For the increasing trend period the forecast results are smoother as the number of seen data is increased. For the decreasing trend period increasing the number of observations creates the opposite effect over the forecasted results.
- Increasing the number of observations used to create the forecasting base does not necessary lead to an increase in the accuracy of the forecast. Figure 4.20 presents the *rmse* and the *mae* for all the analysed cases. It illustrates how for some cases (ARIMA and Caterpillar for NIV increasing trend period and Exp.

Smoothing for NIV decreasing trend period) the errors remain constant despite an increase in the number of seen observations, while for some other cases the errors gradually decrease (ARIMA for NIV decreasing trend) or even spike (exp. smoothing for NIV increasing trend and caterpillar for NIV decreasing trend).



4.20 (a) NIV increasing trend



4.20 (b) NIV decreasing trend

Figure 4.20 RMSE and MAE error comparison

Based on the results presented above it is possible to conclude that:

- None of the presented methods can be considered as a feasible solution for NIV forecasting for time periods longer than 1 day ahead.

- The Caterpillar method is the only methodology that provides more adaptable and realistic results.
- NIV series are not a good predictor of themselves. Their noisy, unstructured, changing, and normal-orientated behaviour leads to see NIV as a clear example of the central limit theorem[1] were NIV is the result of several actions in the BM process.

It is thus necessary to expand NIV's analysis to a multidimensional perspective where NIV's behaviour can be analysed as a function of other market variables.

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[1] *The distribution of an average tends to be Normal, even when the distribution from which the average is computed is decidedly non-Normal.*

CHAPTER 5

The Net Imbalance Volume: Multidimensional Analysis

5.1 Introduction

The results and the conclusions of all the analysis presented in Chapter 4 suggest expanding the analysis of NIV to a multidimensional scale. By doing so, NIV's forecast does not rely only on the information contained in the series itself; in contrast NIV's behaviour is explained in terms of other variables, and its observations are related to some structural rules of this behaviour.

In this way, a connection is established between the market volume (NIV) and the rest of the Balancing Mechanism variables that will be used as explicative and predictor variables for NIV.

The multidimensional analysis of NIV aims two main objectives that differentiate its two main elements (Rencher, 1995, Hair et al., 1984, Kachigan, 1991). The first part is an *exploratory analysis* focused on understanding the behaviour of the Balancing Mechanism's drivers as well as relating how these drivers are captured in the behaviour of NIV. This is also a discriminatory step since the information obtained allows a systematic and rational selection of the variables used as input in the following part of the study. This second part consists on a *multidimensional forecast* of NIV where non-linear techniques are used to predict NIV values from past values of the selected BM variables.

As in the previous chapter the exploratory multidimensional analysis is presented according to the different stages of the CRISP methodology. The multidimensional forecasting, due to the particularities of neural networks techniques, alters slightly the previous structure. In section 5.3.2, the neural networks (NN) methodology is introduced along with the proposed structure of the analysis. The following sections deal with data selection and preparation, the numerical results and a sensitivity analysis of the input variables. A methodology deployment is also described before the final conclusions.

5.2 Multidimensional exploratory analysis

5.2.1 Objectives

This multidimensional analysis is aimed at understanding the possible interactions between the different variables of the Balancing Mechanism (BM) and NIV. This will allow us to determine the variables that could be included in the forecast as well as to describe, when applicable, the nature and characteristics of these interactions.

Three types of analysis uncover the different aspects of variables interactions. Qualitative analyses identify any interaction between variables. Quantitative analyses measure the strength of these influences. Both qualitative and quantitative analyses are purely descriptive or "correlational". Therefore, to analyse the causality and to determine the moment in time when the interactions take place, multivariate time-series analyses are applied.

5.2.2 Data selection

The BM quantities considered in these analyses are divided in two groups according to the moment in time they correspond.

Tables 5.1 and 5.2 provide respectively a full description (ELEXON, 2001a) of the pre-gate closure and post-gate closure variables considered in this analysis. Pre-gate closure variables refer to actions that occur prior or up to gate closure and post-gate closure variables refer to actions that occur after gate closure. In each table, the first column gives the variable name followed by its acronym, when appropriate, the second the variable definition and, when appropriate, its mathematical equation is included in the third column.

Table 5.1 Pre-gate closure variables description

NAME	DEFINITION	EQUATION
Demand forecast	The estimate of the demand for electricity (in MW)	
Submitted Offer Volume (SOV)	The sum of all the available offers submitted by all the BM for a certain period (in MW)	
Submitted Bid Volume (SBV)	The sum of all the available bids submitted by all the BM for a certain period (in MW)	
Indicated Generation (INDGEN)	The sum of all the FPN submitted by the generation units (in MW)	
Indicated Demand (INDDEM)	The sum of all the FPN submitted by the demand (in MW)	
Capped Physical Notification (CPN)	The aggregation for all the units of the minimum between the final physical notifications (FPN) and the maximum export limit (MEL) submitted in each period (in MW)	$CPN = \sum Min(MEL, FPN)$
Gate Closure Imbalance Volume (GCIV)	The difference between the demand forecast and the capped physical notification (in MW)	$GCIV = DF - CPN$
Market Imbalance Volume (MIV)	the pre-trade market position as seen at gate closure (in MW)	$MIV = GCIV + \sum SOTrades$
UKPX	The UK Power Exchange reference price (in £/MW)	

Table 5.2 Post-gate closure variables description

NAME	DEFINITION	EQUATION
Demand	The actual value of the system load for each period (in MW)	
Demand forecast error (DFE)	The difference between the demand forecast and the demand (in MW)	$DFE = DF - Demand$
Accepted Offer Volumes (AOV)	The aggregated volume of offers accepted by the System Operator (SO) (in MW)	
Accepted Bid Volumes (ABV)	The aggregated volume of bids accepted by the System Operator (SO) (in MW)	
Accepted Offer Cashflows (AOC)	The total cash-flow resulting from all the offer acceptances (in £MWh)	
Accepted Bid Cashflows (ABC)	The total cash-flow resulting from all the bids acceptances (in £MWh)	
Balancing Mechanism Imbalance Volume (BMIV)	The sum of the actions taken by the system operator to balance the system between GC and real time (in MW)	$BMIV = \sum AOV + \sum ABV + + \sum French_{trades}$
Post Gate Closure Effects (PCGE)	The net volume of post GC changes in demand and generation (in MW)	$PGCE = NIV - MIV = = BMIV - GCIV$
Remaining Effects (REM)	The composite of any post-gate closure effect not included in the DFE (in MW)	$REM = PGCE - DFE$
System Buy Price (SBP)	The weighted average of the accepted offers (in £/MW)	
System Sell Price (SSP)	The weighted average of the accepted bids (in £/MW)	

Note that the definitions presented for the imbalance prices are the original ones. As described in section 2.4.2, the calculation of SBP and SSP was drastically modified on the 28/02/2003 with the implementation of P78. However the analysed period goes from 01/06/01 to 30/06/02 so the initial definitions are still valid.

5.2.3 Data preparation

The first stage of the data preparation is a filtering process (Pyle, 1999); smoothing moving medians have been applied with a window length of 48 periods. The resulting series represent the daily moving median for each of the analysed variables.

The next stage is the standardization or normalization: each value in the series is standardised using equation 4.3. This step makes it possible to bring together observations that follow similar trends but are differently valued (Gavrilov et al., 2000).

The final step includes the differentiation of the variables. Differentiating a series provides important information about the rate of change and also serves as a high-pass filter (i.e. amplifying the high-frequency variations and attenuating the lower frequency ones). As described in table 5.3, the combination of standardised and standardised differentiated series of the dependent (NIV series) and independent (BM quantities) variables provides a deeper analysis of the interactions and relations between variables.

Table 5.3 Combination of variables transformations

NIV SERIES	BM QUANTITIES	OUTPUT
Standardised series	Standardised series	Interactions between NIV and the different variables
Standardised Differentiated series	Standardised series	Effect of the BM variables on NIV changes
Standardised series	Standardised Differentiated series	Effect of the changes of BM variables on NIV
Standardised Differentiated series	Standardised Differentiated series	Effect of the changes of BM variables on NIV changes

5.2.4 Modelling techniques and numerical results

Both time series analysis and multivariate exploratory techniques are applied in this study. The time series analyses are aimed at uncovering the relationship between the different variables and NIV at different points in time. The multivariate exploratory techniques are aimed at identifying relationships between the BM quantities and NIV and the statistical significance of these relationships.

5.2.4.1 Multidimensional correlation analysis

The multidimensional correlation or cross-correlation analysis is a standard approach to feature detection in the time domain. It gives a measure of the relation between NIV and the rest of the BM variables. In this case the relationship between NIV and each of the BM variables is treated as a bivariate process. The outputs of the analysis are the matrix scatter plots and the value of the samples cross-correlation coefficient *r* for each pair of variables (NIV and the independent BM variable).

The cross-correlation coefficient (Chatfield, 2003) for a sample of N pairs of observations is defined as

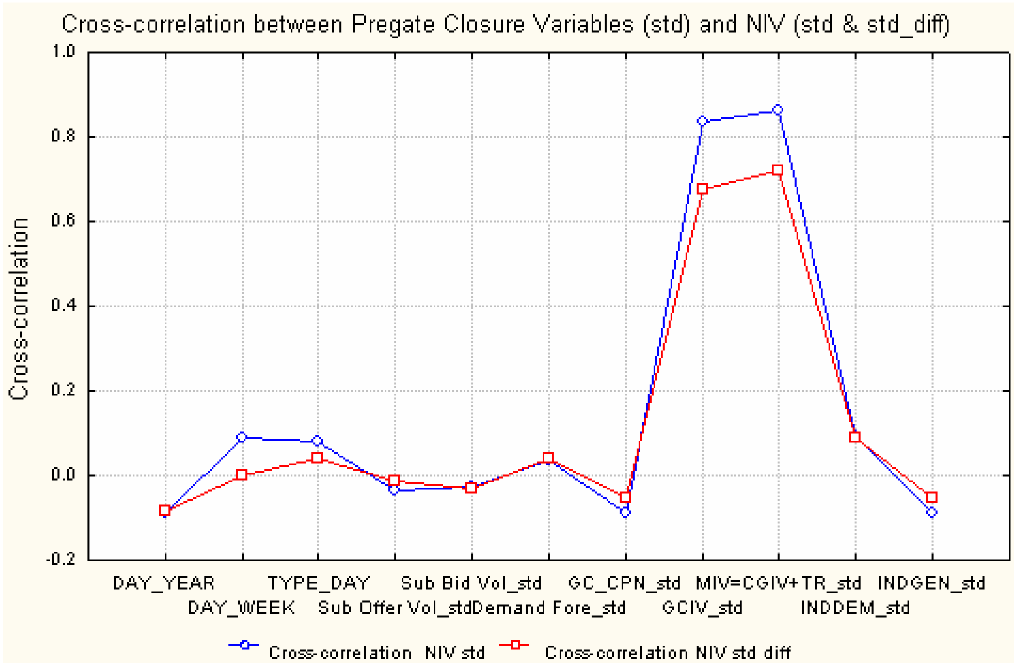
$$r(x,y) = \frac{c_{XY}(k)}{s_X \cdot s_Y} \qquad (5.1)$$

Where s_X, s_Y are the sample standard deviations for x_t and y_t respectively, and $c_{XY}(k)$ is the sample cross-variance

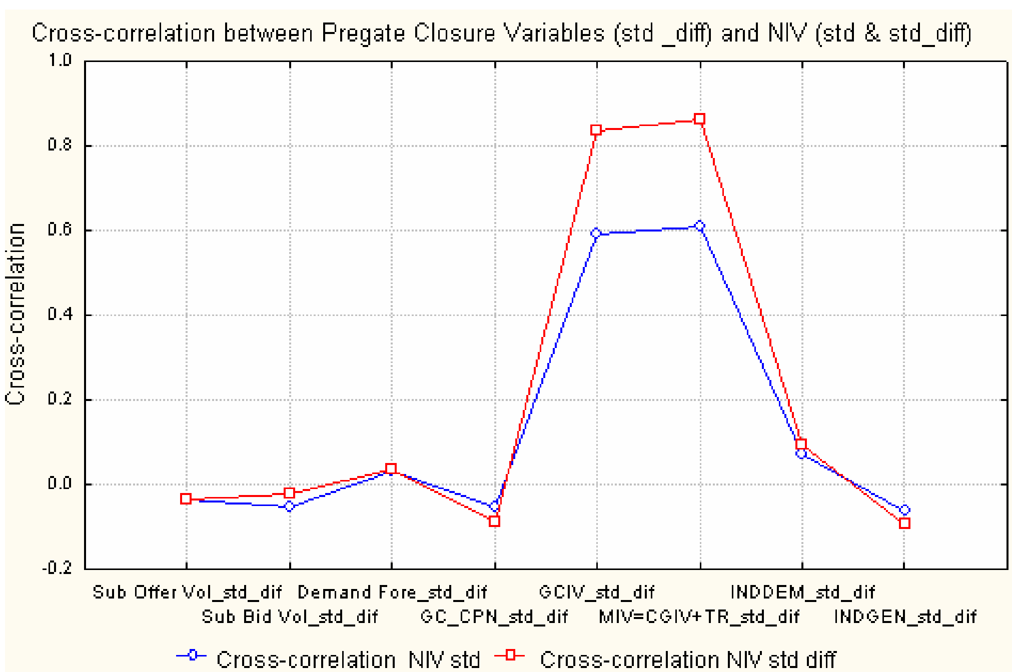
$$c_{XY}(k) = \sum_{t=1-k}^{N-k} (x_t - \bar{x})(y_{t+k} - \bar{y}) / N \quad \text{for } k = 0,1,\ldots,N-1$$

Application to Pre-gate closure variables

Figure 5.1 shows the values of the cross-correlation coefficient *r* (y-axis) defined in equation 5.1 for the BM pre-gate closure variables (x-axis) standardised (5.3(a)) and standardised differentiated (5.3(b)). In addition to the BM pre-gate closure variables Figure 5.3(a) also includes the correlation coefficient between NIV and pure time variables such as day of the year, day of the week (Mon-Sun) and type of day (working and non working)



5.1 (a) Cross-correlation coefficients for NIV and standardised BM variables



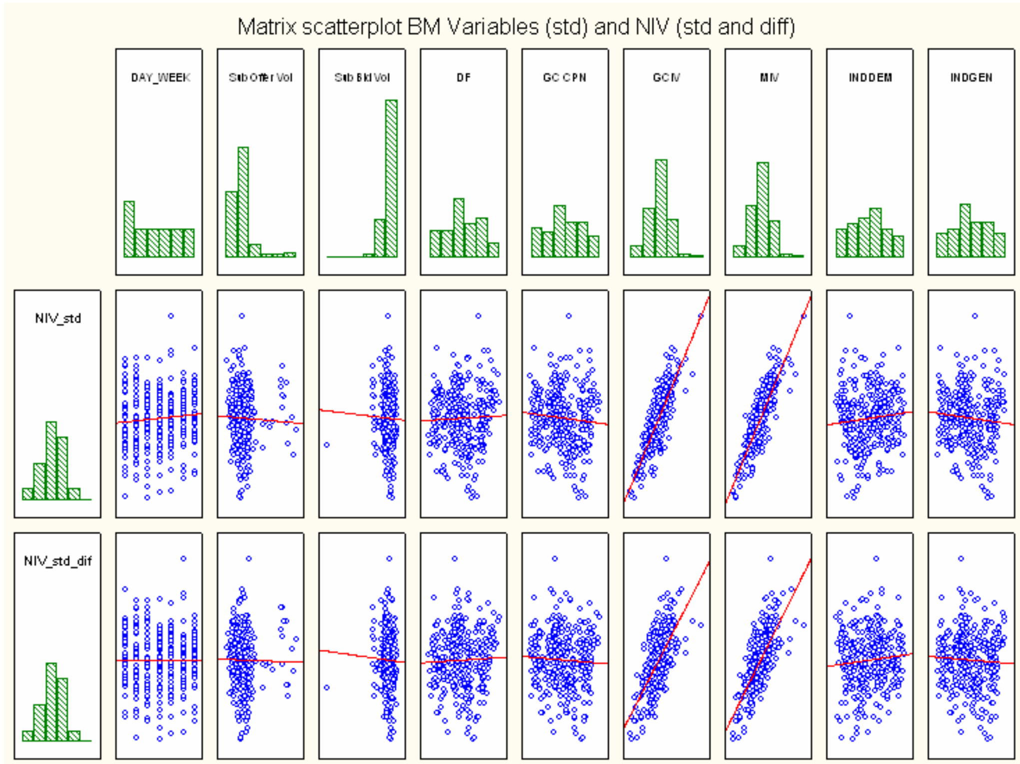
5.1 (b) Cross-correlation coefficients for NIV and standardised differentiated BM variables

Figure 5.1 Cross-correlation coefficients NIV and BM pre-gate closure variables

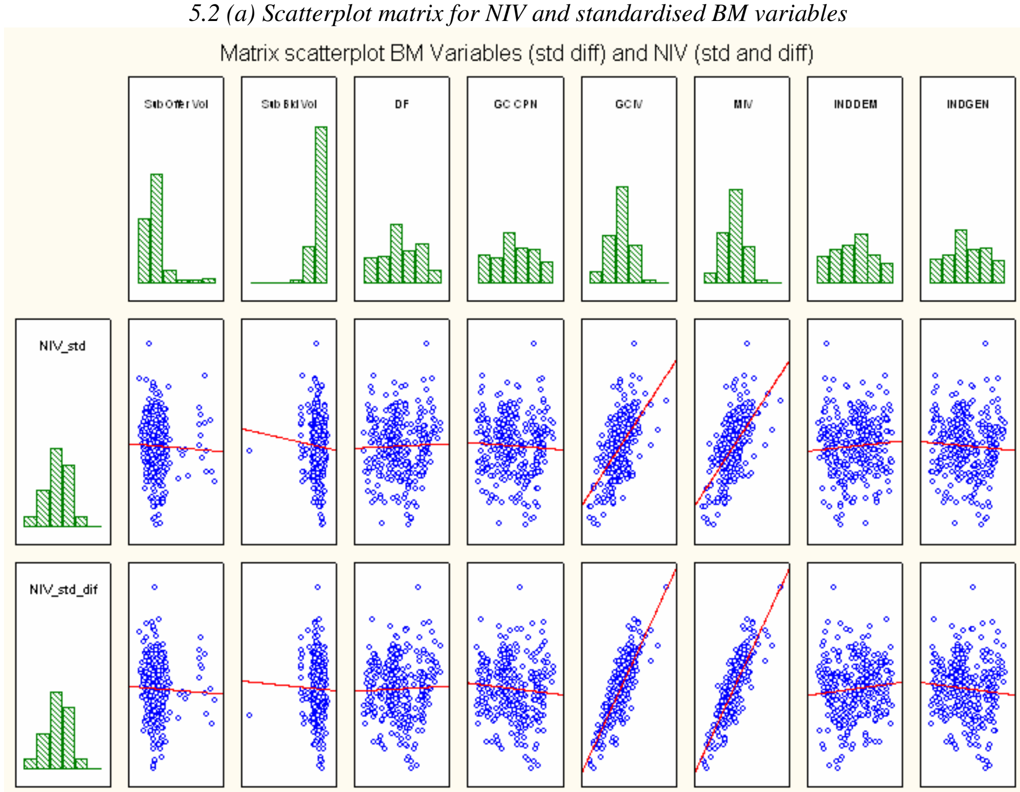
The cross-correlation results presented in figure 5.1 show how NIV has no significant linear correlation with most of the pre-gate closure variables. Only the variables which are physically connected with NIV (i.e GCIV and MIV) show significant results. The cross-correlation between similarly processed variables is higher than between variables with different transformation processes. In this way, there is higher correlation between BM pre-gate closure standardised variables and standardised NIV than between BM pre-gate closure standardised variables and NIV standardised and differentiated (Figure 5.1 (a)). In the same way the cross-correlation is higher between BM pre-gate closure standardised and differentiated variables and standardised and differentiated NIV than between BM pre-gate closure standardised differentiated variables and standardised NIV (Figure 5.1 (b)). This is due to the fact that NIV is more correlated with the actual BM variables than with their rate of change. Similarly NIV's rate of change is higher correlated with the rate of change of the pre-gate closure variables than with their actual values.

Figure 5.2 shows the matricial two-dimensional scatterplots used to visualize relationship between variables. The first column of each matrix represents the histograms for NIV standardised and NIV standardised differentiated. The first row of each matrix includes the histograms for the pre-gate closure variables standardised (Figure 5.2(a)) and standardised differentiated (Figure 5.2(b)). For the rest of the matrix components the y-axis represents NIV standardised, in the second row, and NIV standardised differentiated, in the third row; the x-axis represents the BM pre-gate closure variables with their corresponding transformations.

Figure 5.2 complements the results of Figure 5.1 showing clearly the lack of linearity between NIV and the BM pre-gate closure variables except from GCIV and MIV which are clearly connected with NIV physical meaning.



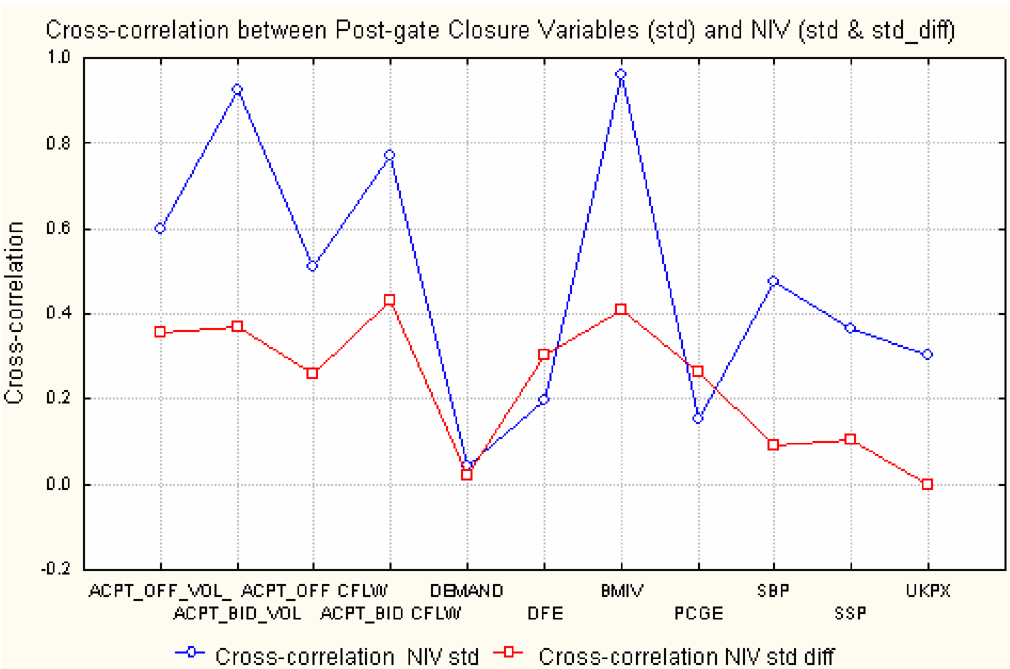
5.2 (a) Scatterplot matrix for NIV and standardised BM variables



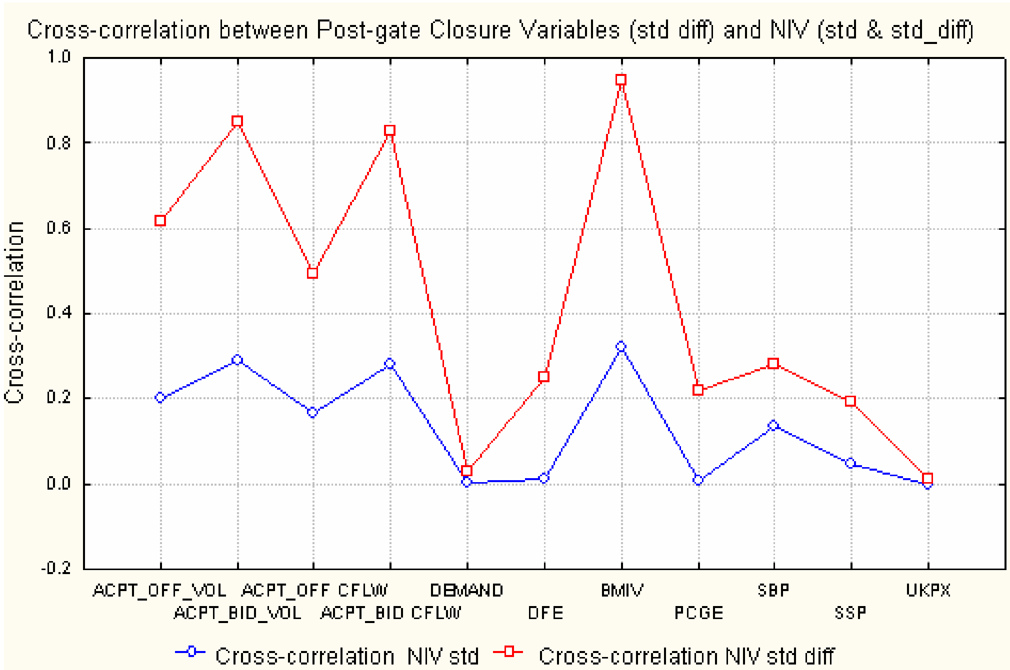
5.2 (b) Scatterplot matrix for NIV and standardised differentiated BM variables
Figure 5.2 Scatterplot matrix NIV and BM pre-gate closure variables

Application to post-gate closure variables

Figure 5.3 shows the values of the correlation coefficient *r* (y-axis) for the BM post-gate closure variables (x-axis) standardised (5.2(a)) and standardised differentiated (5.2(b)).



5.3 (a) Cross-correlation coefficients for NIV and standardised BM variables

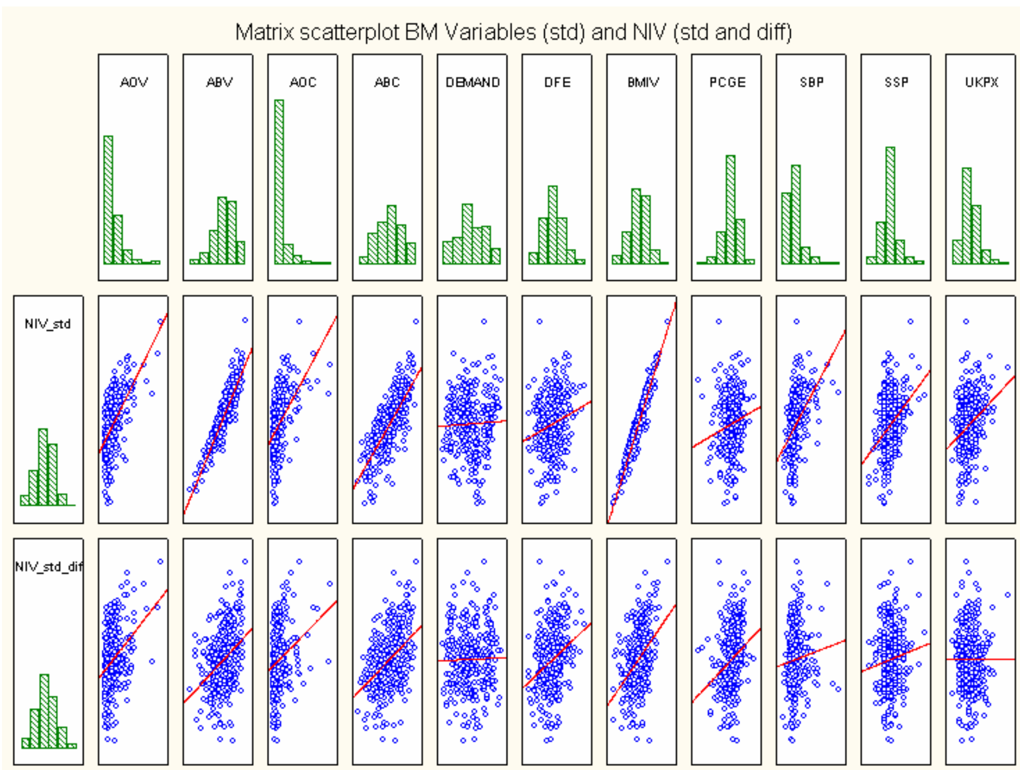


5.3 (b) Cross-correlation coefficients for NIV and standardised differentiated BM variables

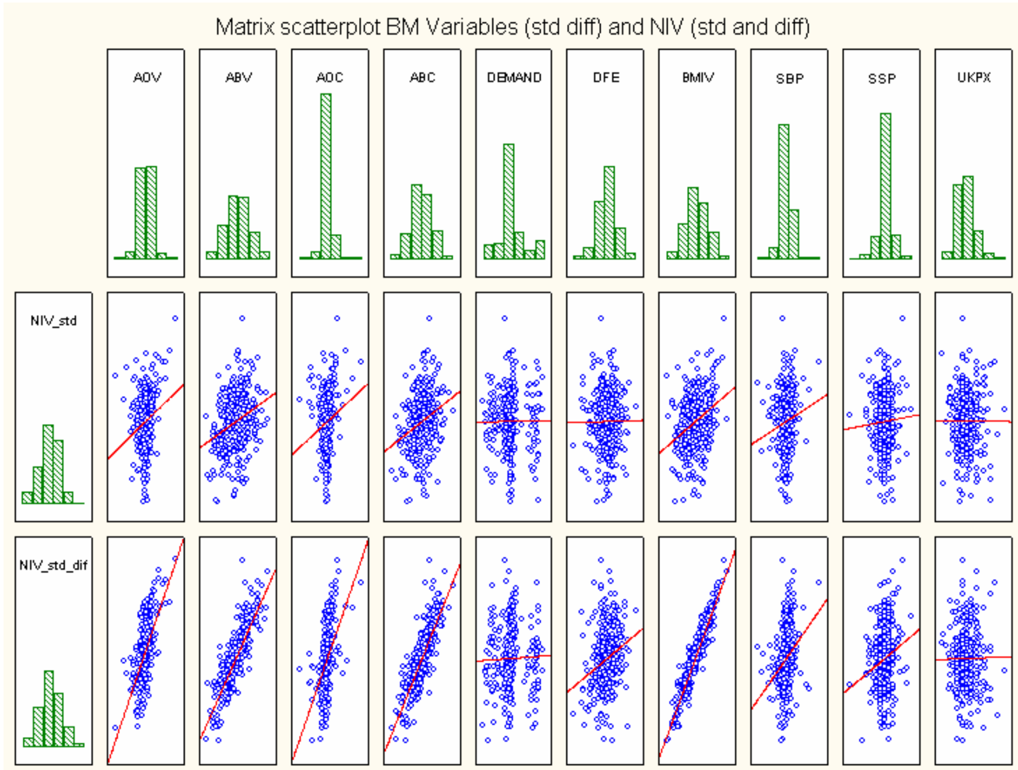
Figure 5.3 Cross-correlation coefficients NIV and BM post-gate closure variables

The results of Figure 5.3 present a very high cross-correlation between NIV and the acceptances of bids as well as with the cashflow derived from these bid acceptances. The cross-correlation is also very high between NIV and the BMIV, which is a priory known result since NIV can be obtained by adding the SO trades to the BMIV. The lowest cross-correlation values are those related with the demand. When considering prices, SBP presents a higher linear cross correlation with NIV than the SSP or the UKPX. As for the BM pre-gate closure variables, there is higher correlation between BM post-gate closure standardised variables and standardised NIV than between BM post-gate closure standardised variables and NIV standardised and differentiated (Figure 5.3 (a)). In the same way the cross-correlation is higher between BM post-gate closure standardised and differentiated variables and standardised and differentiated NIV than between BM post-gate closure standardised differentiated variables and standardised NIV (Figure 5.3 (b)).

Figure 5.4 shows the matricial two-dimensional scatterplot for the post-gate closure variables. The first column of each matrix represents the histograms for NIV standardised and NIV standardised differentiated. The firs row of each matrix includes the histograms for the pre-gate closure variables standardised (Figure 5.4(a)) and standardised differentiated (Figure 5.4(b)). For the rest of the matrix components the y-axis represents NIV standardised, in the second row, and NIV standardised differentiated, in the third row; the x-axis represents the BM post-gate closure variables with their corresponding transformations.



5.4(a) Scatterplot matrix for NIV and standardised differentiated BM variables



5.4 (b) Scatterplot matrix for NIV and standardised differentiated BM variables

Figure 5.4 Scatterplot matrix NIV and BM pre-gate closure variables

Figure 5.4 complements the results of Figure 5.3 showing the strong linear relation between NIV and the bid acceptances as well as their derived cashflow and BMIV. It is also clear the lack of linearity between NIV and Demand and DFE.

5.2.4.2 Cross spectrum analysis

The cross-spectrum is the complementary function to the cross-correlation in the frequency domain (Diggle, 1990, Kendall, 1976). This technique allows uncovering the seasonal relations between NIV and the rest of the BM variables by measuring the linear correlation between series at different frequencies. It is analogous to the spectrum analysis performed in the one-dimensional NIV analysis; the cross spectrum between two series is defined as

$$w_{XY}(\alpha) = \sum_{s=-\infty}^{\infty} \rho_{(XY)s} e^{i\alpha s} = c(\alpha) + iq(\alpha) \tag{5.2}$$

where:

$$\begin{aligned} c(\alpha) &= 1 + \sum_{s=1}^{\infty} \cos s\alpha s \left\{ \rho_{(XY)s} + \rho_{(XY)-s} \right\} \\ q(\alpha) &= \sum_{s=1}^{\infty} \sin \alpha s \left\{ \rho_{(XY)s} - \rho_{(XY)-s} \right\} \end{aligned} \tag{5.3}$$

The spectral density has both a real and an imaginary component. The quantity $c(\alpha)$ is called the co-spectrum or co-spectral density while $q(\alpha)$ is called the quadrature spectrum or quadrature spectral density. The cross-amplitude, which is calculated as the sum of squares of the real and imaginary parts $c^2(\alpha) + q^2(\alpha)$, represents a measure of the covariance between the respective frequency components in the two series.

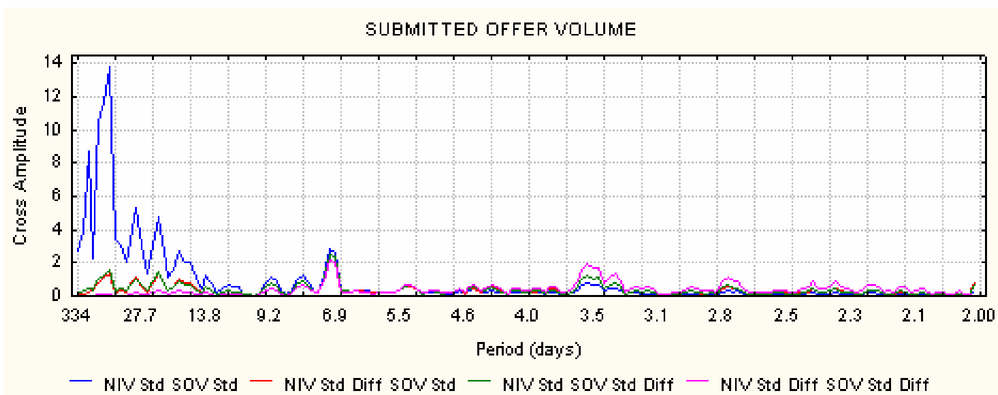
Application to NIV analysis

Figures 5.5 and 5.6 show the cross spectrum results for the pre-gate and post-gate closure variables respectively. In each graph the y-axis represents the cross amplitude values and the x-axis the frequencies range (considering values are considering in daily resolution frequencies refer to fractions of 11.57 μHz). Cross amplitude values are always positive, since it measures the covariance between aligned frequency components (Diggle, 1990). Peak values of the cross amplitude denote interdependence between the two series at the specific frequency where the local maximum occurs. Each graph includes four cases:

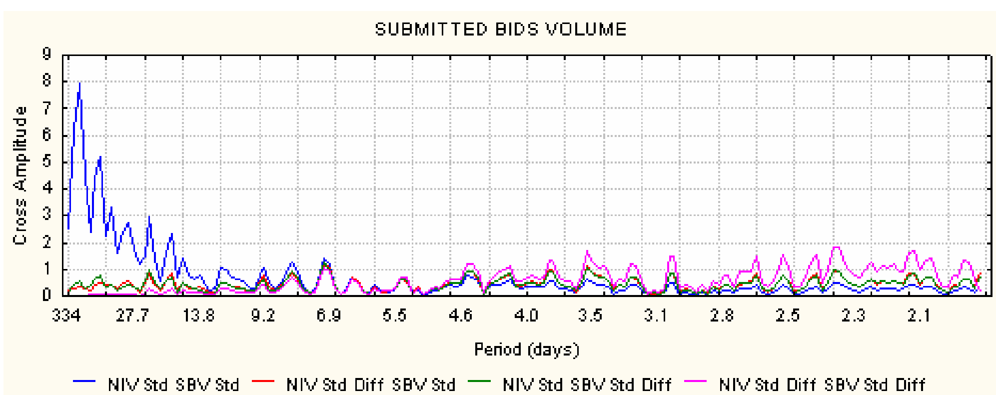
- The blue line represents the cross amplitude for NIV and the corresponding BM variable standardised. In this case the correlations at different frequencies between the two series are considered.
- The red line represents the cross amplitude for NIV standardised and differentiated and the corresponding BM variable standardised. In this case the correlations at different frequencies between the changes in NIV and the BM variables are considered.

- The green line represents the cross amplitude for NIV standardised and the corresponding BM variable standardised and differentiated. In this case the correlations at different frequencies between the NIV and the changes in BM variables are considered.
- The pink line represents the cross amplitude for NIV standardised and differentiated and the corresponding BM variable standardised and differentiated. In this case the correlations at different frequencies between the changes in NIV and the changes in BM variables are considered.

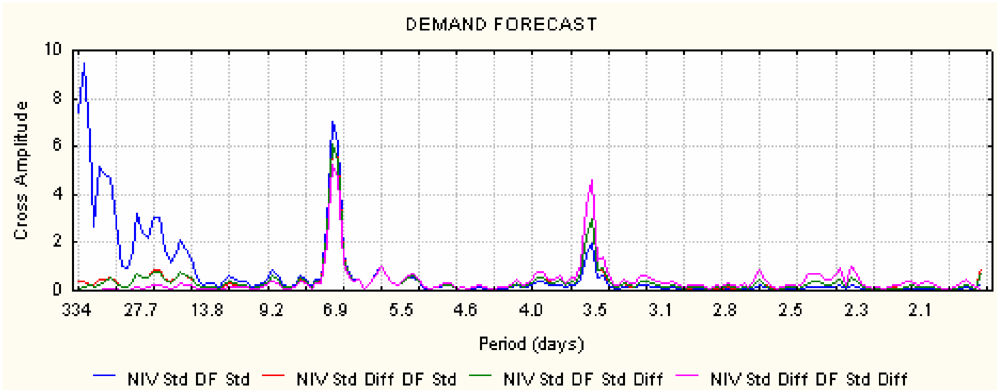
Pre-gate closure variables



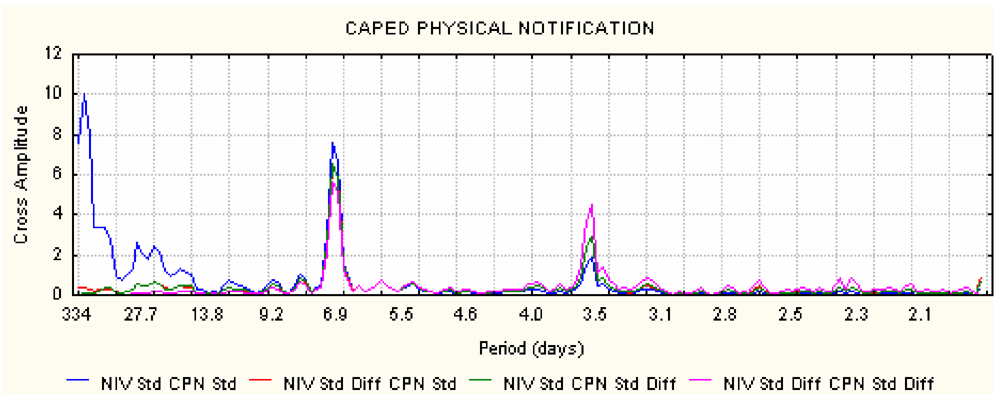
5.5 (a) Cross amplitude for NIV and Submitted Offer Volume



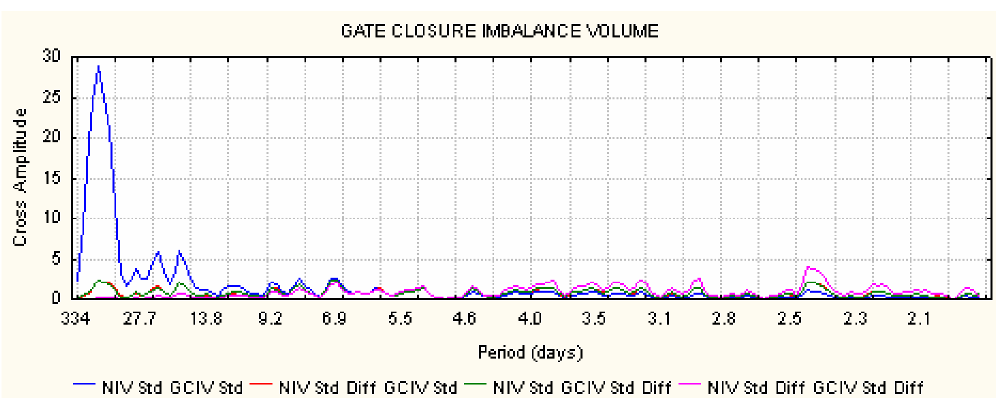
5.5(b) Cross amplitude for NIV and Submitted Bid Volume



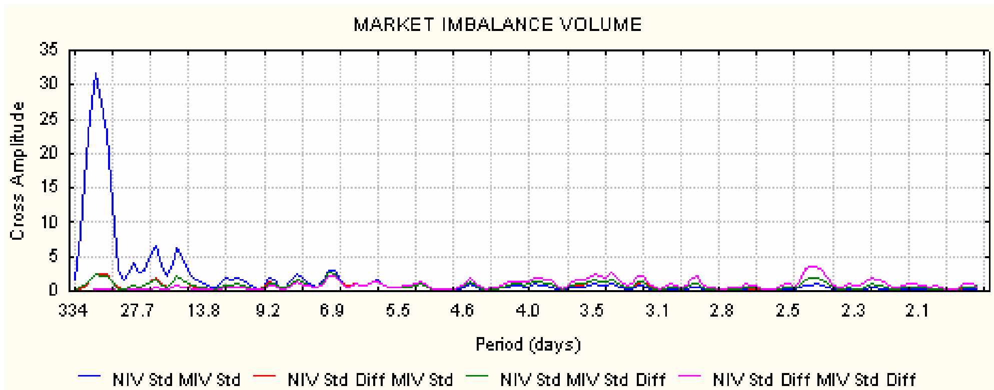
5.5 (c) Cross amplitude for NIV and Demand Forecast



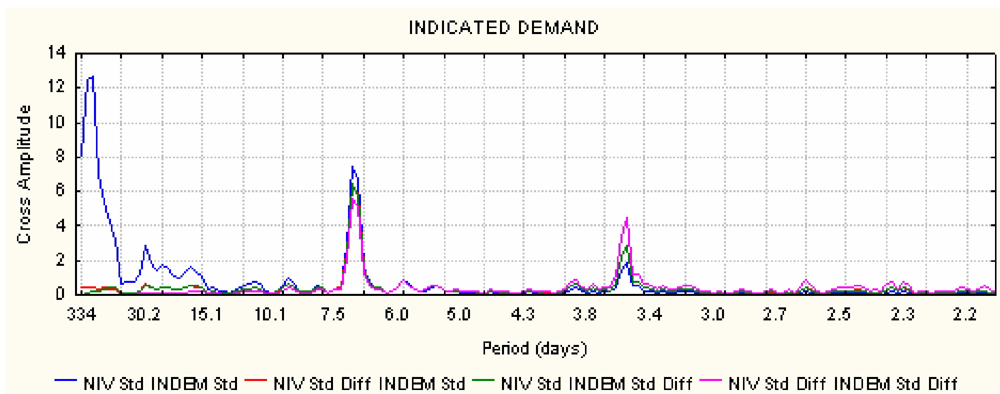
5.5(d) Cross amplitude for NIV and Capped Physical Notification



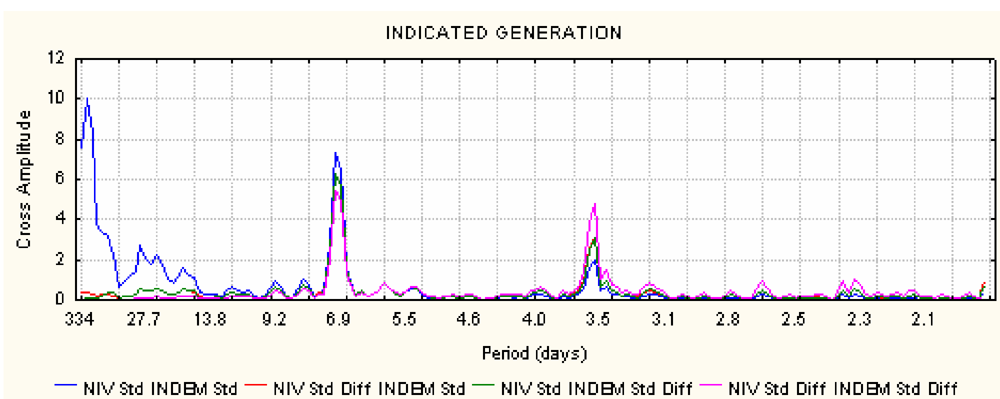
5.5 (e) Cross amplitude for NIV and Gate Closure Imbalance Volume



5.5 (f) Cross amplitude for NIV and Market Imbalance Volume



5.5 (g) Cross amplitude for NIV and Indicated Demand

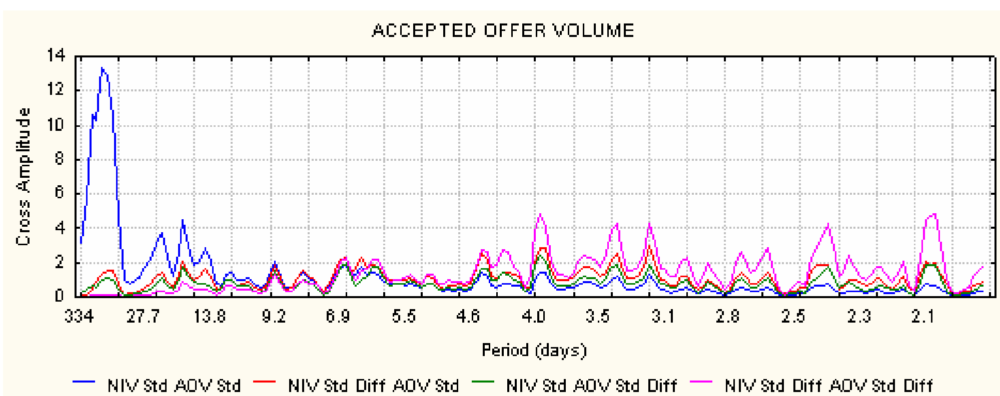


5.5 (h) Cross amplitude for NIV and Indicated Generation

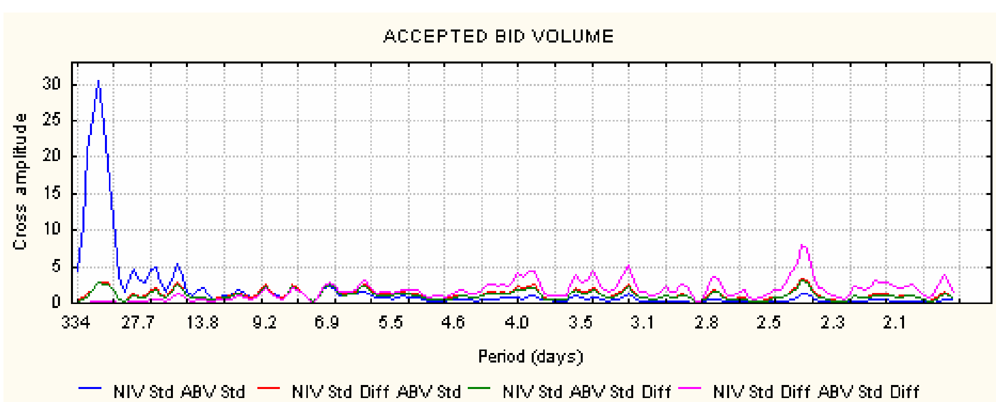
Figure 5.5 Cross Spectrum analysis results for NIV (dependent variable) and pre-gate closure BM variables (independent variables)

"Figure 5.5 shows the linear relation, measured by the cross amplitude, between NIV and the pre-gate closure variables when considering the series decomposition at different frequencies. For the pre-gate closure variables not related with the demand the graphs show a common patter. The highest cross amplitude between standardised variables is for a period of 334 days, which corresponds with the data sample length. This means that the strongest linear relation between variables is actually related with their trend and no seasonal correlation is detected. For demand related variables (demand forecast, indicated demand and CPN) it can be observed some peak values for the series corresponding to 7.2 and 3.5 days (weekly and mid week seasonality) mainly related with the strong seasonal component of these variables. The cross amplitude results between standardised and differentiated variables increase their significance as the cycle lengths decreases. This is due to the fact that changes in NIV are more correlated with changes in the BM pre-gate closure variables. These results also agree with those obtained in figure 5.1 and 5.2."

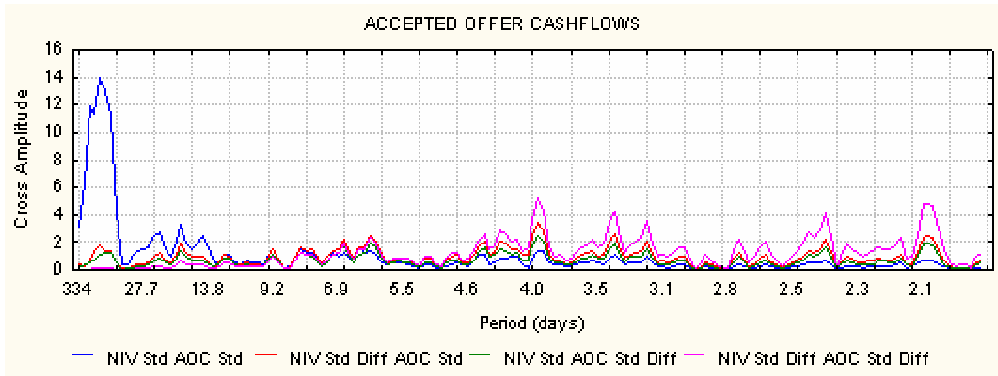
Post-gate closure variables



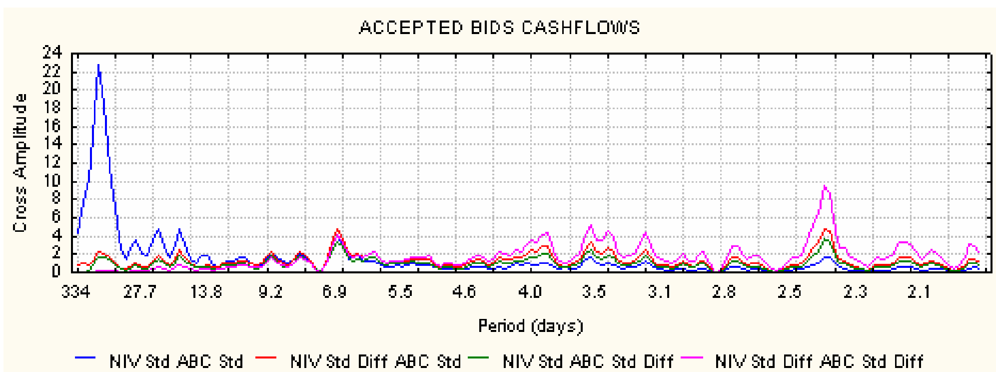
5.6 (a) Cross amplitude for NIV and Accepted Offer Volume



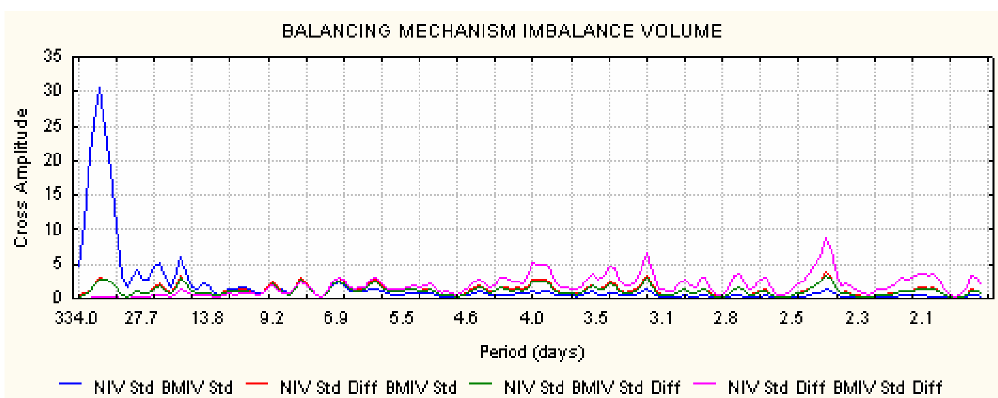
5.6 (b) Cross amplitude for NIV and Accepted Bid Volume



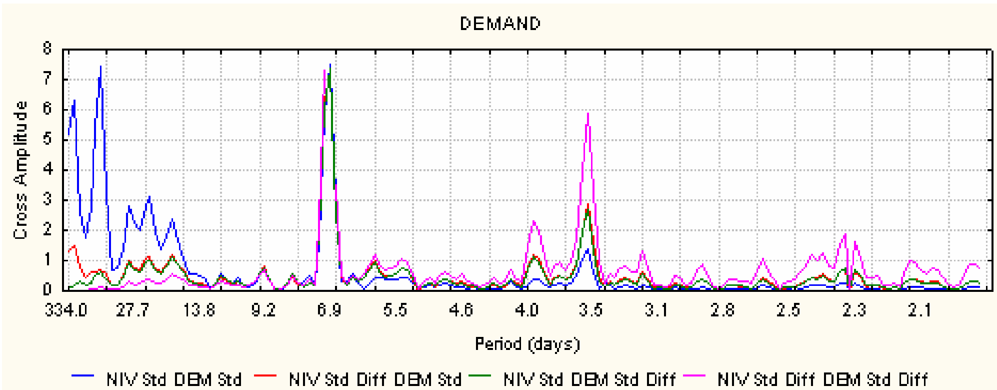
5.6 (c) Cross amplitude for NIV and Accepted Offer Cashflows



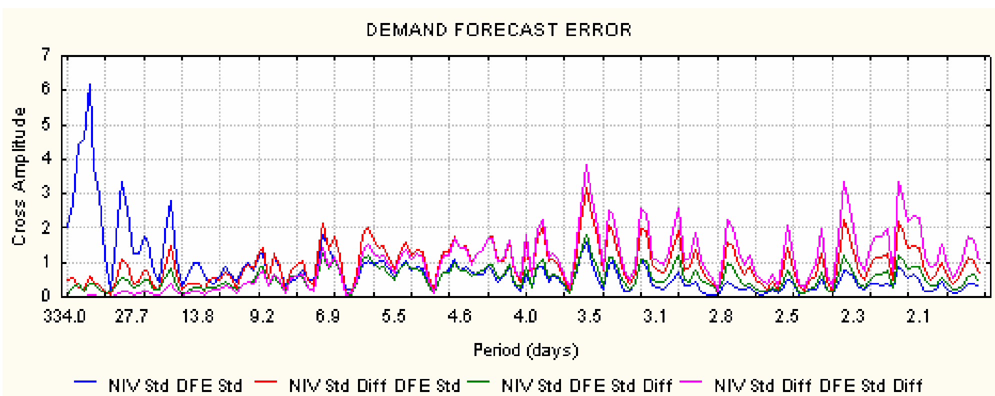
5.6 (d) Cross amplitude for NIV and Accepted Bids Cashflows



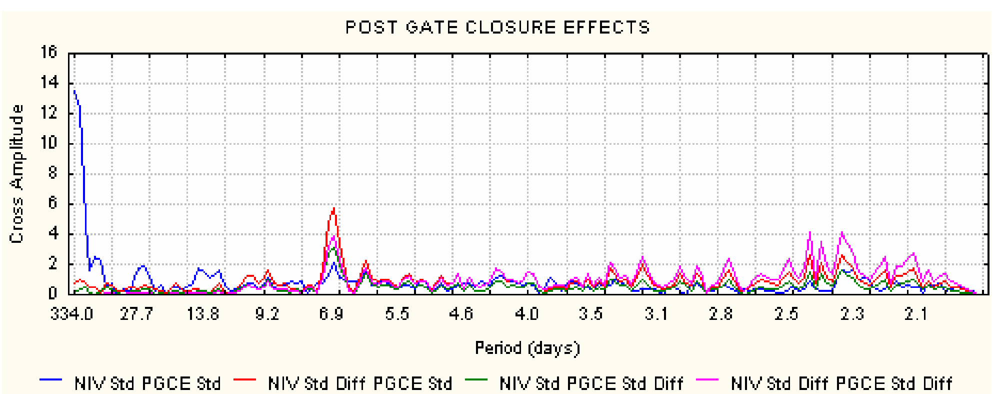
5.6 (e) Cross amplitude for NIV and Balancing Mechanism Imbalance Volume



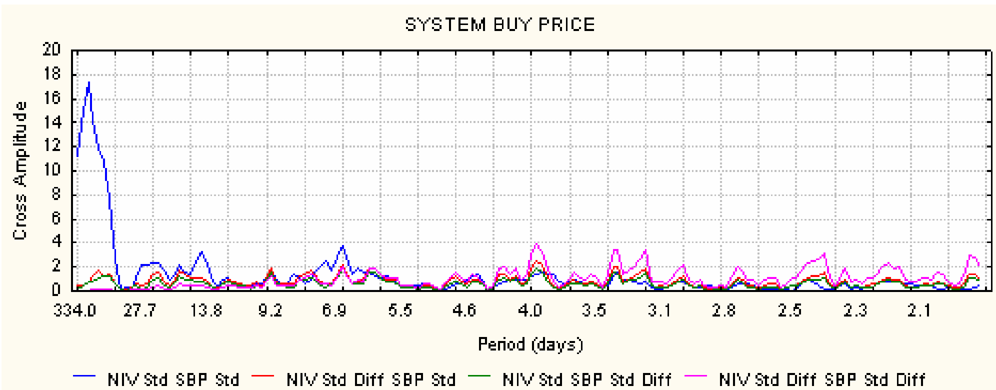
5.6 (f) Cross amplitude for NIV and Demand



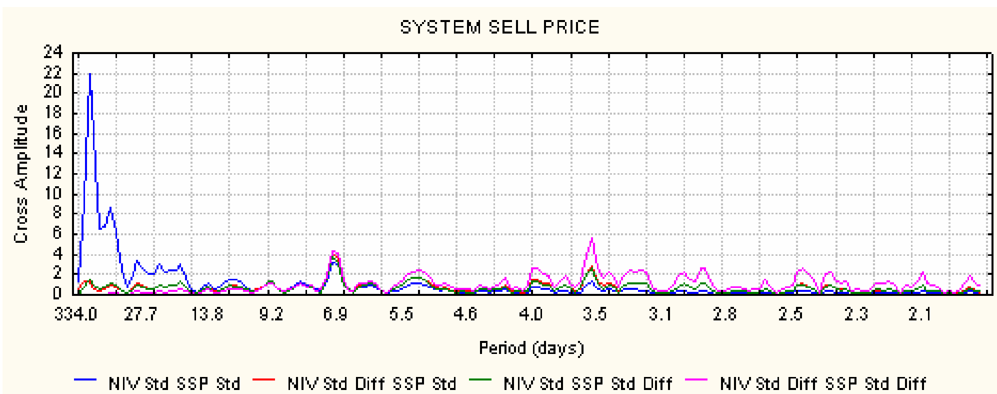
5.6 (g) Cross amplitude for NIV and Demand Forecast Errors



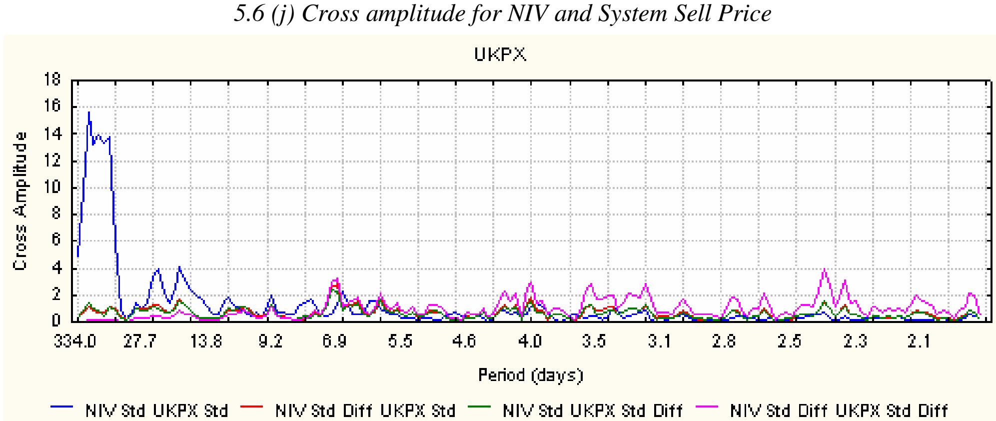
5.6 (h) Cross amplitude for NIV and Post-gate Closure Effect



5.6 (i) Cross amplitude for NIV and System Buy Price



5.6 (j) Cross amplitude for NIV and System Sell Price



5.6 (k) Cross amplitude for NIV and UKPX

Figure 5.6 Cross Spectrum analysis results for NIV (dependent variable) and post-gate closure BM variables (independent variables)

Figure 5.6 shows the linear relation, measured by the cross amplitude, between NIV and the post-gate closure variables when considering the series decomposition at different frequencies. Similarly with the pre-gate closure variables, the post-gate closure variables not related with the demand the graphs show a common patter. The peak cross amplitude between standardised variables is for a period of 334 days, which corresponds with the data sample length. This mean that the strongest linear relation between variables is actually related with their trend and no seasonal correlation is detected. Also the highest cross amplitude values are obtained for the accepted bid volume, accepted bid cashflow and the BMIV, which also were the variables showing the highest cross-correlation coefficients when considering the whole series. For the demand, it can be observed some peak values for the series corresponding to 7.2 and 3.5 days (weekly and mid week seasonality) mainly related with the demand strong seasonal component. The cross amplitude results between standardised and differentiated variables increase their significance as the cycle lengths decreases. This is due to the fact that changes in NIV are higher correlated with changes in the BM pre-gate closure variables. This behaviour is especially remarkable for the differentiated DFE variable, where high frequency (smaller cycle lengths) components present significant cross amplitude with the differentiated NIV series. Therefore, these results indicate a synchronous behaviour at high frequencies between the rate of change of these variables.

5.2.4.3 Distributed lag analysis

This technique is used to analyse relationships between variables that may involve some delay (i.e. to analyse the lagged effect on NIV of different BM quantities). Time-lagged correlations are particularly common in econometrics (Koyck, 1954, Almon, 1965, Kiviet and Dufour, 1997). In power systems analysis they can also be applied to demand analysis (Bentzen and Engsted, 2001).

One of the possible ways of explaining these time lagged relationships would be through a linear regression (Shumway and Stoffer, 2000, Kendall, 1976)

$$Y_t = \sum \beta_i X_{t-i} + \varepsilon \qquad (5.4)$$

Although equation 5.4 seems a simple linear regression, a common problem that often arises when computing the weights for the model shown above is that the values of time-adjacent values of the independent variables are highly correlated. In extreme cases, this makes the values of β impossible to compute. It is also usual for the error term to be autocorrelated which makes it a non-standard model. Furthermore, depending on the characteristics of the problem it may not be possible to control the values of the independent variable or there may even be a non-apparent feedback between X and Y.

In this way it may be easier to model the open-loop causal relationship according to a transfer function model

$$Y_t = \sum \beta(\alpha) X_{t-i} + \varepsilon \tag{5.5}$$

where each of the coefficients of the backward shift operator is expressed as a polynomial function of α and avoids the multicollinearity problem (Almon, 1965)

$$\beta(\alpha) = \alpha_0 + \alpha_1 i + \cdots + \alpha_q i^q \tag{5.6}$$

Note that, disregarding the error (ε), the regression coefficients in distributed lags analysis do not allow for an intercept in the equation. As with many econometric models, the intercept of the regression line is assumed to be zero.

Figures 5.7 and 5.8 show the results of the distributed lags analysis. The x-axis represents the different lags in daily scale and the y-axis is the corresponding *t*-statistic for the two series at different lags. The *t*-statistic assesses how significantly a coefficient differs from 0. In other words, whether the expected range of coefficients contains the value of 0 at a given level of confidence.

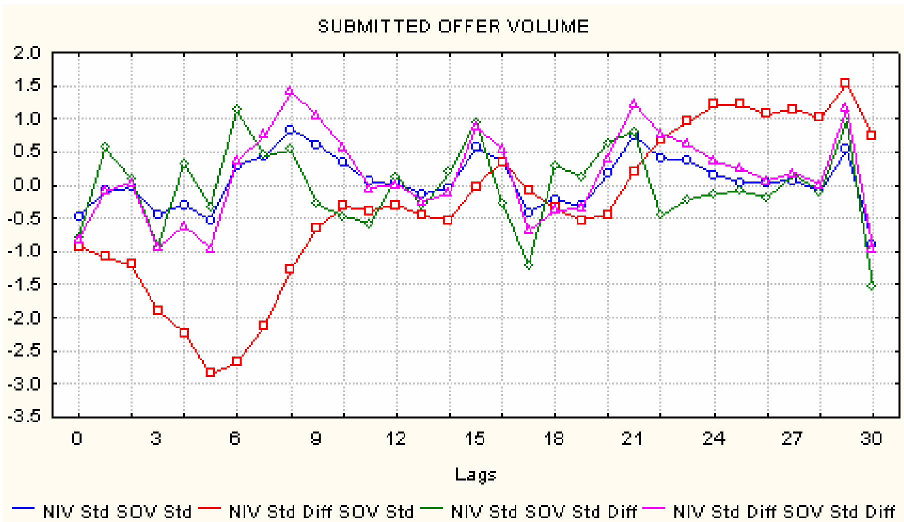
$$t - \text{statistic} = \frac{\textit{Reggresion Coefficient}}{\textit{Standard error}} \tag{5.7}$$

where the standard error is similar to the standard deviation and denotes the expected range of coefficients across multiple samples of the data. Therefore the smaller the standard error the more reliable is the value of the coefficient.

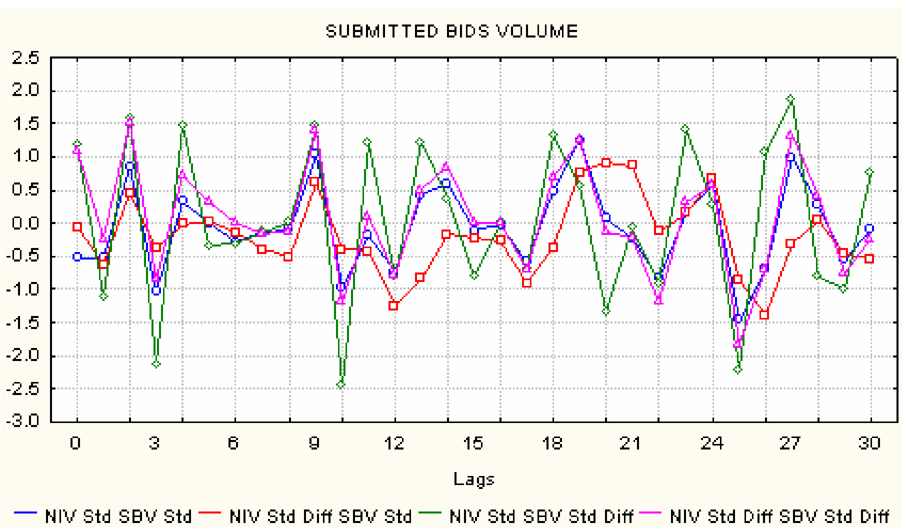
If the *t* value is greater than its critical value then the null hypothesis 0 value for the corresponding coefficient can be rejected. The *t*-critical value is obtained referring to the *t* distribution with n-1 degrees of freedom at a specified α level (significance level).

It is important to observe that the results of the distributed lags analysis should always be considered within the framework of the multiple correlation analysis. This means that the correlation (associated in this case to the t-value) of the variables at different lags is linked to the residual correlation between variables when considering the whole series.

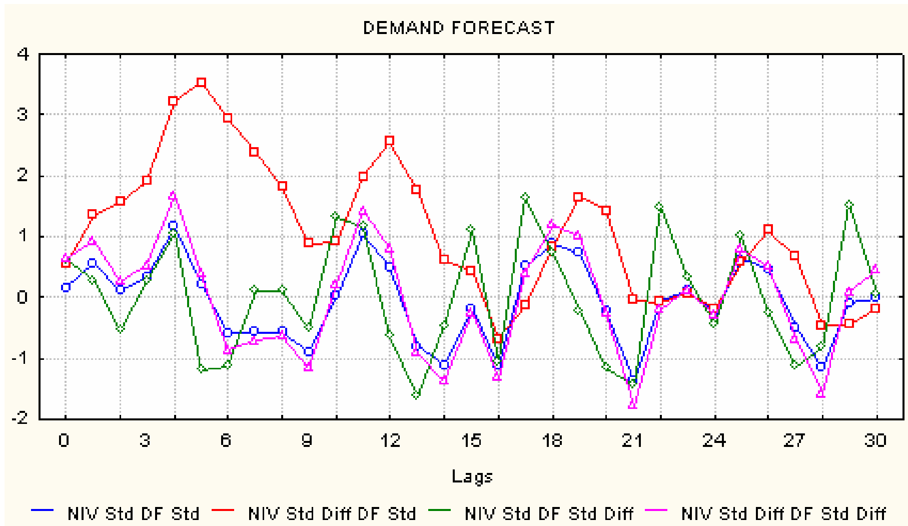
Pre-gate closure variables



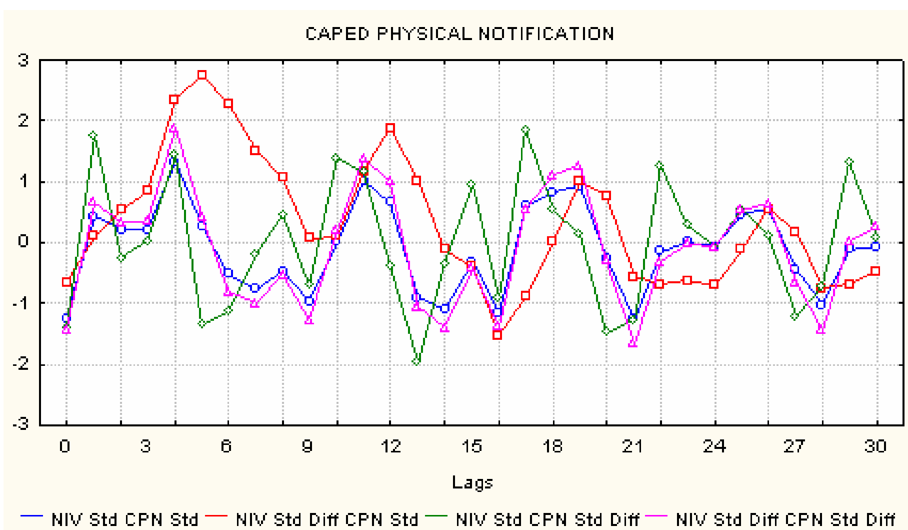
5.7 (a) Distributed lags for NIV and Submitted Offer Volume



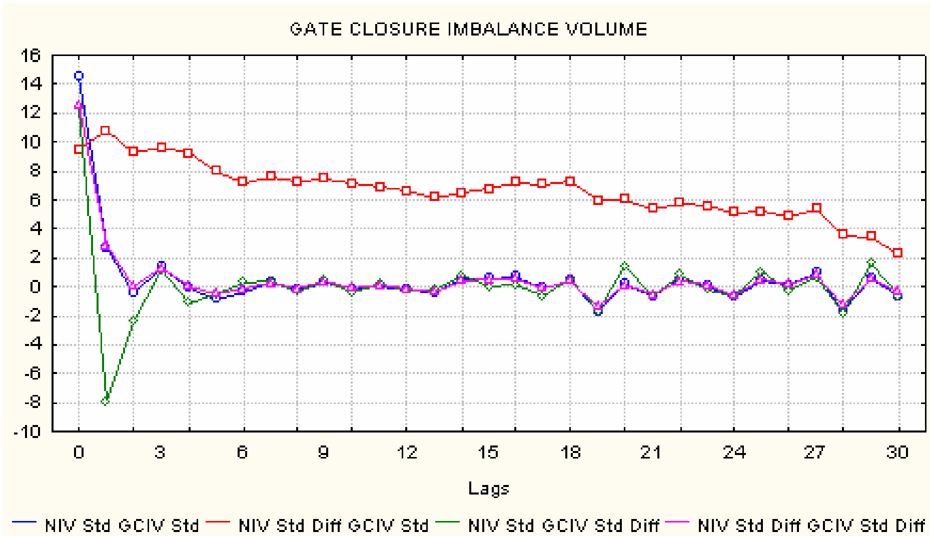
5.7(b) Distributed lags for NIV and Submitted Bid Volume



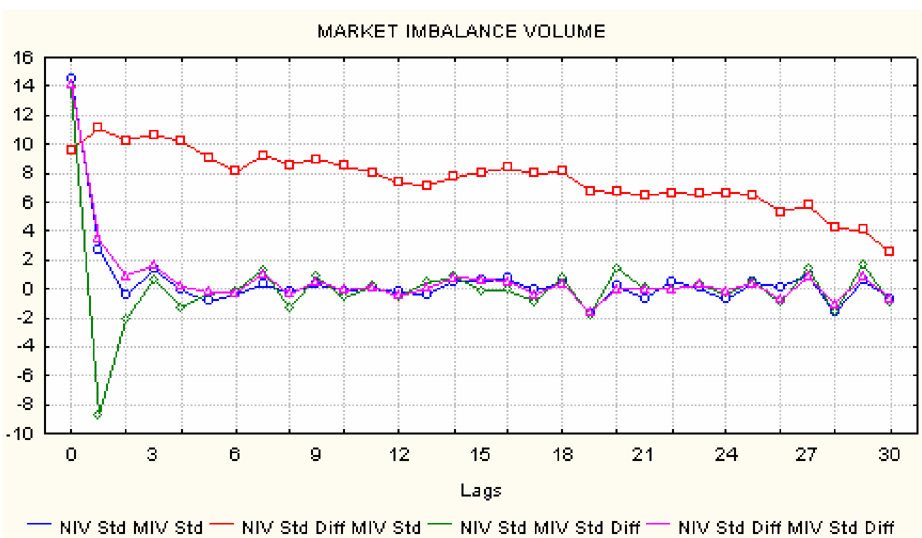
5.7 (c) Distributed lags for NIV and Demand Forecast



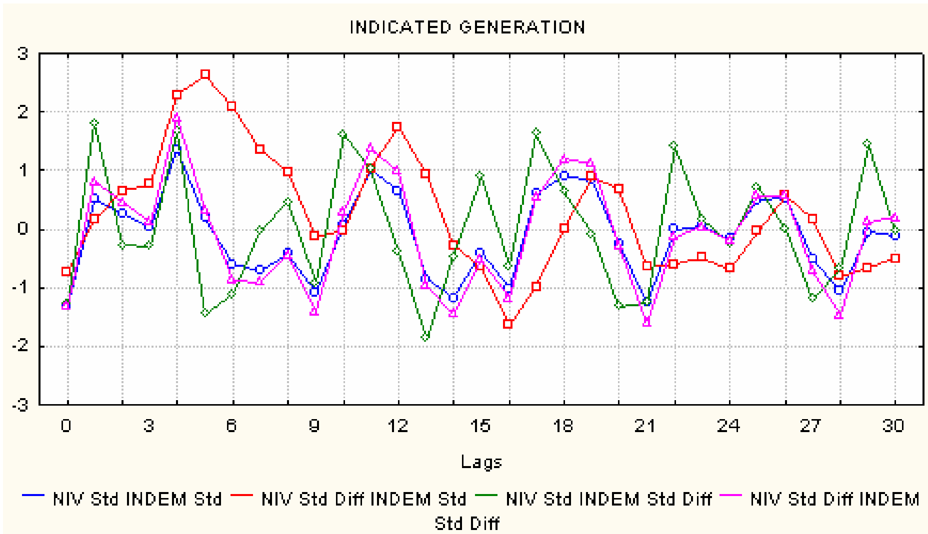
5.7(d) Distributed lags for NIV and Capped Physical Notification



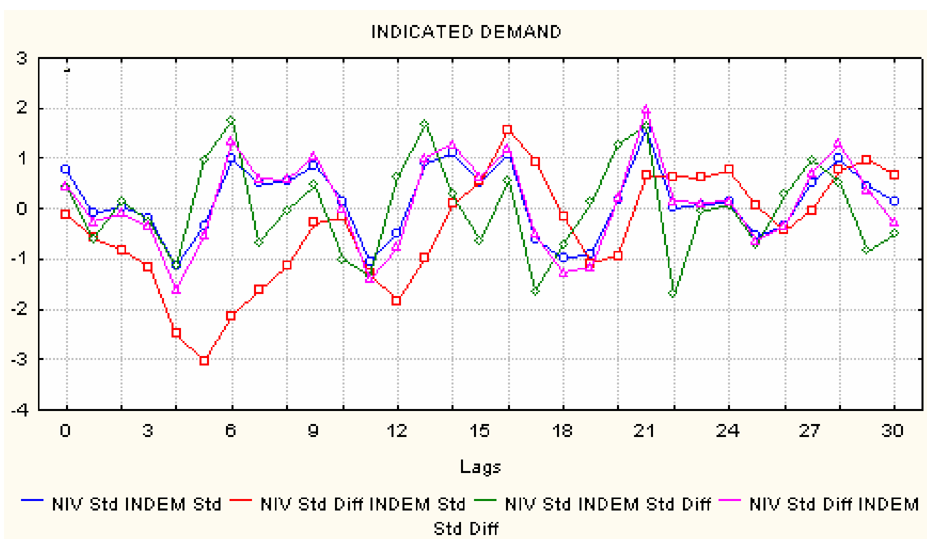
5.7 (e) Distributed lags for NIV and Gate Closure Imbalance Volume



5.7 (f) Distributed lags for NIV and Market Imbalance Volume



5.7 (g) Distributed lags for NIV and Indicated Demand



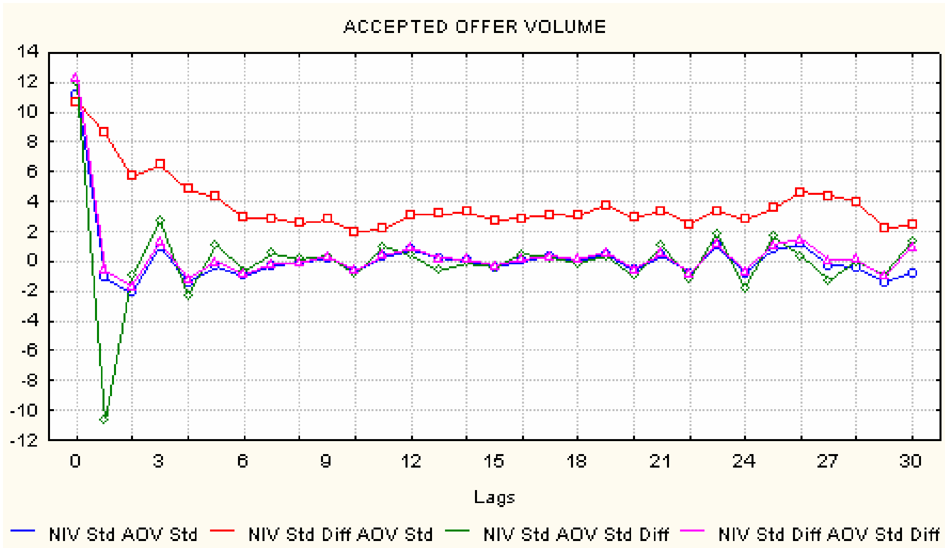
5.7 (h) Distributed lags for NIV and Indicated Generation

Figure 5.7 Distributed lags analysis results for NIV (dependent variable) and pre-gate closure BM variables (independent variables)

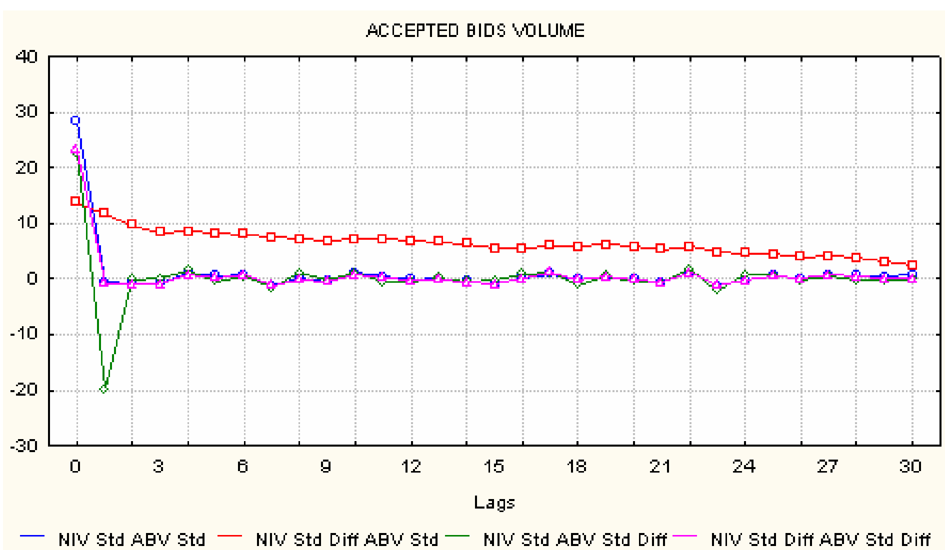
Figure 5.7 shows the results of the distributed lags analysis. These results refer to the analysis of the contribution of the different lags of the explanatory variables (BM pre-gate closure variables) to the linear relation with the independent variable (NIV). This is therefore a linked analysis with the cross-correlation analysis that will determine how much of the linear cross-correlation can be attributed to the previous values of the pre-gate closure variables. In this figure, the blue line refers to the analysis of NIV standardised and BM pre-gate closure variables standardised; the red line refers to the analysis of NIV standardised and differentiated and BM pre-gate closure variables standardised; the green line refers to the analysis of NIV standardised and BM pre-gate closure variables standardised and differentiated; the pink line refers to the analysis of both NIV and the BM pre-gate closure variables standardised and differentiated.

In Figure 5.7 it is shown that in most of the cases there is no clear significant lag that contributes to the residual linear relation between NIV and the BM pre-gate closure variables for any of the considered transformations and variables combinations. Only in the case of GCIV and MIV, which are highly correlated with NIV, the contribution at lag 0 is significantly remarkable. These results also fit the ones of the cross spectrum analysis where NIV is highly correlated with the trend (lag 0) of these variables (Figures 5.5 (e) and 5.5 (f)). No seasonal linear relation is therefore detected between NIV and the BM pre-gate closure variables.

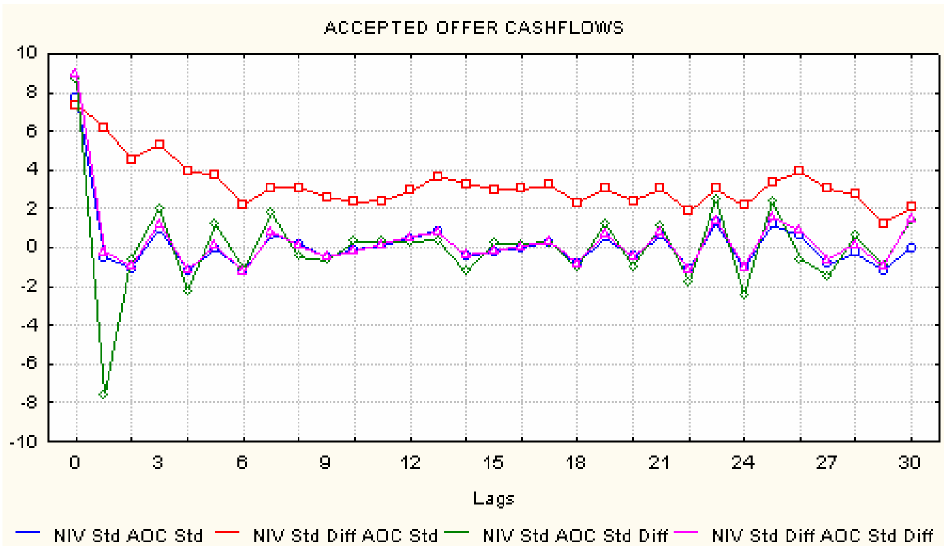
Post-gate closure variables



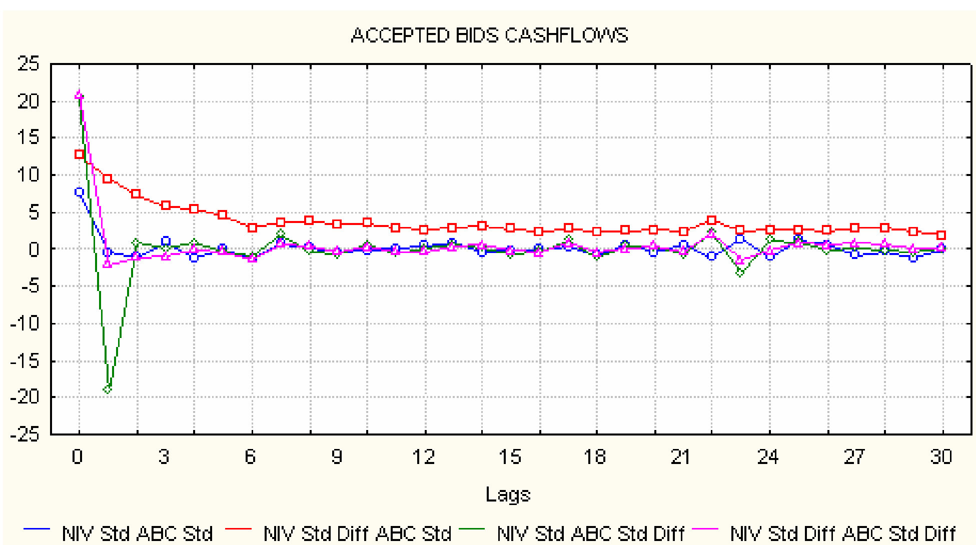
5.8(a) Distributed Lags for NIV and Accepted Offer Volume



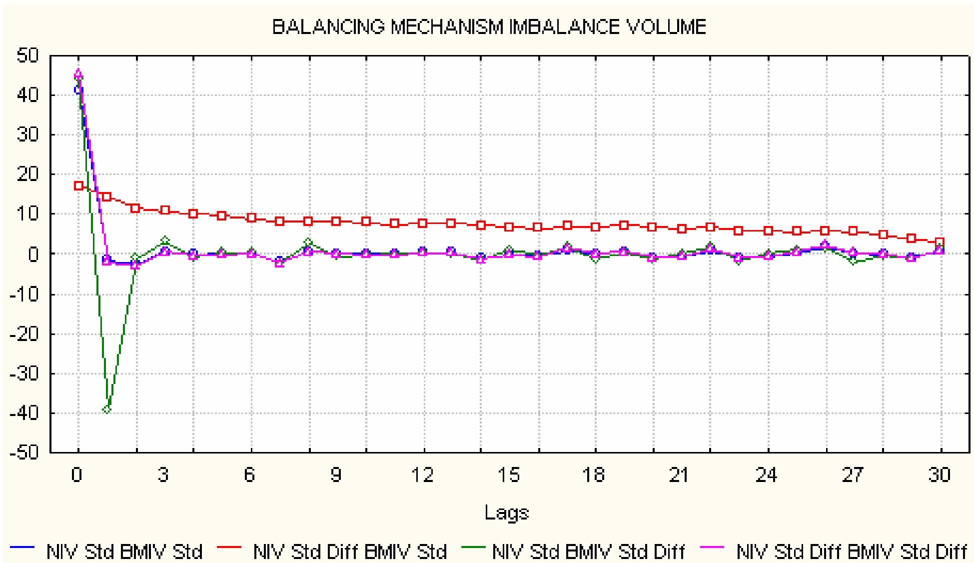
5.8(b) Distributed Lags for NIV and Accepted Bid Volume



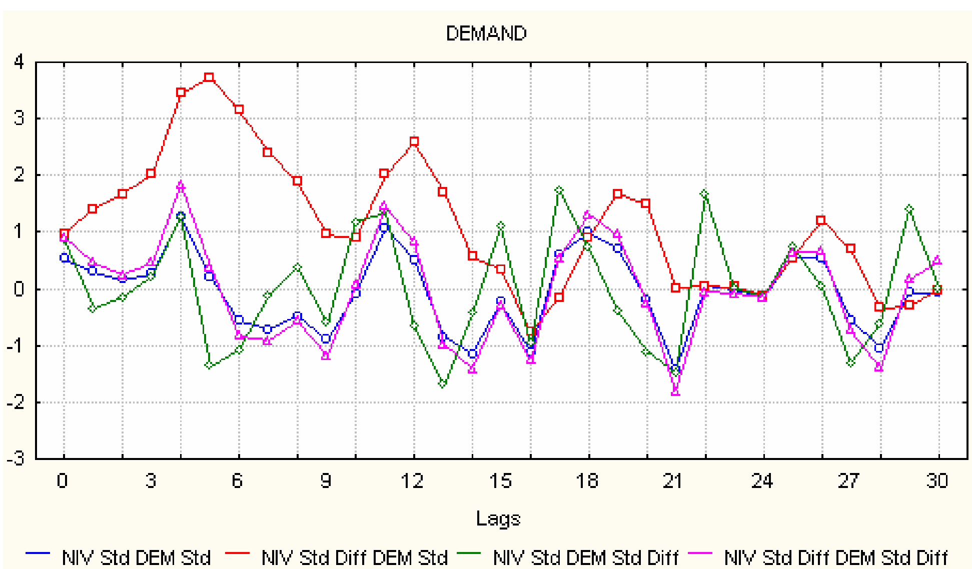
5.8(c) Distributed Lags for NIV and Accepted Offer Cashflows



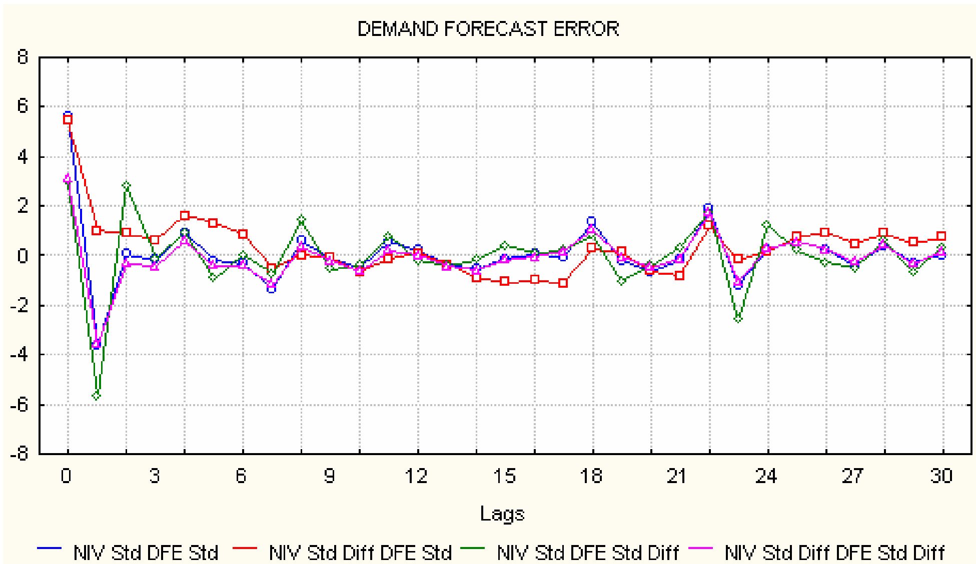
5.8(d) Distributed Lags for NIV and Accepted Bids Cashflows



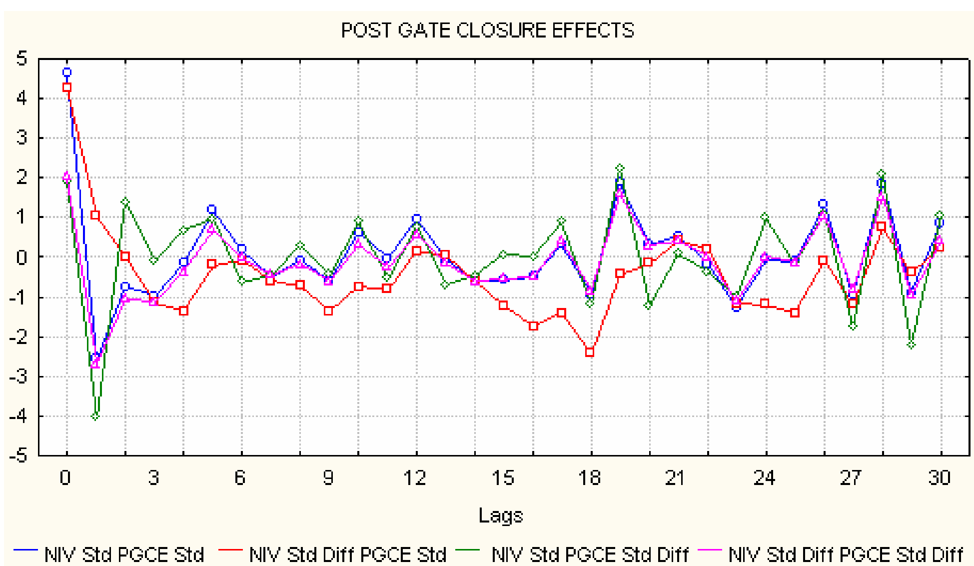
5.8(e) Distributed Lags for NIV and Balancing Mechanism Imbalance Volume



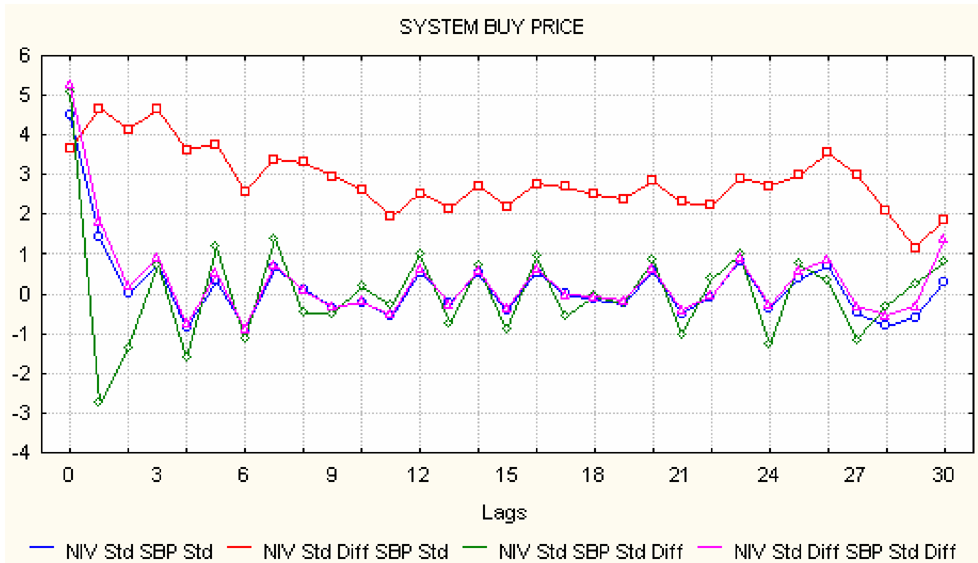
5.8(f) Distributed Lags for NIV and Demand



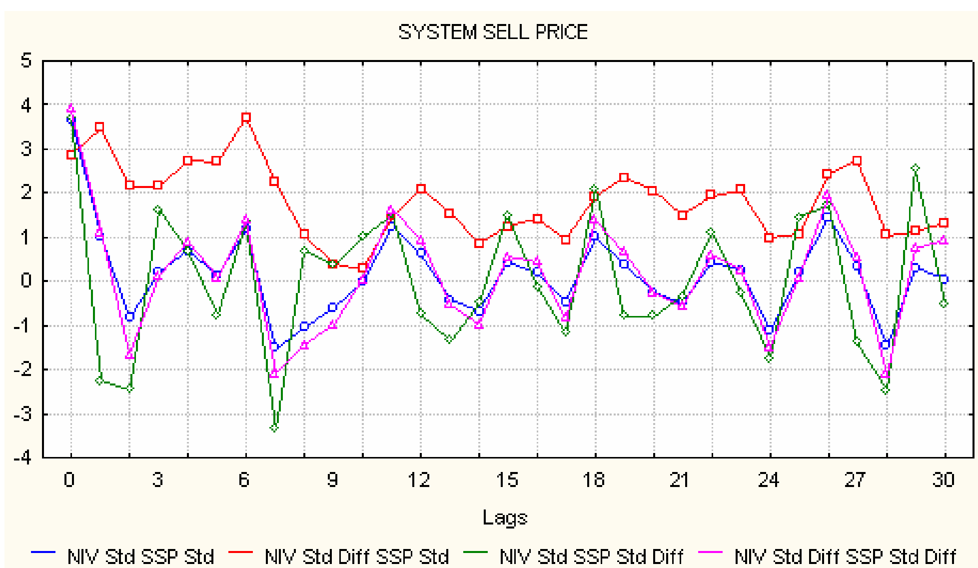
5.8(g) Distributed Lags for NIV and Demand Forecast Errors



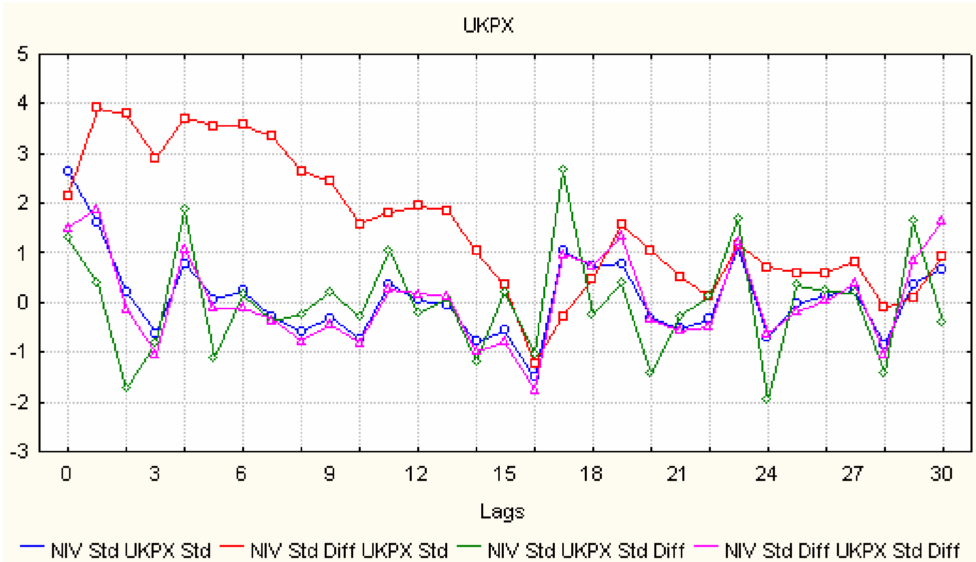
5.8(h) Distributed Lags for NIV and Post-gate Closure Effect



5.8(i) Distributed Lags for NIV and System Buy Price



5.8(j) Distributed Lags for NIV and System Sell Price



5.8(k) Distributed Lags for NIV and UKPX

Figure 5.8 Distributed Lags analysis results for NIV (dependent variable) and post-gate closure BM variables (independent variables)

Figure 5.8 shows the results of the distributed lags analysis for the post gate closure variables. These results refer to the analysis of the contribution of the different lags of the explanatory variables (BM post-gate closure variables) to the linear relation with the independent variable (NIV). This is therefore a linked analysis with the cross-correlation analysis that will determine how much of the linear cross-correlation can be attributed to the previous values of the pre-gate closure variables. In this figure, the blue line refers to the analysis of NIV standardised and BM post-gate closure variables standardised; the red line refers to the analysis of NIV standardised and differentiated and BM post-gate closure variables standardised; the green line refers to the analysis of NIV standardised and BM post-gate closure variables standardised and differentiated; the pink line refers to the analysis of both NIV and the BM post-gate closure variables standardised and differentiated.

For the variables showing a strong linear relation with NIV (i.e. ABV, ABC and BMIV) only the significance of lag 0 is remarkable. These results also fit the ones of the cross spectrum analysis where NIV is highly correlated with the trend (lag 0) of these variables. For the demand residual linear contribution (max. ρ= 0.04), there is no clear significant lag for any of the considered transformations and variables combinations. For the DFE despite the low linear relation between these variables the contribution of lags 0 and 1 is significantly remarkable. It is therefore possible to consider, as for the cross-spectrum results, the existence of a sequential behaviour of NIV and the DFE. For the analysis of the prices there is no seasonal linear relation is detected between NIV and the BM pre-gate closure variables since no lag different from 0 presents a clear significance over the rest.

5.2.4.4 Kohonen Networks

Kohonen networks or Self Organising Maps (SOM) are a widely used data mining methodology for the analysis and visualization of multidimensional data (Dillon and Niebur, 1996, Haykin, 1994, Wehenkel, 1998). It is a neural network technique that transforms complex and non-linear relationships into geometric relationships. (See section 5.3.2 for a detailed description of neural networks). SOM is a clustering tool that uses the spatial organization of the neurons to provide a two-dimensional output where existing similarities in the inputs are revealed. The topology exposed with these networks does not need to correspond to a physical arrangement but to a statistical feature of the input set.

Application areas include, for instance, image processing and speech recognition, process control, economical analysis, and diagnostics in industry and in medicine. In engineering their most common applications are identification and monitoring of complex machine states, control functions and signal mapping in telecommunications (Kohonen and Simula, 1996). More specifically in the area of power systems their applications include transformer fault diagnosis (Dillon and Niebur, 1996) as well as load forecasting (Baumann and Germond, 1993).

Figure 5.9 illustrates the Kohonen network structure where the input units (x_i) are a set of feature vectors (number of observations) in n-space (number of BM variables). The input units are fully connected to a two-dimensional grid of units usually known as the Kohonen layer. Each link between an input and a Kohonen layer node has an associated weight (w_{ij}). The net input to each neuron in the Kohonen layer is equal to the weighted sum of the inputs.

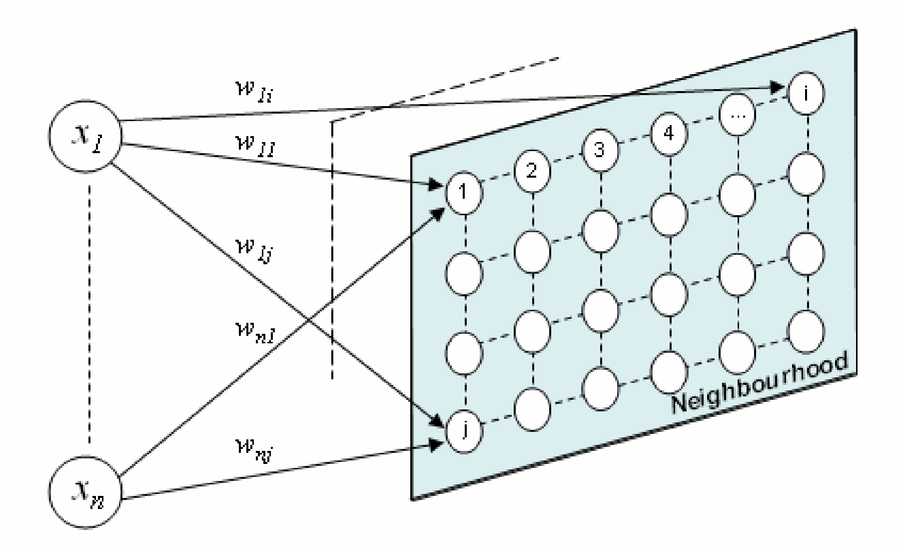


Figure 5.9 Two-dimensional Kohonen Neural network representation (connections are shown partially)

Unlike most neural networks, Kohonen networks use the Euclidean distance between input and weights as the basic operation to calculate the output for each neuron

$$Y = D_{Eucledian} = \sqrt{\sum_{i=1}^{N}(x_i - w_i)} \qquad (5.9)$$

Once the Euclidean distance is calculated for each neuron, the neuron with the smallest distance is the winner (or active neuron). The associated weight is therefore the nearest to the input vector. Only the wining neuron generates an output signal from the Kohonen layer. The learning process continues by modifying the weights of the neurons within a neighbourhood of the wining neuron. In the first iterations the extensions of the neighbourhood is approximately half of the network size but it decreases in each learning step until it reaches zero. As described in Figure 5.10, the feedback between connections is restricted to lateral connections.

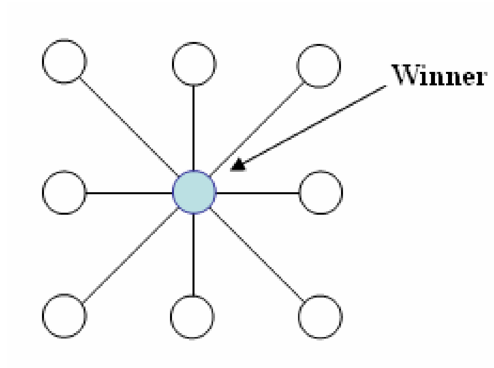


Figure 5.10 Winning neuron and its neighbourhood

After the training process, input vectors close in the input space stimulate neurons which are close to each other on the grid. Other neurons may not be stimulated by any input vector. The final clusters represented by y_i output classes are obtained from the regrouping of the neurons stimulated by the same group of input vectors.

Figures 5.11 and 5.12 represent respectively the contour maps for the pre-gate and post-gate closure variables obtained from the Kohonen Neural network cluster analysis. In each figure the graph located in the upper left hand corner corresponds to the cluster solution considering all the variables. The next graphs represent the distribution for each of the variables. The areas corresponding to high demand forecast, high NIV and low NIV values have been indicated to highlight the behaviour of the other variables under these conditions.

Pre-gate closure variables

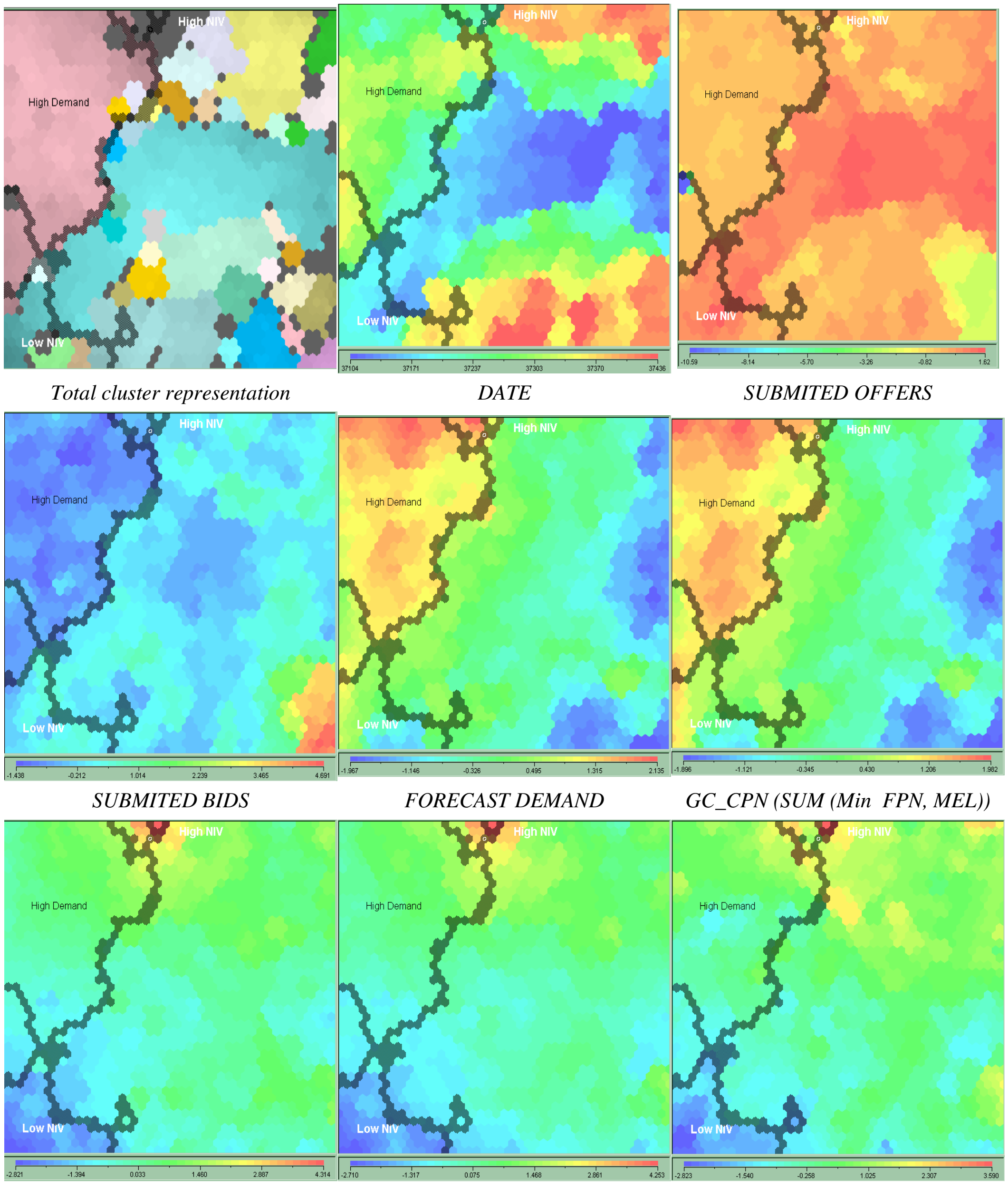
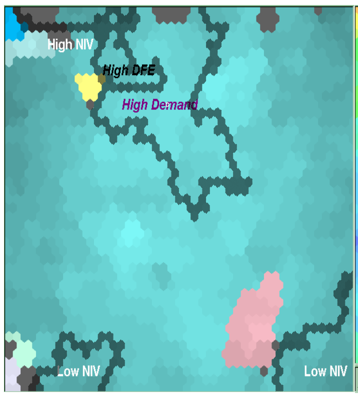
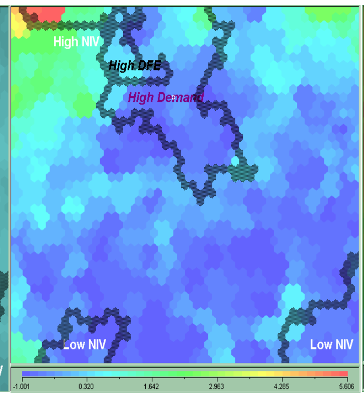


Figure 5.11 Kohonen's Maps BM Pre-gate closure variables and NIV

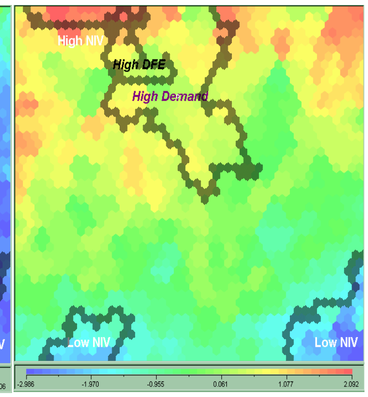
Post-gate closure variables



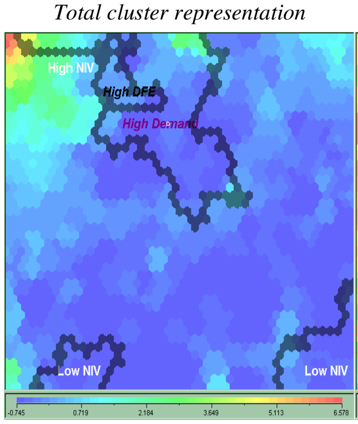
Total cluster representation



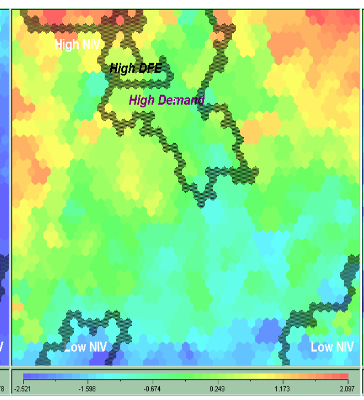
ACCEPTED OFFERS VOLUME



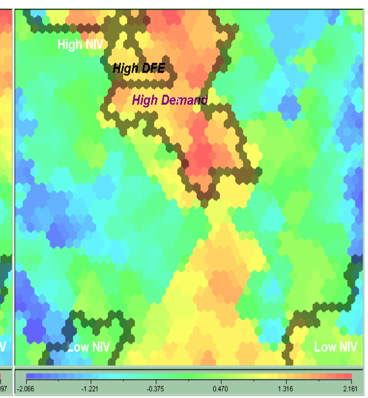
ACCEPTED BIDS VOLUME



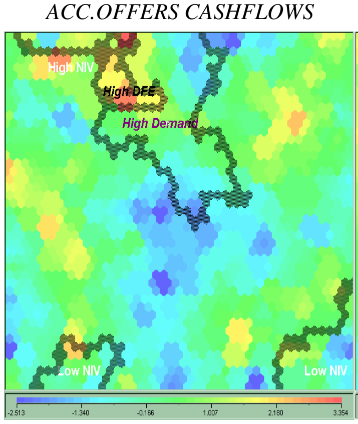
ACC.OFFERS CASHFLOWS



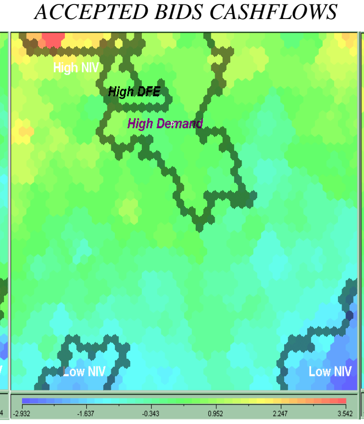
ACCEPTED BIDS CASHFLOWS



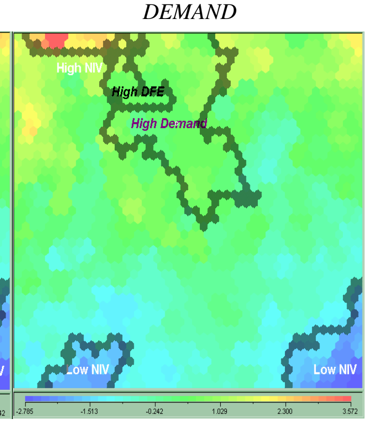
DEMAND



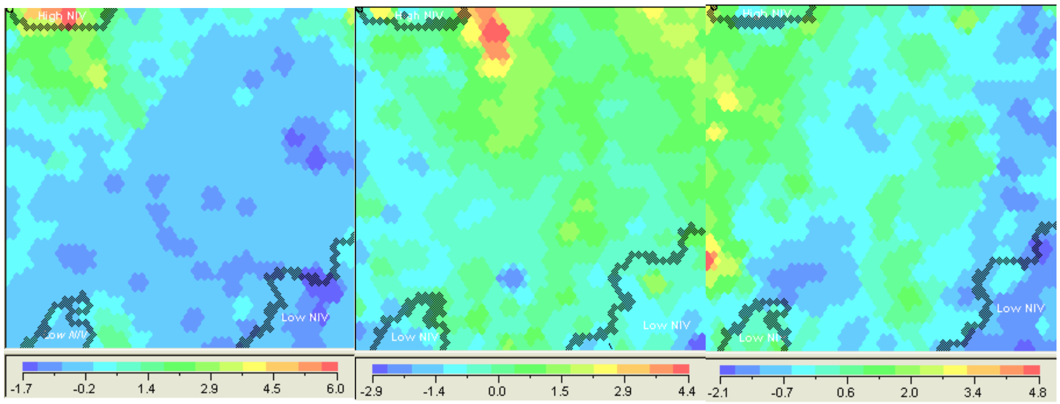
DFE



BMIV



NIV



SBP *SSP* *UKPX*

Figure 5.12 Kohonen's Maps BM Post-gate closure variables and NIV

Figures 5.11 and 12 show respectively for pre-gate and post-gate closure variables the distribution of the different variables values in the obtained cluster maps. The observation and cross-comparison of these results allow exploring the behaviour of different variables for a specific range of value of other variable(s). In this way it is possible to detect that the highest submission of bids volume usually corresponds to high demand values. Also for NIV's case large values of DFE are usually next to large DFE values. The physical relation between NIV and other market variables such as BMIV and GCIV is exposed by similar value distributions across all the clusters.

5.2.5 Conclusions

As general remarks for all the analysed variables it is important to notice that:

- Due to NIV's noisy behaviour, all the analysed relations are stronger in the case of NIV than for NIV differentiated. NIV differentiated series can be consider as the result of a filtering process for NIV's lowest frequency component. Therefore, the resulting differentiated series resumes NIV's erratic and random high frequency components and any possible linear relation with other BM variables is weaker than in the original series.
- Linear relations are only significant for the variables with a physical connection with NIV (e.g. AOV, ABV).

- Despite their strong seasonality, all variables related with or driven by the demand present low or no linear correlation with NIV.
- There is a common pattern in the cross spectrum results for the analysed series (Figures 5.5 and 5.6). For NIV standardised and BM standardised the cross amplitude decreases as the frequency increases, which means that global variables present a higher correlation when considering longer periods or global trends. However for non-demand related variables, and due to their volatile behaviour, rates of changes of NIV and BM variables are highly correlated as the frequency increases (i.e. the periods decrease).
- Pre-gate closure variables are not a good forecasting base to predict NIV. Only the physical relation between GCIV, MIV and NIV value have been confirmed throughout the obtained results of all the performed analysis (e.g. cross-correlation values of 0.84 and 0.86 for GCIV and MIV respectively).
- Post-gate closure variables seem to be better input variables for forecasting NIV. The delayed time relation found between NIV and the DFE and PGCE show that it is necessary to perform a more detailed analysis of the effect of unusual market situations (outages and demand forecast error) over the rest of the market quantities.

A more detailed analysis of the results for each of the BM variables is:

Demand Forecast, GC-CPN, INDGEN, INDDEM:

All these variables present very similar results in their interaction with NIV.

There is no significant correlation between these variables and NIV. This is also apparent from the results of the Kohonen contour maps and can be explained by observing that the highest imbalance in the system does not necessary correspond to a high demand situation.

The clusters obtained for these variables and the ones of Submitted Offer and Bid Volumes present a similar behaviour especially in the high demand areas. This can be an indicator of different bidding strategies of the participant throughout the day.

There is a strong weekly correlation (associated with the cross amplitude value at the frequency 1.61μHz, see Figures 5.5(c), (d), (g), and (f)) between these variables and NIV that is mainly due to the strong cyclical characteristic of the demand forecast and associated variables.

Market Imbalance Volume (MIV), Gate Closure Imbalance Volume (GCIV):

There is a strong conceptual relation in the market representation of these variables and NIV. GCIV is the market volume (difference between demand forecast and generation declaration) at gate closure. MIV is the total obtained from adding the SO forward trades to the GCIV, so it represents the market volume compensated by NG trading activity. NIV is the result of all the actions taken in the BM to compensate the mismatch between generation and demand and in the absence of any PGCE it is equal to the MIV. This strong relation between variables is also obtained in the analysis performed: significant linear correlation, similar clusters distribution and strong relation in temporal analysis (remarkable effect of present and adjacent value –lags 0 and 1– of these variables over NIV).

Accepted Offers and Bids Volumes:

Considering the structure of NIV (*NIV= ∑Accepted Offers +∑ Accepted bids + Interconnector trades + SO trades*) the correlation between NIV and the accepted offers is relatively low (r = 0.6) compared with the correlation with the accepted bids (r =0.9). The reason for this can be found in the fact that the market was usually long during the analysed period. The market has remained long for most of the time and this has marked the balancing mechanism activity with the acceptance of bids. The contour maps of the Kohonen clustering also show how the distribution of NIV is more similar to the accepted bids than it is to the accepted offers.

Figure 5.13 shows a detail of the offers acceptances bid acceptance and NIV for the period between 6/05/02 and 10/05/02. The x-axis represents the time and the y-axis represent the accepted offers, the accepted bids and NIV. The linear relation of the offer acceptances can be easily appreciated. The range for the offer acceptances is wider for the different NIV's value and seems to correspond more to reactions in the BM to meet voltage and frequency requirements.

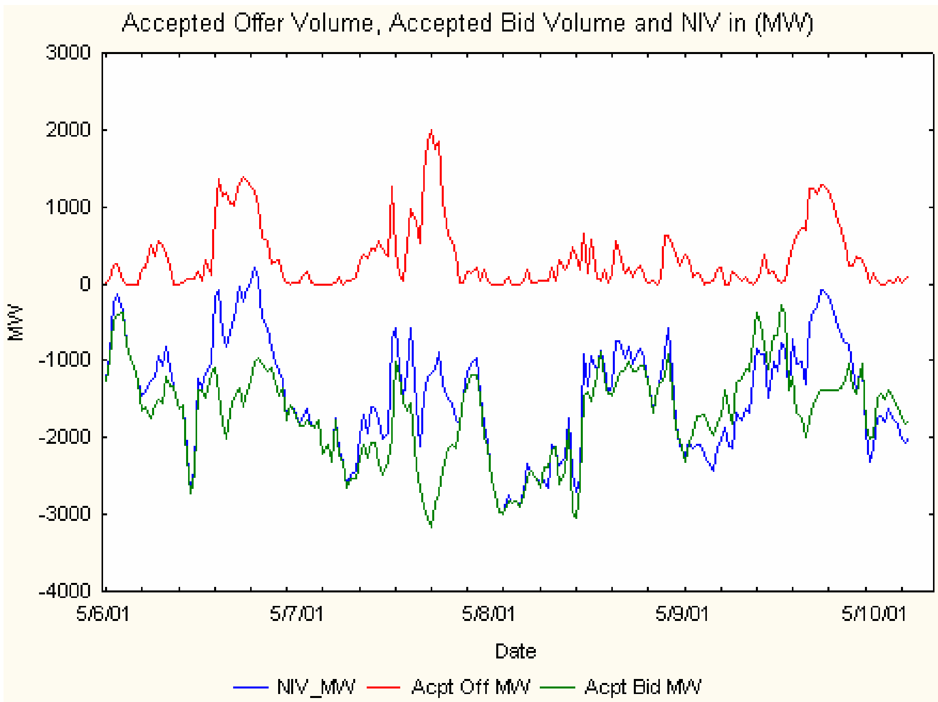


Figure 5.13 Bids and Offers Accepted Volumes and NIV's values

The time series analysis reflects a high correlation between the accepted offer volumes and NIV in weekly frequency. This can be explained as a "synchronous" behaviour between NIV and offer acceptances on a weekly basis.

<u>*Demand and Demand Forecast Error (DFE):*</u>

The relation between NIV and the demand is similar to the one obtained for the demand forecast.

The analysis results show a relation between DFE and NIV. The correlation between these two variables is very low (reaching as low as 0.07). One could therefore conclude that these two variables are disconnected. However the cross spectrum and the distributed lags analysis present consistent results about the influence of DFE on NIV. As can be seen in Figure 5.6(g), the influence of the DFE over NIV is strong for lag 0 and decreases for higher lags. This results and also the distribution of the clusters for these variables in the Kohonen contour maps indicates a *sequential influence* of these variables. Therefore, despite no long term relation between NIV and the DFE there is a short term influence (higher frequencies) between them. In the market context this can be explained from the fact the demand forecast errors are compensated by the BM actions (offer and bid acceptances).

<u>*Balancing Mechanism Imbalance Volume:*</u>

As could be expected from the definition of NIV (NIV= BMIV + SO Trades), all the results point to a very strong relation between this variable and NIV. In particular, the correlation coefficient is equal to 0.96. However this strong similarity is also a symptom of low trading activity by the system operator during the period considered. Figure 5.14 illustrates the fact that the average contribution of trading by the system operator to NIV is only 19%.

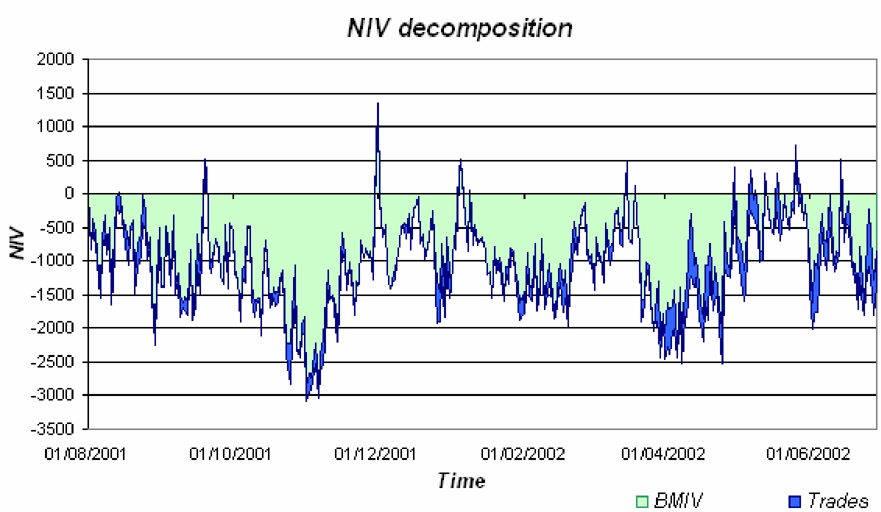


Figure 5.14 NIV's break down NIV= BMIV + Trades

Imbalance Prices (System Buy Price and System Sell Price)

These variables present very different results as can be observed in the contour Kohonen maps.

The distributed lags analysis gives consistent results for the influence of these two variables over NIV with a 0 lag for all the different periods analysed. These results, as happened with the DFE, may be a symptom of a sequential relation between these variables and NIV.

However it may occur because of a non linear interaction between the imbalance prices and NIV, since NIV reflects the balancing activity and imbalance price are a weighted average of offers and bids acceptances. Figure 5.15 shows the scatter plot of NIV and imbalance prices for different lengths of the market. The x-axis represents the SBP, the y-axis represents SSP and the z-axis represents NIV.

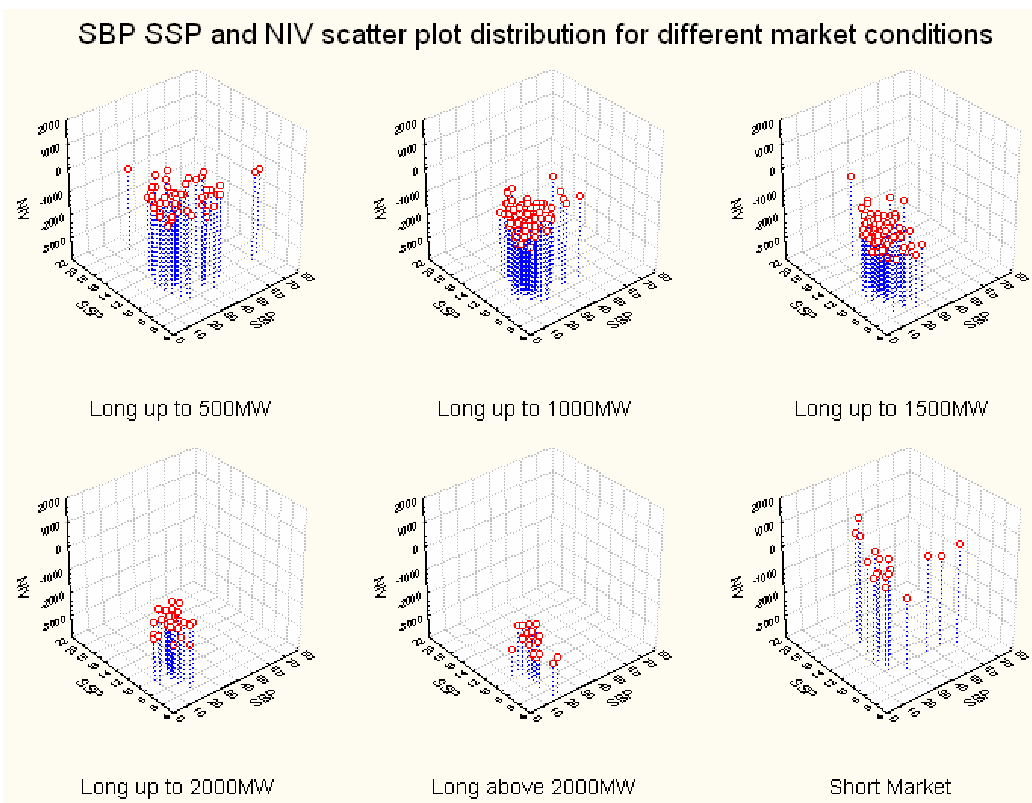


Figure 5.15 Scatter plots: x: SBP(£/MWh), y: SSP(£/MWh) and z: NIV(MW)

When the length of the market increases the SBP decreases; SSP follows a similar pattern but larger lengths are required to create this decreasing trend. Short market conditions increase both imbalance prices and their spread. Short market conditions present a higher imbalance risk (uncertainty and price) for the different market participants.

5.3 Multidimensional NIV forecasting

5.3.1 Objectives

The results obtained in the previous analysis lead to expand NIV's analysis to a multidimensional domain in order to forecast NIV in a more effective way.

The main objective of this analysis is to forecast NIV in different time frames. This forecast is based on the relations between the past or seen values of the balancing mechanism variables and the future or unseen values of NIV. However the relations linking the past and future values of these variables are neither simple nor linear. Neural networks provide a powerful tool to uncover these complex associations while maintaining the time structure of the analysed series.

5.3.2 Modelling techniques

5.3.2.1 Neural Networks overview

Neural Network (NN) techniques have been enhanced by improvements in computational performance and in the flexibility of the software used for their implementation (Veelenturf, 1995, Kolarik and Rudorfer, 2004, Kim, 2004, Zoran Vojinovic, 2001, Wehenkel, 1998). Needless to say, not every problem can be solved by a neural network. Therefore, an important requirement for their use is to know (or at least strongly suspect) that there is a relationship between the proposed known inputs and unknown outputs. This relationship may be noisy but it must exist. In general, when using NN, the exact nature of the relationship between inputs and outputs is unknown.

The successful application and performance is generally attributed to NN main characteristics:

- NN are powerful analytical techniques. They can model complicated non-linear relations keeping in check the dimensionality problem when dealing with a large number of variables.
- NN are adaptable techniques. They have a built-in capability to adapt their interconnections weights to changes in conditions. In particular a NN trained to operate in a specific environment can be easily retrained to deal with changes in its environment.
- NN are relatively easy to use. NN learn from example transforming a trained network into an "expert" on the input information. They are capable of producing outputs for conditions not encountered during the learning process.

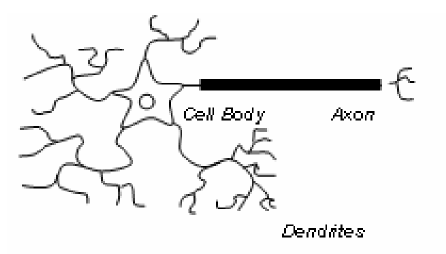
Neural network techniques are inspired by the biological learning process of the brain neurons. They are network structures consisting of a number of nodes connected through directional links. Each node (neuron) represents a processing unit and the links between them relate the causal relation between connected nodes. All the nodes are adaptive which means that their output depend on flexible parameters associated with them.

The basic unit of a NN is the artificial neuron. The model of the artificial neuron described in Figure 5.16 includes the basic elements:

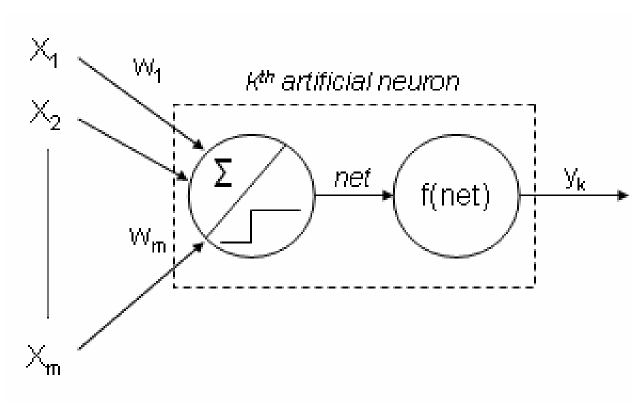
- A group of connecting links. Each of the neurons of the network receives a number of inputs that can proceed either from original data, or from the output of other neurons in the network. Each input comes via a connection that has a strength (or weight) w_{ki}. The first index refers to the specific neuron and the second one to the input of the synapse from where it comes from.
- An adder that sums the input signals x_i multiplied by their corresponding weights w_{ki}

- A single threshold value. The sum of the weighted inputs is formed, and the threshold subtracted, to compose the activation of the neuron.
- An activation function. The activation signal is passed through the neuron transfer function to produce the corresponding output. Several forms of activation functions can be used (Kantardzic, 2002, Wehenkel, 1998). Table 5.4 gives some of the most commonly used.

There are three main kinds of neurons defined by their position in the network and these are: input neurons, hidden neurons and output neurons.



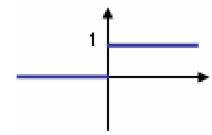
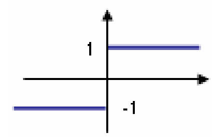
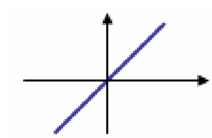
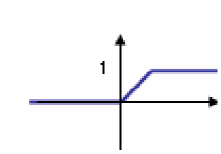
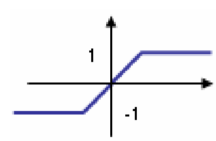
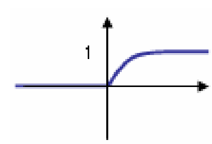
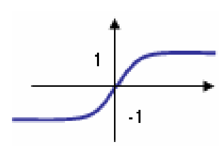
Simplified configuration of an organic neuron



Artificial Neuron

Figure 5.16 Model of an artificial neuron

Table 5.4 Neurons activation function

ACTIVATION FUNCTION	INPUT/OUTPUT RELATION	GRAPH
Hard Limit	$y = \begin{cases} 1 & if \quad net \geq 0 \\ 0 & if \quad net < 0 \end{cases}$	
Symmetrical Hard Limit	$y = \begin{cases} 1 & if \quad net \geq 0 \\ -1 & if \quad net < 0 \end{cases}$	
Linear	$y = net$	
Saturating Linear	$y = \begin{cases} 1 & if \quad net > 1 \\ net & if \quad 0 \leq net \leq 1 \\ 0 & if \quad net < 0 \end{cases}$	
Symmetric Saturating Linear	$y = \begin{cases} 1 & if \quad net > 1 \\ net & if \quad 0 \leq net \leq 1 \\ -1 & if \quad net < 0 \end{cases}$	
Log-Sigmoid	$y = \dfrac{1}{1 + e^{-net}}$	
Hyperbolic Tangent Sigmoid	$y = \dfrac{e^{net} - e^{-net}}{e^{net} + e^{-net}}$	

5.3.2.2 The Neural network learning process

One of the most significant properties of a NN is its capability to learn from its environment and to improve its performance through the learning process (Wehenkel, 1998, Azoff, 1994, Sarle, 1997, Bishop, 1995). The learning process can be defined as the process by which the network's free parameters (i.e. weights and thresholds) are adapted through a simulation process so as to minimize the prediction error made by the network. In this way, the historical cases are used to fit the model represented by the network. The error of the network for a particular configuration of its parameters is determined by running the historical cases and comparing the output given by the network with the actual outputs. The differences between real and computed outputs are combined together using an error function to summarise the error over the entire training set. In this analysis the applied error functions are the mean absolute error and the root mean square error (equations 4.22 and 4.23).

In linear models it is possible to determine the model configuration that minimises the error. However, due to their non linear characteristics, NNs can be adjusted to minimize their error but it is impossible to determine if this is the global minimum (Veelenturf, 1995, StatSoft, 2004).

The objective of the network learning can also be defined using the concept of the error surface (StatSoft, 2004). The error surface is formed with the N free parameters of the network and the network error. Therefore the error surface is N+1 dimensional. The network training is an exploration of this surface with the ideal objective of finding its lowest point. Since it is impossible to analytically determine where the global minimum is, the training algorithms start from an initial configuration of weights and thresholds (a random point in the error surface). Then, the gradient of the surface is calculated and used to make a downhill move while incrementally seeking for a local minimum. This process is repeated at each point until the algorithm stops in a low point that is either the global or a local minimum.

The different types of learning algorithms are determined by the way the free parameters change. The best know example of neural network training algorithm is *back propagation*. Other second order algorithms are *conjugate gradient descent*, *quasi-Newton* and *Levenberg-Marquat*.

Back propagation algorithm

The basic idea of this algorithm is to calculate the gradient vector of the error surface in a layer by layer function, starting with weights in the output layer and finishing with the ones in the first layer of hidden neurons.

To express the general formulation for this algorithm let us consider a feed-forward structure (see section 5.3.2.3), where the neurons are ordered in sequential order 1 to *K*. The net input of the neuron *j* is n_j

$$n_j(z) = \sum_{i=1,j-1} w_{i,j} x_i(z) \quad (5.10)$$

Where $w_{i,j}$ is the weight for the connection between neurons *i* to *j,* and $x_i(z)$ the output of neuron *i* for the object *z*. Since each neuron *j* has an associated activation function the output of neuron *j* is

$$x_j(z) = f_j(n_j(z)) \quad (5.11)$$

In this way the algorithm progresses iteratively through a number of passes. In each of them the learning cases are each processed through the network and real and computed outputs are compared and the error function is calculated. This error together with the error surface gradient is used to adjust the weights. The general error function associated with the learning data set LS is

$$ERR(w_{i,j}, LS) = \sum_{z \in LS} h(\mathbf{x}(z), \mathbf{y}(z)) \quad (5.12)$$

Where h(.) is a differentiable error function for the neuron output vector $\mathbf{x}(z)$ and the real output $\mathbf{y}(z)$. The mean absolute error and the root mean square error are examples of this error function.

The components of the gradient vector of the error are calculated as follows

$$\frac{\partial ERR(w_{i,j}, LS)}{\partial w_{i,j}} = \sum_{z \in LS} \sum_{k=1,k} \frac{\partial h(\mathbf{x}(z), \mathbf{y}(z))}{\partial x_k} \frac{\partial x_k}{\partial w_{i,j}} \quad (5.13)$$

In this case the partial derivatives $\frac{\partial x_k}{\partial w_{i,j}}$ are back propagated. In this way, the error of the lower order neurons is calculated from the error in the higher order neurons according to the following equation

$$\frac{\partial x_k}{\partial w_{i,j}} = x_x \delta_j \quad (5.14)$$

Where δ_j is obtained using the following backward recursion:

$$\delta_j = \begin{cases} 0 & if \quad j > k \\ f_j'(n_j) & if \quad j = k \\ f_j'(n_j) \sum_{p=j+1,k} w_{j,p}\delta_p & if \quad j < k \end{cases} \tag{5.15}$$

The proof of this equations is omitted but the interested reader can refer to (Haykin, 1994, Bishop, 1995) and to (Wehenkel, 1998, Veelenturf, 1995) for explanatory examples. Since the calculated gradient vector points in the direction of the steepest descent on the error surface, by moving along this line a distance proportional to the learning rate (Haykin, 1994, StatSoft, 2004) the error is decreased.

Figure 5.17 shows, for a feed-forward network, the general network computation structure and the information flow in the back propagation algorithm.

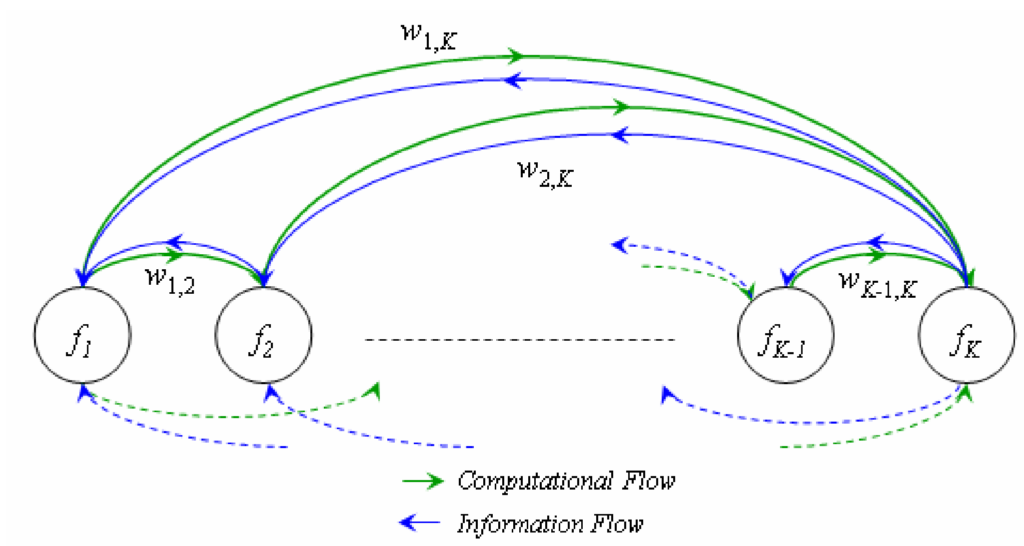


Figure 5.17 Computational and information flow in a back propagated training algorithm

Conjugate gradient descent and quasi-Newton algorithms

Both of these algorithms, as well as the back propagation, are included in the line search algorithm (White, 1992, Bishop, 1995). The basic principle of their behaviour is first to identify a direction on the error surface, then project a line in that direction, locate the minimum on that line, move to that point and repeat. Different approaches to select the appropriate direction result in the different algorithms.

As explained before, in the back propagation algorithm the line of direction is the steepest descent. In the gradient descent algorithm the idea is to select conjugate directions to avoid possible interferences (StatSoft, 2004). This means that after the algorithm has found an initial appropriate direction, this direction must stay minimized. In this way and depending of the shape of its vicinity, the minimum is reached in far fewer steps than would be the case using the method of steepest descent.

The quasi-Newton training algorithm does not need the calculation of second derivatives (StatSoft, 2004, White, 1992). It directly calculates the Newton direction which is exactly the direction pointing towards the minimum. This algorithm requires more computation and more memory requirements per iteration than the conjugate gradient methods, but it generally converges in fewer iterations.

Levenberg-Marquardt algorithm

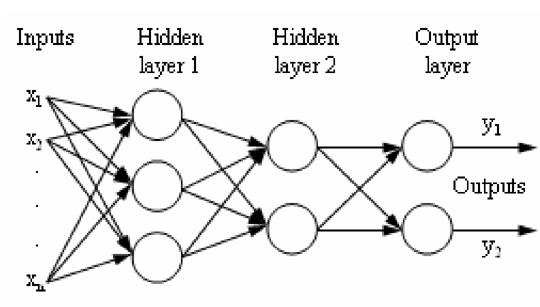
This is a model-trust region algorithm. In this case the minimum is not assumed to be in a specific direction but is deemed to have a simple shape that allows direct access.

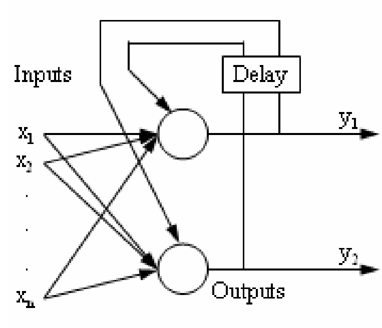
This algorithm is extensively described in (Hagan and Menhaj, 1994) and is usually faster than the ones presented above. However it can only be used in networks with a single output neuron. Moreover, its memory requirements are proportional to the square of the number of weights. Therefore, this algorithm is discarded from this analysis since it only performs well with small networks.

5.3.2.3 Neural networks architectures

The architecture of an artificial neural network is defined by the characteristics of its nodes and the way the different neurons are connected. Typically the specification of a NN consists of the number of inputs, the number of outputs, the total number of nodes that are equal to the total processing elements of the entire network, and their organization and interconnections.

Depending on the way the neurons are interconnected the networks can be classified into feed-forward and recurrent. A feed-forward network propagates the processing from the input side to the output without any loops or feedback. In this networks there are no connections between nodes in the same layer; the output of a node in each layer is always the input of the nodes in the following layer. A recurrent network contains feedback links that creates circular paths. Figure 5.18 gives an example of both types of networks.





5.18 (a) Feedforward network *5.18 (b) Recurrent network*

5.18 Categories of neural networks interconnections

One important characteristic of NIV forecasting is the structure of the time series of both the input variables and the forecasted output. This transforms the problem of forecasting NIV into a specialized form of regression. As such, it can be tackled by any structure of neural network suitable for regression purposes, providing that the data set is suitably pre-processed into the correct form. Choosing the optimal NN structure is thus an important task. The architectures that have been used in this analysis are (Bishop, 1995, Haykin, 1994, Sarle, 1997, Han and Kamber, 2001, White, 1992, StatSoft, 2004):

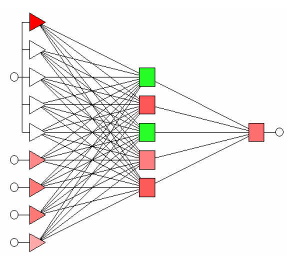
- **Linear network (LN):** This is the simplest of all the possible networks. The network has no hidden layers and a linear output activation function. When computing the network, it effectively multiplies the input by the weights matrix then adds the bias vector.

- **Multilayer perceptron (MLP):** This is one of the most popular network architectures. The units are layered in a feedforward topology. The network has a simple interpretation as a form of input-output model, where the number of input and output neurons is determined by the problem. The weights and thresholds are the free parameters of the model. Such networks can model functions of any complexity; the number of layers and the number of units in each layer determines the complexity of the function.

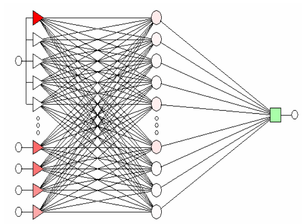
- **Radial Basis Function (RBF):** These networks are characterized by one or more layers of hidden units. The activation function for each of the units is defined by a sigmoid which allows them to model non-linear functions even with only one layer of hidden units. The output is obtained as a linear function of the hidden units' response. These networks can be trained very quickly.
- **Probabilistic Neural Networks (PNN):** These networks have been extensively used for classification problems where each output gives the probability that the input is member of a particular class. However a similar approach can be used in regression and forecasting problems considering the output as the expected value for the model given certain input conditions. They are defined by at least three layers: input, radial, and output layers. The greatest disadvantage is the network size since each of them contains the entire set of training cases. These networks are therefore space-consuming and slow to execute.
- **Generalised Regression Networks (GRNN):** They are similar to the Probabilistic Neural Networks but they only perform the regression task. These networks are defined by a first hidden layer that contains the radial units. A second hidden layer contains units that help estimate the weighted average. A GRNN trains almost instantly but tends to be large and slow.

Figure 5.19 shows a representation of these different architectures. In this figure the shape of the neurons denotes their characteristics. Triangular neurons pointing to the right indicate input neurons. These neurons perform no processing, and simply introduce the input values to the network. Square neurons indicate dot product synaptic function units. Circular neurons refer to radial synaptic function units.

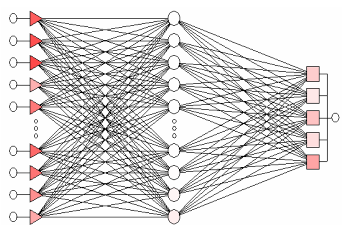
Input and output variables are illustrated using a small open circle joined to the corresponding input or output neuron.



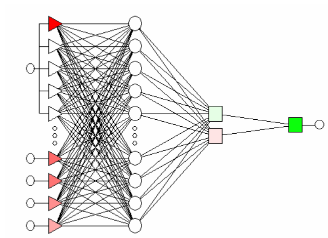
Multilayer Perceptron



Radial Basis Function



Probabilistic Neural Networks



Generalised Regression Networks

Figure 5.19 Neural networks architectures

5.3.3 Analysis structure

The main stages in the development of the neural networks used to forecast NIV follow the standard procedure (JingTao YAO, 2001, StatSoft, 2004):

- *Data selection:* The selection of variables is guided by the physical quantity that they represent and by the results of the multivariable exploratory analysis. Experience demonstrated that the choice of variables has a strong influence on the quality of the results. Including too many variables or the wrong variables can lead to dimensionality problems.

- *Cases selection:* Three different data sets are required to develop a neural network for forecasting. The training data set is used to train various candidate networks. The selection data set is used to select the best trained network among these candidates. Finally the test data set (containing only unseen data) is used to measure the performance of the networks. The number of cases needed for both the training and the selection data sets depends on the number of connections and the complexity of the function to be modelled. However over-fitting problems can arise if excessively large sets are used. It is important to keep in mind that the future is not the past so that if the circumstances captured by the training data set have change these relations may not be valid. On the other hand neural networks only learn from the cases and conditions included in the training data set. Care should therefore be taken to include various types of cases and situations in the training data set. Since the network minimizes the overall error the proportion of cases is critical and should always reflect the actual conditions. For example, a network trained with 300 cases of long market conditions and 50 cases of short market conditions will always bias its prediction towards the long market conditions.

- *Data preparation:* Neural networks usually require pre- and post-processing of the data to adapt first the input variables to the characteristics of the neurons' activation functions and second to transform the output to the normal data range.
- *Training:* This process consists of a progressive adaptation of the NN parameters to learn the desired behaviour. Several networks of different architectures are trained using the training data set. Each network produces its own prediction for the unseen data set.
- *Assessment:* Once the different networks have been created, several measures of performance are obtained (error measurements, training performance, sensitivity analysis and residuals analysis). These results can also be used as a feedback to modify the parameters of the networks. The best architecture is selected based on performance over the selection data set.

This development process does not produce a unique network that can be used in all cases. Various architectures may produce optimal results for different forecasting conditions. A different optimal network therefore must be created for each forecasting scenario. The parameters of the networks also need to be adjusted to the timeframe considered.

Two forecasting scenarios were considered:

- CASE 1: One month ahead forecast performed on a daily basis. Each forecast value represents the median NIV value for a whole day.
- CASE 2: One week ahead forecast. In this case working and non-working days have been considered independently. This forecast is made on the basis of EFA blocks. Each forecasted value corresponds to the median NIV value for the corresponding EFA block.

5.3.4 Data selection and preparation

5.3.4.1 Variables selection

According to the results obtained in the multidimensional exploratory analysis the variables that have been included in this analysis are:

- *Demand forecast.* Despite the exploratory analysis shows no linear correlation between NIV and demand forecast this variable is included since it is one of the main variables to define the market conditions.
- *Capped Physical Notification (CPN).* This variable is included because of its relevance in the description of the participants' position at gate closure.
- *Submitted Offer Volume (SOV) and Submitted Bid Volume (SBV).* These two variables are included because together with the CPN they inform about the system increasing (offers) and decreasing (bids) flexibility.
- *Balancing Mechanism Imbalance Volume and Gate Closure Imbalance Volume.* These variables are included since they are a strongly related with NIV.
- *Demand forecast error, REM.* These two variables are the components of the PGCE and are included in the analysis due to the influence between them and NIV detected by the time series exploratory analysis.
- *Imbalance Prices (SBP & SSP).* These variables are included in the forecasting base since they provide representative information of the balancing mechanism activity.

- *Type of day (Monday, Tuesday,…) and EFA Block Number (if required).* These variables provide the temporal information to the forecasting base.

Other variables are also included in the forecasting base. Their purpose is to highlight the effect of the balancing mechanism actions (MINAOAB) and include the effect of changes in generation declaration (from day-ahead to gate closure) (ΔMEL) are:

- *Min (|Accepted Offers, Accepted Bids|) (MINAOAB).* This variable reflects the system balance actions for each period. Figure 5.20 represents this variable for long and short market conditions.

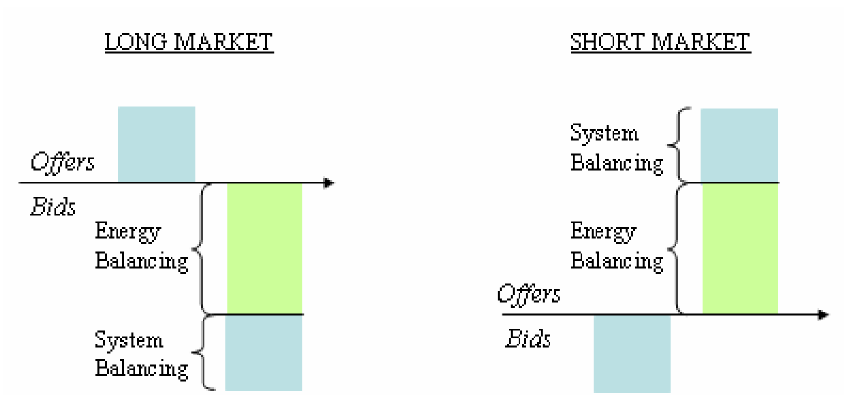


Figure 5.20 MINAOAB variable representation

- *Gate closure MEL on bars (GCMELOB).* It is the MEL of all the units on bars for each period.
- ΔMEL. It is the difference between day ahead MEL and GCMELOB.

The rest of the variables presented in section 5.2.2 are excluded from the forecasting base. Variables can be excluded either for negative results in the exploratory analysis (e.g. accepted offers and bids cash-flows) or because their conceptual representation is included in other variables (e.g demand is not included since demand forecast and DFE are considered in the forecasting base).

5.3.4.2 Variables preparation

All variables are filtered using smoothing moving medians with windows of 48 and 8 periods for the forecasting scenarios CASE 1 and CASE 2 respectively. The series are then normalized as shown by equation 4.3. Finally the time relation between the input and output variables is transformed to expose the information in such a way that the present values of the input variables can predict future values of NIV. In order to achieve this, the training and selection cases are formulated as follows:

Let K_i, be an input case of the known (training) data set. It is defined as a vector:

$$K_i = (V_1^i, V_2^i, ..., V_m^i, X^{i+1})$$

where: i: is a time index (e.g. i=1 corresponds to day one or the first EFA block)

> V_1^i : is the value of the first input variable of the balancing mechanism in the corresponding time (i)
>
> X^{i+1} : is the value of NIV (output) at time i+1

In the training and selection data sets, all the components of the vectors (input and output) are known values.

The unknown or test data set is composed of vectors U_N defined as:

$$U_N = (V_1^N, V_2^N, ..., V_m^N, X^{N+1})$$

where: N: is a time index

> V_1^N : corresponds to the value of the first input variable of the balancing mechanism in the corresponding time (N)
>
> X^{N+1} : corresponds to the NIV (output) value at time N+1

In the test data set, known values of the BM variables (input) allow us to compare forecasted values of NIV with the known values.

5.3.4.3 Cases Selection

The analysed data correspond to the period from May 2001 to November 2002.

For case 1 six different sub-cases have been studied. Each of them corresponds to a four weeks period of data. The training, selection and test data sets for each sub-case are defined in table 5.5.

Table 5.5 Definition of the training, selection and test data sets for case 1

BM variables input	**Forecasting Scenarios**						**Forecasting NIV**
	Case 1.1	Case 1.2	Case 1.3	Case 1.4	Case 1.5	Case 1.6	
May-01	Selection						
Jun-01		Selection					
Jul-01			Selection				
Aug-01				Selection			
Sep-01					Selection		
Oct-01						Selection	
Feb-02	Training						
Mar-02	Training	Training					
Apr-02	Training	Training	Training				
May-02	**Test**	Training	Training	Training			**Jun-02**
Jun-02		**Test**	Training	Training	Training		**Jul-02**
Jul-02			**Test**	Training	Training	Training	**Aug-02**
Aug-02				**Test**	Training	Training	**Sep-02**
Sep-02					**Test**	Training	**Oct-02**
Oct-02						**Test**	**Nov-02**

Case 2 consists of twelve different sub-cases, each of them corresponding to a week's worth of data. The forecasted period correspond to twelve consecutive weeks (weeks 17 to 29 in 2002) divided in working and non-working days. The training, selection and test data sets were selected as follows:

- Working days: The selection data set consists of the week preceding the test data. The training data set consists of the four-week period finishing two weeks prior to the test data set.
- Non-working days: The selection data set consists of the non-working days of the previous week. The training data set correspond to a two week period finishing two weeks prior to the test data set.

5.3.5 Numerical results

5.3.5.1 Case 1: One-Month forecast

Table 5.4 shows the architectures and the performance of the five best networks for each sub-case. These "best" networks have been selected using a compromise criterion that balances the error in the selection data set and the diversity of the trained networks. This criterion will preserve networks with a range of architectures, complexity and performance trade-offs. In this way the group of best selected networks should try to keep diversity, not only when considering the network's architecture but also difference sizes, and minimise the error performance. In this table the first column refers to the forecast solutions and the first row to the analyzed case. For each month the first column corresponds to the network architecture; the numbers following the network names indicate the number of units in the input, hidden and output layers. The second and third rows are the root mean squared error (RMSE) and the mean absolute error (MAE) in MW respectively. They are defined in equations 4.22 and 4.23. For each month, the optimal solution (with minimum errors) appears in bold.

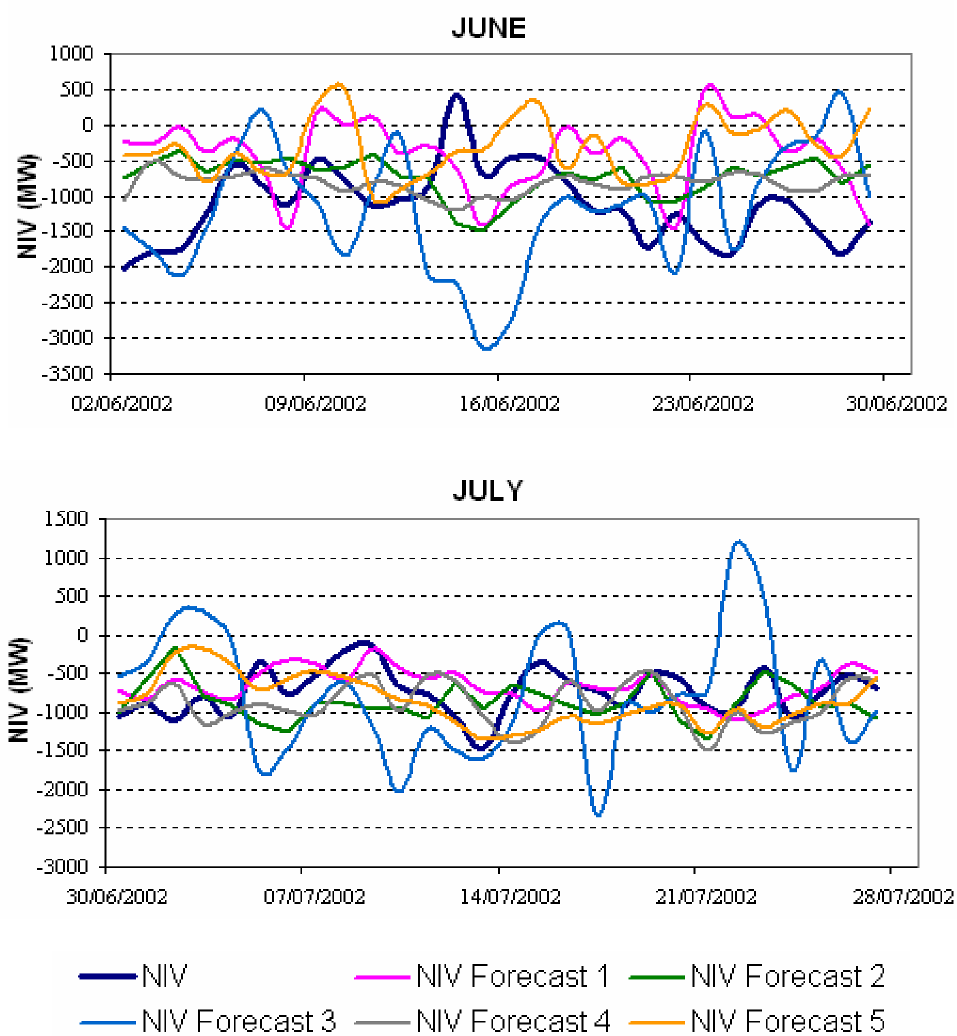
Table 5.6 Five best neural networks for each sub-case of case 1

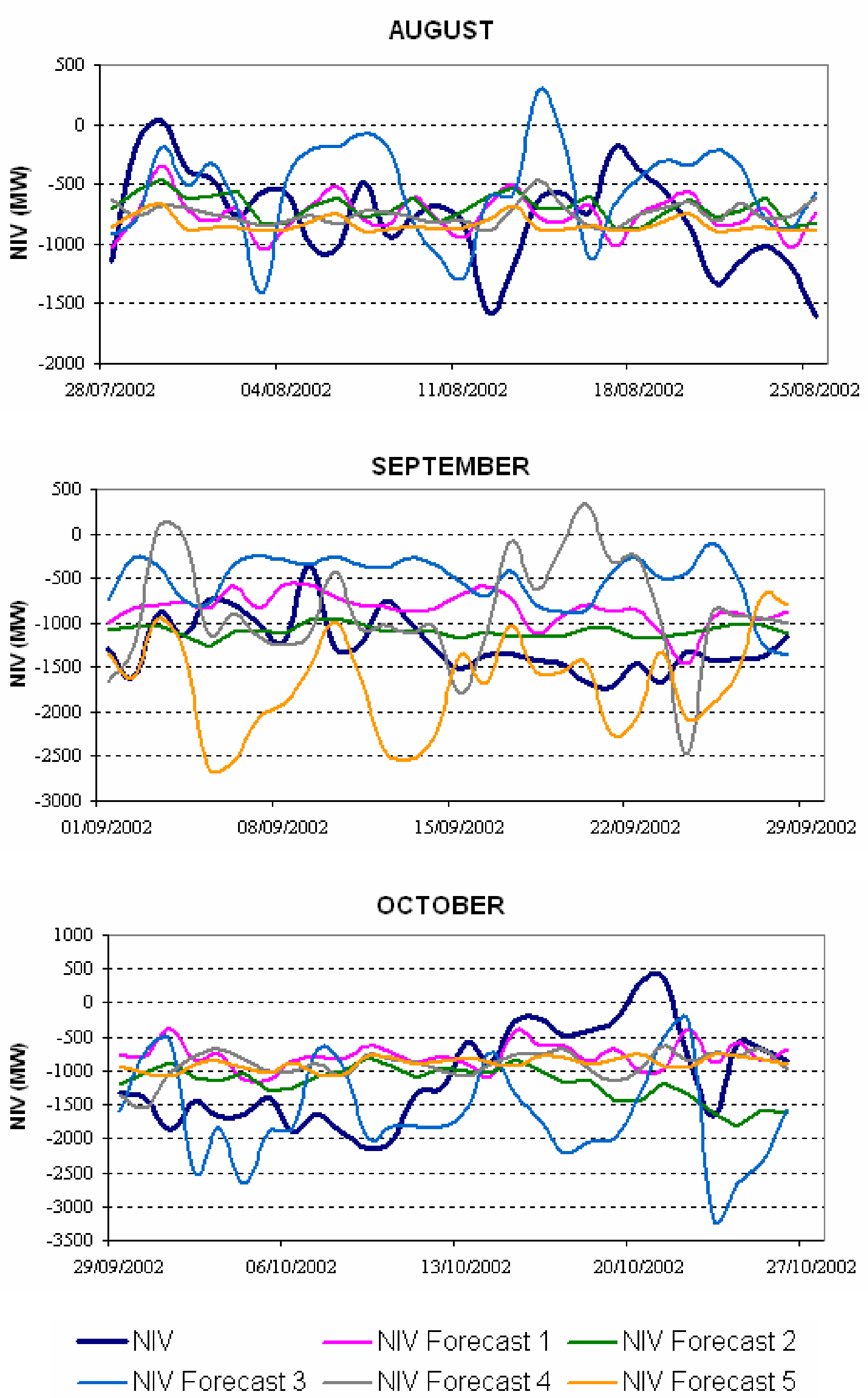
	JUNE			JULY		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 14:92-93-2-1:1	1052.9	903.4	**RBF 14:72-23-1:1**	**316.3**	**240.3**
For 2	RBF 14:80-23-1:1	778.5	650.6	GRNN 14:46-93-2-1:1	428.5	348.9
For 3	LINEAR 14:46-1:1	1127.3	839.1	LINEAR 14:46-1:1	863.2	709.2
For 4	**MLP 14:72-5-1:1**	**679.8**	**556.6**	MLP 12:80-4-1:1	394.6	314.0
For 5	MLP 14:36-5-1:1	1005.8	847.6	MLP 14:36-5-1:1	423.0	340.3

	AUGUST			SEPTEMBER		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 14:92-93-2-1:1	1052.9	903.4	**RBF 14:72-23-1:1**	**316.3**	**240.3**
For 2	RBF 14:80-23-1:1	778.5	650.6	GRNN 14:46-93-2-1:1	428.5	348.9
For 3	LINEAR 14:46-1:1	1127.3	839.1	LINEAR 14:46-1:1	863.2	709.2
For 4	**MLP 14:72-5-1:1**	**679.8**	**556.6**	MLP 12:80-4-1:1	394.6	314.0
For 5	MLP 14:36-5-1:1	1005.8	847.6	MLP 14:36-5-1:1	423.0	340.3

	OCTOBER			NOVEMBER		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 14:92-93-2-1:1	1052.9	903.4	**RBF 14:72-23-1:1**	**316.3**	**240.3**
For 2	RBF 14:80-23-1:1	778.5	650.6	GRNN 14:46-93-2-1:1	428.5	348.9
For 3	LINEAR 14:46-1:1	1127.3	839.1	LINEAR 14:46-1:1	863.2	709.2
For 4	**MLP 14:72-5-1:1**	**679.8**	**556.6**	MLP 12:80-4-1:1	394.6	314.0
For 5	MLP 14:36-5-1:1	1005.8	847.6	MLP 14:36-5-1:1	423.0	340.3

These results show that the optimum network architectures are multilayer perceptron and radial basis function. Linear networks perform badly in all cases. Figure 5.21 shows the actual values of NIV in MW, and the forecasts produced by each of the networks described in Table 5.6.




AUGUST
NIV (MW)
500
0
-500
-1000
-1500
-2000
28/07/2002
04/08/2002
11/08/2002
18/08/2002
25/08/2002
SEPTEMBER
NIV (MW)
500
0
-500
-1000
-1500
-2000
-2500
-3000
01/09/2002
08/09/2002
15/09/2002
22/09/2002
29/09/2002
OCTOBER
NIV (MW)
1000
500
0
-500
-1000
-1500
-2000
-2500
-3000
-3500
29/09/2002
06/10/2002
13/10/2002
20/10/2002
27/10/2002
NIV
NIV Forecast 1
NIV Forecast 2
NIV Forecast 3
NIV Forecast 4
NIV Forecast 5

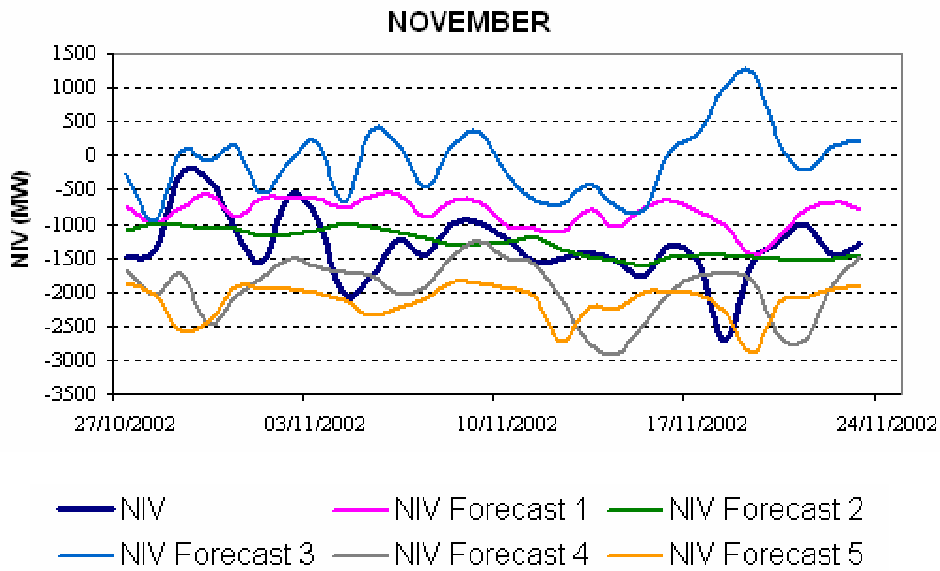


Figure 5.21 Actual and forecasted values of NIV for the month-ahead forecasts using the five best networks

5.3.5.2 Case 2: One-week forecast

Tables 5.7 and 5.8 show, respectively for working and non working days, the architectures of the five best networks for each sub-case and their corresponding errors. For each week, similarly to the monthly forecast, the first column corresponds to the network architecture; the numbers following the network names indicate the number of units in the input, hidden and output layers. The second and third rows are the root mean squared error (RMSE) and the mean absolute error (MAE) (in MW) respectively. The optimum solution appears in bold.

Table 5.7 Five best neural networks for each sub-case of case 2 (working days)

	WEEK 1			**WEEK 2**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	**GRNN 15:64-79-2-1:1**	**612.9**	**507.3**	RBF 15:78-14-1:1	2326.5	2008.7
For 2	RBF 15:43-14-1:1	755.5	599.1	GRNN 15:88-10-2-1:1	1526.3	1130.9
For 3	RBF 15:43-28-1:1	679.0	558.0	GRNN 15:43-12-2-1:1	1494.2	1112.5
For 4	MLP 15:43-4-1:1	737.6	570.0	**MLP 15:90-2-1:1**	**1293.1**	**971.1**
For 5	MLP 15:43-14-9-1:1	739.5	595.3	MLP 15:25-4-1:1	1562.0	1281.8

	WEEK 3			**WEEK 4**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 15:64-96-2-1:1	986.8	820.9	GRNN 15:56-12-2-1:1	1156.2	985.2
For 2	RBF 15:41-7-1:1	1226.2	1035.2	GRNN 15:32-10-2-1:1	1159.5	983.4
For 3	**RBF 15:41-14-1:1**	**663.3**	**481.0**	RBF 15:78-28-1:1	992.2	857.3
For 4	MLP 15:90-2-1:1	1473.1	1211.3	MLP 15:34-14-10-1:1	1019.4	898.8
For 5	MLP 15:32-3-1:1	2098.0	1612.6	**MLP 15:26-14-7-1:1**	**766.6**	**648.1**

	WEEK 5			**WEEK 6**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 15:97-12-2-1:1	944.0	778.3	GRNN 15:64-81-2-1:1	945.1	779.8
For 2	**RBF 15:86-3-1:1**	**435.6**	**338.7**	RBF 15:43-14-1:1	706.1	581.2
For 3	RBF 15:86-7-1:1	586.0	465.0	RBF 15:43-18-1:1	844.7	750.7
For 4	MLP 15:162-9-1:1	671.3	506.1	**MLP 15:44-14-10-1:1**	**535.2**	**440.1**
For 5	MLP 15:90-3-1:1	579.8	477.7	MLP 15:18-5-1:1	795.3	697.4

	WEEK 7			**WEEK 8**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	RBF 15:43-28-1:1	1288.9	1160.6	GRNN 15:88-20-2-1:1	1001.9	796.8
For 2	GRNN 15:46-12-2-1:1	1072.5	825.6	RBF 15:43-7-1:1	534.8	412.7
For 3	GRNN 15:43-10-2-1:1	1072.3	824.5	RBF 15:43-3-1:1	529.9	419.0
For 4	MLP 15:43-4-1:1	815.0	648.4	**MLP 15:43-6-1:1**	**464.2**	**382.3**
For 5	**MLP 15:43-14-4-1:1**	**671.2**	**527.4**	MLP 15:43-14-1:1	545.6	461.9

	WEEK 9			**WEEK 10**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 15:64-10-2-1:1	595.0	487.3	GRNN 15:28-10-2-1:1	514.9	415.6
For 2	RBF 15:43-7-1:1	450.6	370.3	RBF 15:32-28-1:1	642.9	554.9
For 3	RBF 15:43-3-1:1	457.0	376.4	RBF 15:43-43-1:1	597.6	513.9
For 4	MLP 15:32-14-1:1	369.9	314.8	MLP 15:42-1-1:1	607.4	477.3
For 5	**MLP 15:32-11-5-1:1**	**358.9**	**302.2**	**MLP 15:43-14-3-1:1**	**584.5**	**453.5**

	WEEK 11			**WEEK 12**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 15:28-20-2-1:1	565.1	445.8	GRNN 15:56-20-2-1:1	646.1	442.6
For 2	GRNN 15:64-12-2-1:1	551.5	438.5	**RBF 15:44-7-1:1**	**633.3**	**418.8**
For 3	RBF 15:39-28-1:1	1056.6	786.9	RBF 15:44-3-1:1	704.8	629.7
For 4	**MLP 15:90-6-1:1**	**381.2**	**310.7**	MLP 15:62-10-5-1:1	662.0	478.3
For 5	MLP 15:18-13-11-1:1	536.5	437.7	MLP 15:18-8-1:1	656.4	473.7

Table 5.8 Five best neural networks for each sub-case of case 2 (non-working days)

	WEEK 1			**WEEK 2**		
	Network design	*Error RMSE*	*Error MAE*	*Network design*	*Error RMSE*	*Error MAE*
For 1	**RBF 15:62-14-1:1**	**201.0**	**249.9**	MLP 15:62-14-6-1:1	627.3	820.7
For 2	RBF 15:53-9-1:1	583.3	806.2	GRNN 15:38-24-2-1:1	671.9	894.8
For 3	RBF 15:71-15-1:1	344.7	432.2	Linear 15:20-1:1	805.8	1046.2
For 4	RBF 15:71-14-1:1	214.6	273.5	**MLP 15:68-14-3-1:1**	**612.7**	**782.3**
For 5	RBF 15:71-16-1:1	345.3	471.1	MLP 15:35-13-2-1:1	786.0	948.2

	WEEK 3			**WEEK 4**		
	Network design	*Error RMSE*	*Error MAE*	*Network design*	*Error RMSE*	*Error MAE*
For 1	RBF 15:44-4-1:1	4163.8	6309.3	GRNN 15:12-24-2-1:1	321.3	403.8
For 2	RBF 15:44-9-1:1	3080.3	4523.3	RBF 15:71-2-1:1	445.5	533.3
For 3	GRNN 15:80-24-2-1:1	738.6	997.9	RBF 15:71-4-1:1	602.9	733.1
For 4	MLP 15:71-9-1:1	1568.0	1998.4	MLP 15:19-1-1:1	241.8	295.8
For 5	**MLP 15:9-1-1:1**	**256.9**	**284.8**	**MLP 15:9-8-1-1:1**	**233.9**	**308.3**

	WEEK 5			**WEEK 6**		
	Network design	*Error RMSE*	*Error MAE*	*Network design*	*Error RMSE*	*Error MAE*
For 1	GRNN 15:207-24-2-1:1	428.1	598.0	GRNN 15:138-24-2-1:1	517.7	639.5
For 2	RBF 15:207-2-1:1	296.1	375.1	RBF 15:207-4-1:1	548.5	713.5
For 3	RBF 15:207-4-1:1	292.6	373.8	RBF 15:207-9-1:1	549.8	706.5
For 4	**MLP 15:144-4-1:1**	**242.2**	**306.4**	**MLP 15:36-2-1:1**	**307.3**	**406.3**
For 5	MLP 15:108-7-5-1:1	269.9	323.2	MLP 15:153-10-4-1:1	418.5	509.2

	WEEK 7			**WEEK 8**		
	Network design	*Error RMSE*	*Error MAE*	*Network design*	*Error RMSE*	*Error MAE*
For 1	GRNN 15:40-24-2-1:1	394.5	442.4	RBF 15:44-4-1:1	996.9	947.5
For 2	RBF 15:71-9-1:1	320.3	403.0	GRNN 15:20-24-2-1:1	531.7	528.7
For 3	RBF 15:71-14-1:1	433.8	555.9	RBF 15:44-9-1:1	533.1	555.9
For 4	**MLP 15:18-4-1:1**	**248.1**	**316.5**	**MLP 15:19-2-1:1**	**465.9**	**458.5**
For 5	MLP 15:53-13-3-1:1	465.6	618.4	MLP 15:17-3-1:1	564.7	377.7

	Week 9			**Week 10**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 15:40-24-2-1:1	396.1	556.6	GRNN 15:23-24-2-1:1	398.7	479.3
For 2	GRNN 15:20-24-2-1:1	259.6	369.4	RBF 15:89-2-1:1	359.5	484.8
For 3	RBF 15:80-1-1:1	291.0	422.2	RBF 15:89-1-1:1	261.3	384.8
For 4	**MLP 15:27-5-1:1**	**224.1**	**297.6**	**MLP 15:27-4-1:1**	**228.3**	**301.5**
For 5	MLP 15:19-1-1:1	456.1	502.5	MLP 15:80-15-10-1:1	297.2	354.5

	Week 11			**Week 12**		
	Network design	*Error*		*Network design*	*Error*	
		RMSE	*MAE*		*RMSE*	*MAE*
For 1	GRNN 15:27-24-2-1:1	159.7	218.3	**RBF 15:18-1-1:1**	**278.8**	**400.3**
For 2	RBF 15:71-4-1:1	603.0	801.1	GRNN 15:18-24-2-1:1	306.5	423.8
For 3	RBF 15:71-5-1:1	559.9	781.6	GRNN 15:40-24-2-1:1	327.5	483.8
For 4	**MLP 15:72-8-1:1**	**202.9**	**265.5**	MLP 11:44-14-3-1:1	452.1	672.6
For 5	MLP 15:15-2-1:1	232.9	285.6	MLP 14:19-4-1:1	337.1	502.6

Tables 5.7 and 5.8 show that, for forecasts over a one-week period, the multilayer perceptron is the network architecture that provides optimum solutions for most of the analyzed cases and for both working and non working days.

Table 5.9 shows the minimum errors for working and non-working days separately and a weighted average for the weekly error. This table shows that there is a big difference between the forecasting accuracy for working and non-working days. Forecasts for non-working days are more accurate than for working day. Possible reasons for this difference include:

- The number of cases considered: for working days the forecast is based on 30 cases while for non-working days it is based on 12 cases only.
- The difference in input data: NIV is less volatile for non-working days than it is for working days. The standard deviation of NIV for working days is 835.47 MW while it is only 721.11 MW for non-working days.

Table 5.9: Minimum error measures for case 2 (weekly forecasting) (in MW)

		WORKING		NON-WORKING		TOTAL	
		RMSE	*MAE*	*RMSE*	*MAE*	*RMSE*	*MAE*
Week 1	May	612.9	507.3	201.0	249.9	495.1	433.7
Week 2	June	1293.1	971.1	612.7	782.3	1098.5	917.1
Week 3	June	658.9	481.0	256.9	284.8	544.0	424.9
Week 4	June	765.0	648.1	233.9	295.8	613.1	547.4
Week 5	June	435.6	338.7	242.2	306.4	380.3	329.4
Week 6	July	535.2	440.1	307.3	406.3	470.0	430.5
Week 7	July	671.2	527.4	248.1	316.5	550.1	467.1
Week 8	July	464.2	382.3	465.9	377.7	464.7	380.9
Week 9	July	358.9	302.2	223.3	297.6	320.1	300.9
Week 10	August	514.9	415.6	228.3	301.5	432.9	383.0
Week 11	August	381.2	310.7	159.7	218.3	317.9	284.3
Week 12	August	563.1	379.9	278.8	400.3	481.8	385.7
	Average	*604.5*	*475.4*	*288.2*	*353.1*	*514.0*	*440.4*

5.3.6 Model assessment

5.3.6.1 Model robustness

This analysis is intended to check the robustness of the presented methodology to changes in the input variables conditions. More specifically it focuses on the effect that linearly dependent variables have over the final forecast. For this purpose two different sets of input variables have been created:

CASE A: Considering all the market variables as defined in section 5.3.4.1 except for the Balancing Mechanism Imbalance Volume that have been decomposed in Accepted Bid Volumes, the Accepted Offer Volumes and the System Operator Trades.

CASE B: Considering all market variables as defined in section 5.3.4.1.

The analysis is based on the monthly forecast conditions: four week forecast cases with one median value forecasted for each day. Only the optimum networks architectures will be considered, according to the results obtained in the first approach to monthly forecast. Table 5.10 shows the architectures considered for each of the analysed months:

Table 5.10 Optimal network architectures for each month

June	Multilayer Perceptron
July	Radial Basis Function
August	Multilayer Perceptron
September	Radial Basis Function
October	Multilayer Perceptron
November	Radial Basis Function

Table 5.11 shows the errors for the optimum solutions in each of the analysed cases

Table 5.11 Error measurements for cases A and B (monthly forecast) (in MW)

		JUNE					**JULY**				
		For 1	For 2	For 3	For 4	For 5	For 1	For 2	For 3	For 4	For 5
Case A	RMSE	971.7	783.9	**598.7**	847.3	943.8	474.8	629.7	934.1	448.5	940.6
	MAE	804.7	636.9	**472.9**	700.6	833.1	294.3	471.0	704.8	377.5	677.2
Case B	RMSE	1103.0	822.9	1338.1	907.5	862.8	373.8	496.7	295.4	458.7	**344.6**
	MAE	919.6	639.5	977.2	804.4	745.4	296.7	423.4	237.2	378.7	**274.8**
		AUGUST					**SEPTEMBER**				
		For 1	For 2	For 3	For 4	For 5	For 1	For 2	For 3	For 4	For 5
Case A	RMSE	425.4	443.7	368.4	376.1	**348.2**	428.1	423.8	431.0	430.7	433.7
	MAE	343.9	350.4	308.6	311.9	**288.2**	375.5	371.6	379.8	380.2	382.6
Case B	RMSE	397.0	365.9	412.3	397.3	373.4	514.1	454.2	613.0	**425.9**	383.3
	MAE	335.5	304.1	329.6	334.2	300.9	445.2	403.9	543.0	**364.3**	299.1
		OCTOBER					**NOVEMBER**				
		For 1	For 2	For 3	For 4	For 5	For 1	For 2	For 3	For 4	For 5
Case A	RMSE	741.3	696.2	734.5	806.5	**663.9**	475.0	476.6	476.0	474.9	481.9
	MAE	655.4	598.2	576.5	640.7	**574.1**	360.2	366.6	363.2	361.8	367.0
Case B	RMSE	745.4	670.6	864.4	862.1	832.4	**434.6**	461.6	461.1	458.2	458.2
	MAE	595.1	571.0	735.7	721.5	700.0	**313.3**	368.8	364.5	362.2	362.2

These results show that Case A provides optimum solution in all the MLP networks and that Case B provides an optimum solution in all the RBF networks.

Considering the average error for all the forecasted solutions for each case:

Average error Case A: 477.5 MW

Average error Case B: 481.8 MW

Difference: 4.3 MW

Considering the average of the minimum errors for each month for each case:

Average Min. error Case A: 393 MW

Average Min. error Case B: 394 MW

Difference: 1 MW

Therefore, the results from this analysis show not only that NN methodology is robust, but also that each network architecture performs optimally for different characteristics of input variables.

5.3.6.2 Sensitivity analysis

As part of the assessment process, a sensitivity analysis was performed to evaluate the relative importance of the input variables on the accuracy of the forecast. This evaluation was based on the effect that omitting a predictor from the development of the neural network has on the accuracy of the forecast. Predictors were then ranked on the basis of the deterioration that their omission causes (Hunter et al., 2000). In this way to define the sensitivity of a particular variable, *X*, the network is first run, using the test data set, considering all the input variables, the error (RMSE) is calculated. Then the network is run again using the same cases, but this time replacing the observed values of *X* with the missing value, and again the network error is calculated. The ratio between the two obtained errors correspond to the deterioration of the model and therefore the importance of the input variable *X*. Sensitivities are calculated for all the input variables, and they are ranked in order.

This process was repeated for six separate monthly forecasts and for twelve separate weekly forecasts for working days. Tables 5.12 and 5.13 show, for the monthly and weekly cases respectively, the relative importance of each predictor based on this sample. It also shows the range of the rankings (1 for most important, 15 for least important) and a raw cumulative score. These results suggest that some variables are better predictors than others but that the relative importance varies from month to month or week to week. In no case does the suppression of a predictor improves the accuracy of the forecast.

Table 5.12: Sensitivity Analysis for monthly forecast

Predictor	Overall rank	Min rank	Max rank	Cumulative rank
BMIV	1	2	11	36
GCMELOB	2	2	12	37
REM	3	3	12	39
SBV	4	4	10	39
ΔMEL	5	4	9	40
SOV	6	2	14	43
GCIV	7	1	13	46
DFE	8	4	14	48
CPN	9	1	13	49
DF	10	1	12	52
SSP	11	1	14	53
Day Type	12	1	14	64
SBP	13	6	14	66
MINAOAB	14	9	14	69

Table 5.13: Sensitivity Analysis for weekly forecast (working days)

Predictor	Overall rank	Min rank	Max rank	Cumulative rank
SBP	1	1	12	67
MINAOAB	2	1	14	74
DF	3	2	12	78
CPN	4	1	13	86
EFA Block	5	1	14	90
GCMELOB	6	1	14	90
SSP	7	1	15	93
REM	8	4	14	98
GCIV	9	3	15	101
SOV	10	1	15	105
BIMV	11	5	13	106
DFE	12	4	15	111
SBV	13	1	14	112
Day Type	14	1	15	113
ΔMEL	15	2	15	116

5.3.7 Comparison with linear methods

Multi-dimensional forecasting using neural networks gives a better accuracy than one-dimensional linear methods. Neural networks outperform methods based on linear regression even when the time horizon is larger than the one considered in the one-dimensional forecasting.

Table 5.14 compares the monthly forecast obtained with neural networks and with a production-grade program based on linear regression methods. Table 5.15 presents a similar comparison for weekly forecast grouped monthly and Table 5.16 summarises the results for working and non-working days in the weekly scenario.

In all the cases neural networks outperform methods based on linear regression even when the time horizon is larger than the one considered in the one-dimensional forecasting.

Table 5.14 Error comparison for monthly forecast

	LINEAR METHOD		NN FORECAST		ERROR REDUCTION	
	RMSE (MW)	*MAE (MW)*	*RMSE (MW)*	*MAE (MW)*	*RMSE (MW)*	*MAE (MW)*
June	738	577.0	598	472.9	**139**	**104.1**
July	666	540.0	295	237.2	**370**	**302.8**
August	555	439.0	348	288.2	**206**	**150.8**
September	685	541.0	383	299.1	**301**	**241.9**
October	971	787.0	663	574.1	**307**	**213.9**
November	867	690.0	434	313.3	**432**	**376.7**

Table 5.15 Error comparison for weekly forecast

	LINEAR METHOD		NN FORECAST		ERROR REDUCTION	
	RMSE (MW)	*MAE (MW)*	*RMSE (MW)*	*MAE (MW)*	*RMSE (MW)*	*MAE (MW)*
June	738.0	577.0	658.96	554.70	**79.0**	**22.3**
July	666.0	540.0	451.25	394.84	**214.8**	**145.2**
August	555.0	439.0	410.86	351.01	**144.1**	**88.0**

Table 5.16 Error comparison for working and non working days

	LINEAR METHOD		NN FORECAST		ERROR REDUCTION	
	RMSE (MW)	*MAE (MW)*	*RMSE (MW)*	*MAE (MW)*	*RMSE (MW)*	*MAE (MW)*
Working	834	654	698.3	552	135	102
Non-working	1073	848	648.52	537	424	311

5.3.8 Model implementation

The presented analyses demonstrate that NN is a feasible technique for NIV forecasting. However it is important to remark that there is not a unique network that can be considered the solution for all the analysed conditions. A different network must be created for each forecasting scenario. The basic steps involved in the development of monthly/weekly NNs are:

- Data transformation. This involves the transformation of the data according to the forecasting conditions (i.e. smoothing process in EFA blocks or daily resolution). In this case moving medians have been used but other possibilities include moving averages or simple exponential (see section 4.2.2).
- Cases selection. The training, selection and unseen data set are then created. The conditions presented in this analysis can be used as a guideline but further adjustments can be done when more data becomes available. The more updated information the network can use for learning, the better the forecast becomes. However it is important to avoid overtraining since that would lead to an inflexible network and inaccurate results.
- Variables selection. The analysis presented shows the effect of different input variables in different networks architectures. However future market or forecasting conditions may require the introduction or the exclusion of some of the analysed variables.
- Initial training approach. This first simulation will indicate the most appropriate architecture for the analysed case. It should consider:
    - All networks architectures
    - As a training algorithm it is recommended to use the back-propagation algorithm since it provides a quick solution and handles well both long and small data sets. Second order algorithms can easily prone to stick to local minima in the early training stages.
    - Automatic selection of subset variables. This allows the creation of a subset of input variables according to the sensitivity analysis included in the training process

  - The optimum networks are obtained with a compromised criterion between lowest error in the selection data sets and networks diversity
  - Analysis of the networks performance and selection of the best network architecture. The error measurements will be based on the selection data set.
- Refining network training process considering:
  - Best (and second best if appropriate) network architecture
  - Optimum networks are retained based on the minimum error of the selection data set
  - Network reconfiguration. On each case if under-learning occurs more neurons are added to the hidden layers or even a complete hidden layer. Whereas, if over learning occurs neurons or even layers should be removed
  - All variables are included
  - Although back-propagation can be used as a fine tuning algorithm other second order algorithms, such us the conjugate gradient descent and quasi-Newton algorithms, can also be considered.
- Results analysis. Based on both the networks performance and the sensitivity analysis of the input variables. As a result the optimum network(s) design (number of neurons, thresholds, weights) and input variables are selected. Input unseen data set into the optimum network to obtain the final forecast.

Due to the complexity of the analysed variable and the constant artificial changes imposed by market rules and modifications, the long term forecast the obtained results may be revised according to real-time values. This must be done independently of the training and selection data sets performance.

5.3.9 Conclusions

While the neural networks that have been developed are able to predict NIV for both weekly and monthly horizons, each forecasting situation requires the creation of a new network. No single network architecture provides optimal results for all market conditions.

Comparing the results obtained for cases 1 and 2 shows that increasing the frequency of observations does not improve the accuracy of the results. A more accurate forecast is obtained on a monthly basis (average MAE: 363 MW) than on a weekly basis (average MAE: 440 MW). This can be explained by the nature of the data: a daily aggregation of NIV is less scattered than an aggregation in six blocks of four hours per day (i.e. aggregated in so-called EFA blocks).

The number of cases and their selection for the required data sets can be modified as more data becomes available. Different forecasting scenarios may require different number of cases to be included in the data sets. The more updated information the network can use for learning, the better the forecast becomes. However it is important to avoid overtraining since that would lead to an inflexible network and erroneous results.

Multidimensional forecasting using neural networks gives a better accuracy than the one-dimensional method described in chapter 4. Neural networks outperform methods based on linear regression even when the time horizon is larger than the one considered in the one-dimensional forecasting.

CHAPTER 6

Analysis of unusual market conditions

6.1 Introduction

Any extreme natural event such as floods, earthquakes or hurricanes has an intense impact on the affected area's economy. Historically the analysis of extreme events has focused on the analysis of the frequency of floods. The purpose of these analyses is the estimation of the so called T-year flood discharge, which is the discharge once exceeded on average in a period of T-years. In recent years extreme events have also been of interest in areas such as actuarial and financial analysis. In both cases, extreme events are linked by the analysis of the risk that their consequences represent. In the first case, the risk associated with very large claims associated with a catastrophic event must be considered to calculate the appropriate premium. Risk analysis in finance is driven by the parameters Value-at-Risk and

Capital-at-Risk that deal with the upper tail of loss and gain distributions. Further areas of analysis include corrosion analysis, telecommucations, materials analysis, ecology and the longevity of human life.

In electricity markets, extreme events are defined as unscheduled or abnormal market conditions. Due to the complexity of market mechanisms and the relevance of risk exposure for the financial activities related with market behaviour, it is more than within reason to evaluate the impact that abnormal events may have on the different market variables. Despite its relevance, the analysis of unusual conditions research is still an unexplored area in power systems. The existing approaches follow two main threads; the first one is focused of the effects of extreme weather conditions over the system assets. Don Koval (Don Koval and Shen, 1999) considers the problem of assessing the impact that extreme weather conditions have on outages in the Canadian transmission. The second thread is the analysis of electricity price spikes. Bystrom (Bystrom, 2003) applies extreme values theory to investigate the tails of price change distributions. Guan (Guan et al., 2001), provides useful information about the effect of market power and strategic bidding on the Californian price spikes. A broader theoretical perspective to the price spikes is given by Hughes (Hughes and Parece, 2002) who discusses the effect that capacity constraints, demand factors, and market organizations have on the occurrence of extreme prices.

This analysis also makes an important contribution to the existing methodology. The classical techniques applied when modelling extreme events are complemented with other analytical methods that were not specifically designed for this purpose. Moreover, quantitative exploratory analyses are combined with time-based techniques to cover the different aspects involved in the occurrence of an unusual event. Another innovative aspect is the multidimensional approach that has been adopted. This analysis cover the fact that several events can disturb the market and some of them could coexist in time. Likewise the market reaction is not measured by a unique index. Instead, the effect of an event is evaluated over several passive variables.

The organisation of this chapter is as follows. First the objectives and structure of the analysis are presented. Then the data and case selection criteria are discussed. The next part describes the initial quantitative approach. The characterisation of unusual events and the consequences analysis follow. Finally conclusions are drawn from this analysis of unusual events.

6.2 Objectives and analysis structure

The many studies developed to evaluate the impact of unusual events provide useful information in some specific aspects such as event detection, distribution modelling, and long term market reaction (Lui, 2003, Palutikof et al.). However, they fail to provide a global perspective on unusual events, their effects and the dynamics of both the event and it consequences. The analysis carried out in this chapter comprises both the study and description of unusual events as well as their consequences. The analysis of the trigger events aims to detect them and characterise them. The first step is to identify what are the possible conditions that disturb the market (variables and cases). Then it is necessary to characterise them. This characterisation includes:

- Modelling their likelihood of occurrence by obtaining the parameters of their probability distribution
- Analysing the duration of the events
- Calculating the return period, i.e. the time between events. The possibility that different events might happen simultaneously is also considered

When analysing the consequences of unusual conditions, the specific aims are to analyse the market reaction after the events happen and to analyse incremental changes over time in the market under these unusual conditions. For each this of these objectives a double perspective is considered:

- Global deviation of variables: evaluate the differences between normal and unusual conditions
- Deviation from moving averages: calculate the relative change of the variables over their trends

The market reaction is also separately monitored for the case of a unique event and, when appropriate, for the case of multiple coexistent events.

Figure 6.1 summarises this strategy.

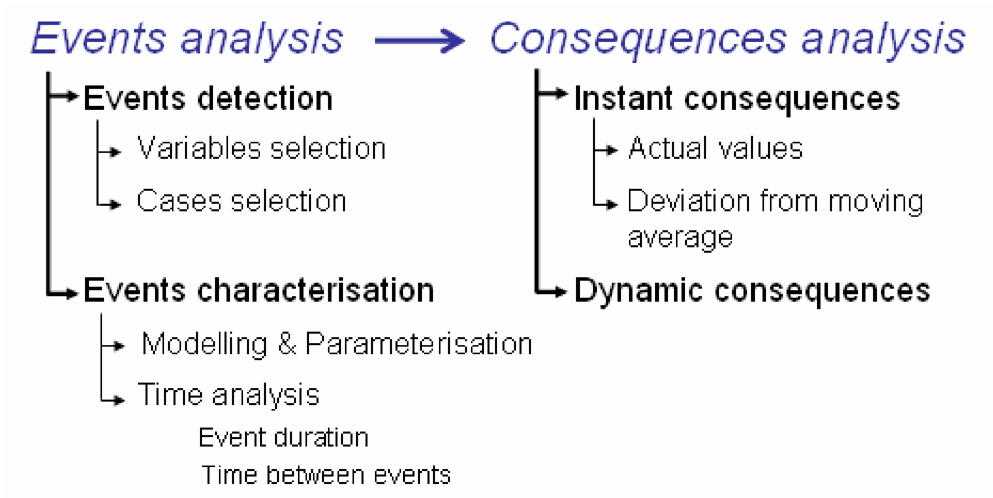


Figure 6.1 The analysis of unusual events

As a general objective this analysis does not only identify and analyse the occurrence of unusual events but, by doing so, it also checks the robustness of the market design, and the market mechanisms affected by a disturbance. Moreover the analysis of unusual events highlights any possible difference between theoretical and practical market responses.

6.3 Data description

The variables included in this analysis can be classified as trigger (active or input) variables and passive (output) variables. Within the first group trigger variables can be further divided into continuous and instant, as well as plain and ratio variables.

The active variables define the occurrence of an event. They refer mainly to demand forecast errors, sudden big demand variations, available capacity changes (continuous variables) and generation loss data (instant variable). The passive variables refer to balancing mechanism variables and imbalance prices.

Other time-related variables are also included, such as month, day (Sunday, Monday…) and day period (1 to 48). The time resolution of the data is the half-hour market period and the analysis stretches from 1 April 2001 until 30 November 2002.

Tables 6.1 and 6.2 provide respectively a full description of the trigger and passive variables considered in this analysis. In each table, the first column gives the variable name followed by its acronym, when appropriate, the second the variable definition and, when appropriate, its mathematical equation is included in the third column.

Table 6.1 Trigger Variables description

NAME	DEFINITION	EQUATION
Demand forecast error (DFE)	The difference between the demand forecast and the demand (in MW)	$DFE = DF - Demand$
MEL day change	The difference between MEL day ahead (DAMEL) and GCMELOB (in MW)	$MEL_{\text{day change}} = = DAMEL - GCMELOB$
Remaining Effects (REM)	The composite of any post gate closure effect not included in the DFE (in MW)	$REM = PGCE - DFE$
$\frac{DFE}{GCIV}$	Ratio between the demand forecast error and the gate closure imbalance volume	
$\frac{DFE}{Demand}$	Ratio between the demand forecast error and the demand	
$\frac{\Delta MEL}{\Delta Demand}$	Incremental ratio of MEL and demand	$\frac{MEL_t - MEL_{t-1}}{Demand_t - Deamand_{t-1}}$
Plant loss	The aggregated value of total loss of generated output identified by a redeclaration of MEL to zero (in MW)	

Table 6.2 Passive Variables description

NAME	DEFINITION	EQUATION
Demand forecast	the estimate of the demand for electricity (MW)	
Demand	The actual value of the system load for each period (MW)	
Submitted Offer Volume (SOV)	The sum of all the available offers submitted by all the BM units for a certain period (in MW)	
Submitted Bid Volume (SOV)	The sum of all the available bids submitted by all the BM units for a	

NAME	DEFINITION	EQUATION
	certain period (in MW)	
Accepted Offer Volumes (AOV)	The aggregated volume of offers accepted by the System Operator (SO) (MW)	
Accepted Bid Volumes (ABV)	The aggregated volume of bids accepted by the System Operator (SO) (MW)	
Accepted Offer Cashflows (AOC)	The total cash-flow resulting from all the offer acceptances (in £MWh)	
Accepted Bid Cashflows (ABC)	The total cash-flow resulting from all the bids acceptances (in £MWh)	
Capped Physical Notification (CPN)	The aggregation for all the units of the minimum between the final physical notifications (FPN) and the maximum export limit (MEL) submitted in each period (in MW)	$CPN = \sum Min(MEL, FPN)$
Gate Closure Imbalance Volume (GCIV)	The difference between the demand forecast and the capped physical notification (in MW)	$GCIV = DF - CPN$
Net imbalance volume (NIV)	The sun of all offer acceptances, bid acceptances, French interconnector trades and SO forward trades (n MW)	$NIV = \sum AOV + \sum ABV + \sum French_{trades} + \sum NGC_{trades}$
System Buy Price (SBP)	The weighted average of the accepted offers (in £/MW)	
System Sell Price (SSP)	The weighted average of the accepted bids (in £/MW)	
UKPX	The UK Power Exchange reference price (in £/MW)	

6.4 Selection of unusual events

6.4.1 Selection criteria

One of the first steps to analyse unusual events is to identify how they manifest themselves in the data. This means that a criteria must be developed to select when an event stops being usual.

Classic extreme value theory considers two methodologies to detect and select the extreme (unusual) values in the data. These are the block maxima/minima and the peaks-over-threshold (POT) methods.

6.4.1.1 The block maxima/minima

There is an extent theory behind the block maxima/minima method and its extension for the generalised method for fitting the Generalised Extreme Value distribution (GEV). This widely exceeds the scope of our analysis and only a brief description of its basis is included in this chapter but the interested reader can refer to (Embrechts et al., 1997, Reiss and Thomas, 2001) for a detailed description of the methodology.

The main idea is to divide the data into n consecutive blocks of length s.

$$\begin{aligned} X^{(1)} &= (X_1^{(1)},\ldots,X_s^{(1)}) \\ X^{(2)} &= (X_1^{(2)},\ldots,X_s^{(2)}) \\ \vdots & \qquad \vdots \\ X^{(n)} &= (X_1^{(n)},\ldots,X_s^{(n)}) \end{aligned}$$

These blocks are considered to be independently identically distributed (iid), but within each vector the various components are likely to be dependent. The length of the blocks should be chosen according to the conditions. From each of these blocks the maximum and minimum values are filtered to finally obtain two series of length n containing the maximum and minimum values.

$$\begin{aligned} X_i &= \max(X_1^{(i)},\ldots,X_s^{(i)}) \\ X_j &= \min(X_1^{(j)},\ldots,X_s^{(j)}) \end{aligned} \qquad i = 1,\ldots,n$$

Figure 6.2 describes block maxima criteria for the creation of the maxima series.

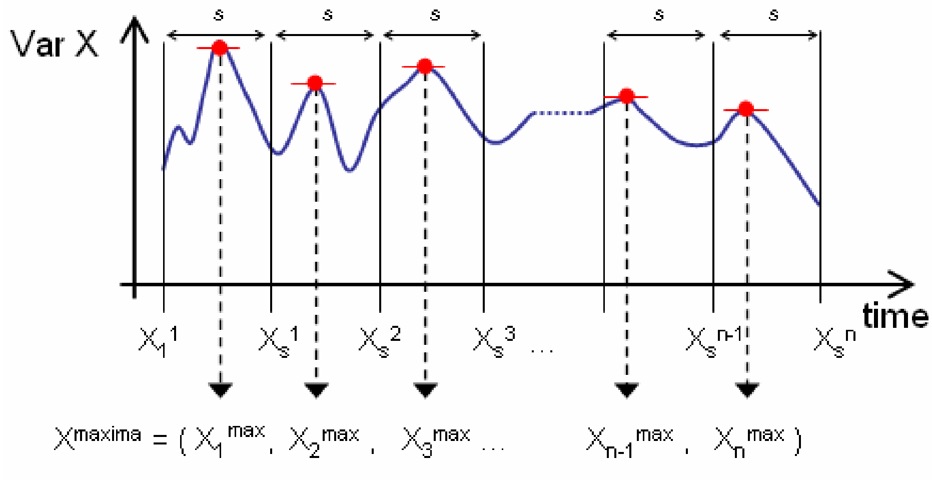


Figure 6.2 The block maxima method

The main advantage of this approach is that it is simple and easy to implement. However it has also an important drawback since there is a high risk of loosing unusual observations within the same block that can contribute to the understanding of unusual conditions.

6.4.1.2 The Peak-Over-Threshold Method

This is an alternative to the block maxima method for selecting unusual conditions (Bystrom, 2003, Embrechts et al., 1997, Reiss and Thomas, 2001). In this case, rather than analysing an isolated maximum value, a threshold u is set. All the values exceeding the threshold in the series are considered unusual observations (figure 6.3). Thus the number of unusual conditions is determined by the magnitude of the threshold u.

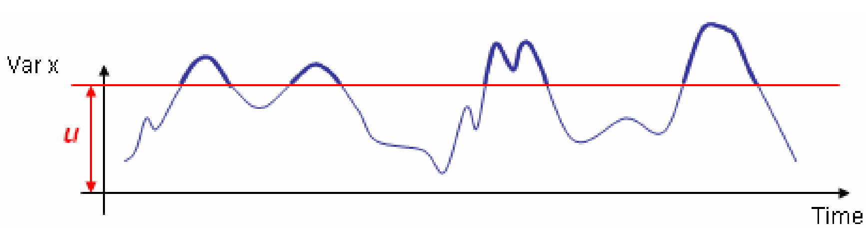


Figure 6.3 Peaks-Over-Threshold selection criteria

The selection of the threshold is the critical step of the analysis. On the one hand, the threshold must be high enough to select only truly unusual events, while on the other hand it should be low enough to ensure that enough data are selected. Threshold selection does not have a unique solution. Its determination includes some trial and error as well as the application of common sense. In our analysis, the compromise is found to set the minimum and maximum thresholds for each trigger variable to the values corresponding to its 5 and 95 percentiles (figure 6.4).

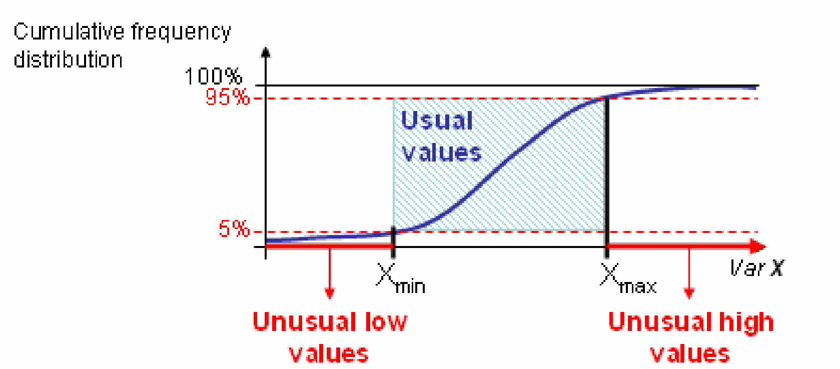


Figure 6.4 Threshold selection criteria

6.4.2 Application to trigger variables

The previous section presented the existing methodologies for cases selection. However the characteristics of the data need to be taken into account in the selection of the unusual conditions:

- Continuous plain variables: the POT criteria can be directly applied.
- Non-continuous plain variable (plant loss): every occurrence is considered an event.
- Ratio variables: the application of the POT criteria does not cover all the conditions of interest for this analysis. Each variable requires a specific analysis:

- $\frac{DFE}{GCIV}$: If $\frac{DFE}{GCIV}$>0 with DFE >0 (DF>Demand) and GCIV>0 (short market conditions), then the POT criteria can be applied to select unusual cases.

  If $\frac{DFE}{GCIV}$ >0 with DFE <0 (Demand>DF) and GCIV<0 (long market conditions). These cases do not represent any risk for the market operation.

  If $\frac{DFE}{GCIV}$<0 with DFE<0 (Demand>DF) and GCIV >0 (short market conditions). All these cases are included in the analysis.

  If $\frac{DFE}{GCIV}$<0 with DFE >0 (DF>Demand) and GCIV <0 (long market conditions). These cases mean a safe market condition operation and are not included in the analysis.

- $\frac{DFE}{Demand}$: Unusual cases are selected using the POT criteria

- $\frac{\Delta MEL}{\Delta Demand}$: If $\frac{\Delta MEL}{\Delta Demand}$>0 then both rates of change follow the same trend and unusual cases can be selected using the POT criteria.

  If $\frac{\Delta MEL}{\Delta Demand}$< 0 with ΔMEL>0 and ΔDemand<0. These cases represent no risk for the market operation and are not included in the analysis.

  If $\frac{\Delta MEL}{\Delta Demand}$< 0 with ΔMEL<0 and ΔDemand>0. In these cases there is a decrease of the available capacity and an increase in the demand. All these cases are considered unusual conditions.

Table 6.3 presents a summary of the thresholds defining the unusual cases for all the trigger variables.

Table 6.3 Unusual conditions thresholds

VARIABLE	LOWER THRESHOLD	UPPER THRESHOLD
DFE (MW)	-644	750
MEL Day Change (MW)	-2146	836
REM (MW)	-1489	1574
$\frac{DFE}{GCIV}$	<0; when DFE<0 and GCIV >0	1.5
$\frac{DFE}{Demand}$	-0.019	0.021
$\frac{\Delta MEL}{\Delta Demand}$	<0; when ΔMEL<0 and ΔDemand>0	3.486

6.5 Quantitative analysis

6.5.1 Objectives

The aim of this study is to detect and filter non-meaningful variables and cases initially considered as unusual conditions. It also provides a base of information and a broad view of the behaviour of the market in the case of an event.

6.5.2 Methodology

The analysis is based on the observation of statistical indexes such as mean, standard deviation, maximum and minimum, and the time location of the event occurrences (month, day type and period).

The study considers separately the occurrence of each event, and both trigger and passive variables are included.

The global, initial and broad nature of the analysis does not make it possible to draw any definite conclusions about the variables reaction. However, as a filtering technique it can help us select meaningful events.

6.5.3 Results and conclusions

Table 6.4 presents the statistical indicators for each variable when all the cases are included. For the trigger variables the upper and lower thresholds are also included. In the following sections the same statistical indexes are calculated for the specific case as well as the indexes difference between events and general conditions. Tables for each case can be found in Appendix 1.

The global nature of the data creates a further complication of measuring the indirect impacts since some local effects can be masked within the overall market reaction.

Table 6.4 Descriptive statistics for all cases included.

VARIABLE	MEAN	STD.DEV.	MIN	MAX	THRESHOLDS UPPER	THRESHOLDS LOWER
DFE (MW)	40.7	432.31	-2790	2585.0	-644	750
MEL day change (MW)	-420.8	998.32	-8252	4741.4	-2146	836
REM (MW)	77.56	950.80	-16743	4912.0	-1489	1574
DFE/Dem	0.001	0.01	-0.079	0.1	-0.019	0.021
ΔMel/ΔDemand	0.4	19.64	-1324	1240.2	<0*	3.848
DFE/GCIV	-0.9	116.30	-14125	2752.4	<0**	1.5
DF (MW)	34192.0	6259.36	20242	53093.0		
DEMAND (MW)	34151.3	6234.47	20576	52889.0		
PGCE (MW)	118.3	688.13	-17169	3781.6		
ΔDemand (MW)	0.1	964.27	-2435	4320.0		
ΔMEL (MW)	0.1	790.63	-18968	11778.0		
SBP (£/MW)	34.5	71.91	0	5003.3		
SSP (£/MW)	9.6	7.97	-500	206.8		
AOV (MW)	316.5	388.52	0	3033.3		
ABV (MW)	-1089.9	699.07	-4864	0.0		
SOV (MW)	69166.1	10854	34335	130917		
SBV (MW)	-74106.9	10559	-160214	-40894		
AOC (£MWh)	7302.1	16554.29	-591	846374.9		
ABC (£MWh)	-3696.4	5941.55	-34898	343691.7		
GCIV (MW)	-891.7	927.17	-4538	16844.1		
NIV (MW)	-1057.6	872.55	-4681	2643.6		
NGC TRADES (MW)	-240.6	323.79	-2689	1009.1		
FRENCH TRADES (MW)	-44.0	179.94	-1755	1116.8		

VARIABLE	MEAN	STD.DEV.	MIN	MAX	THRESHOLDS UPPER	THRESHOLDS LOWER
CPN (MW)	35090.5	6340.98	15457	53656.1		
UKPX	13.3	8.66	1	134.5		

(*when ΔMEL<0 and ΔDemand>0, ** when DFE<0 and GCIV >0)

It is important to notice that the comments given below do not try to explain the market reaction but rather to identify the conditions that require further study and those which are not worth to carry forward. Since only the statistical indexes for the averages and std. deviations are considered, there is no solid ground to make any further conclusions about the events characteristics or the market reaction A detailed analysis for each case is presented in the following sections.

DFE below the lower threshold

In these conditions the demand is larger than its forecast. The market variables are considerably affected especially the offer acceptances that should compensate the deviation of the demand. The overall market length (NIV) is affected by an average decrease of 45%. However the market participants do not modify their patterns under these circumstances and at gate closure the market is longer than normal (GCIV 36% average increase).

DFE above the higher threshold

In these conditions the demand is lower than its forecast. As in the previous case the market is affected by these circumstances. There is an increase in the acceptance of bids and a consequent increase in the market length (NIV increases by 45% in absolute value from its average).

MEL day change below the lower threshold

These cases refer to a large increase in generation declaration from the day ahead to gate closure. The statistical indexes show no significant effect on the market conditions. However, the time occurrence of these values (figure 6.5) is highly concentrated on Monday (day 2) which indicates that the unusual values are not due to any physical event but rather to an information delay from the market participants to the system operator, from Sunday to Monday. These cases are, therefore, no longer considered for further analysis.

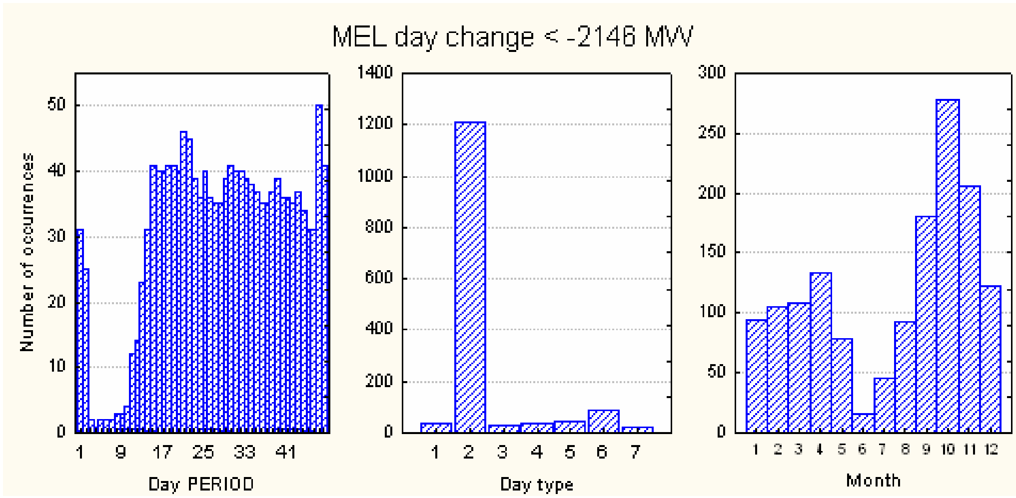


Figure 6.5 Time distribution of MEL day change (below the lower threshold) occurrences

MEL day change above the higher threshold

These cases refer to the conditions where there is a large decrease in declared generation from the day ahead to gate closure. As in the previous case, there is no significant impact on the market. Figure 6.6 shows that these values are highly concentrated during the summer periods when plant commissioning is more frequent. These abnormal values can be treated as an information event, with no significant consequences on the market behaviour, rather than an indicator of a physical event. These cases are excluded from further analysis.

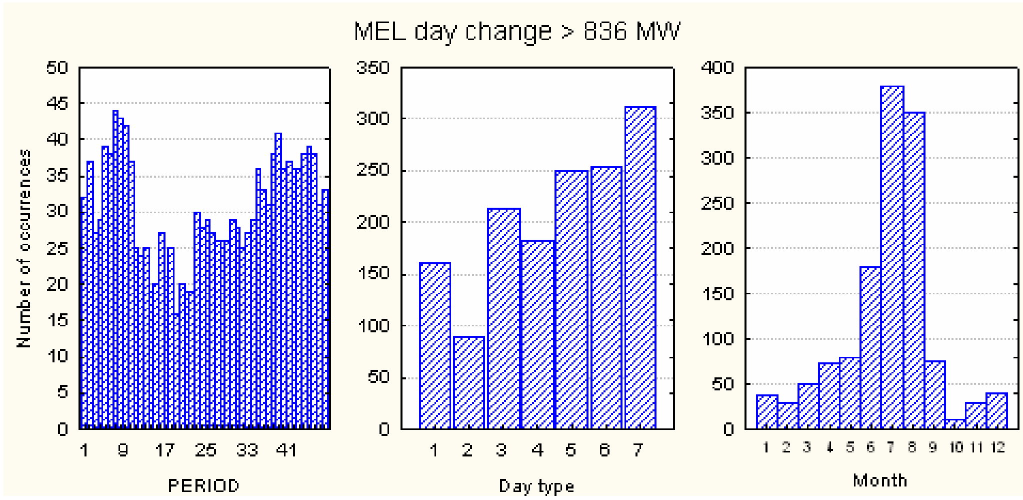


Figure 6.6 Time distribution of MEL day change (above the higher threshold) occurrences

REM below the lower threshold

These cases consider the conditions where there is a post gate closure event (not due to DFE) of large over-generation. These conditions alter the market variables normal values (bid/offer acceptances, CGIV and NIV) and are considered for further analysis.

REM above the higher threshold

These cases indicate a post gate closure event of large under-generation. Market variables, such as bids and offer acceptances and market volumes, are affected. A further analysis of such market conditions is presented below.

Negative $\dfrac{DFE}{GCIV}$*, with negative DFE and short market at gate closure*

Under these conditions the demand is larger than its forecast and the market is short at gate closure. Most of the market variables are highly affected by these conditions: acceptances of offers increase to 193% of its average value and the acceptances of bids decrease significantly. Market volumes and imbalance prices are also considerably affected and these conditions are clearly identified as significant events.

$\underline{\frac{DFE}{GCIV}}$ *above the higher threshold*

These conditions can either refer to a positive DFE and short market conditions at gate closure (i.e. GCIV>0) or to a demand that exceeds its forecast (i.e. DFE<0) combined with long market conditions at gate closure (i.e. GCIV<0). The average values for DFE (126 MW) and GCIV (27.3MW) reveal that most of the cases refer to the first scenario. Since the error in the demand forecast is large and the declared generation covers the actual demand, the market behaviour does not reflect any significant change. Therefore these events are not analysed further.

$\underline{\frac{DFE}{Demand}}$ *below the lower threshold*

This conditions refer to the cases when there is a large forecast error (the demand is greater that its forecast) relative to the demand value. This cases are directly related with large DFE, as shown in figure 6.7 over 80% of these cases are included in the DFE below the lower threshold. The market reaction is therefore similar to the one described for that scenario.

$\underline{\frac{DFE}{Demand}}$ *above the higher threshold*

In this cases there is a large forecast error (demand forecast exceeds its actual value) relative to the demand value. As with the previous case, these cases are directly related to large DFE. As shown in figure 6.7, 82% of cases $\frac{DFE}{Demand}$ above the higher threshold correspond to cases with DFE above the higher threshold. The market reaction is therefore similar to the one described for large DFE errors.

Both of these market conditions can be considered represented when looking at extreme values of DFE and the trigger variable $\frac{DFE}{Demand}$ is not carried forward for further analysis.

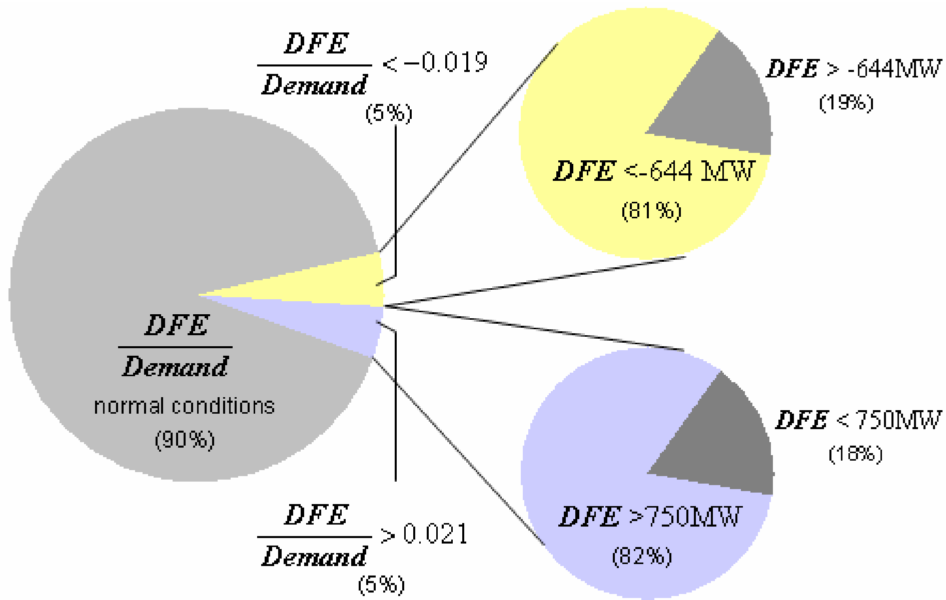


Figure 6.7 $\frac{DFE}{Demand}$ *and DFE drill down analysis*

<u>*Negative* $\frac{\Delta MEL}{\Delta Demand}$ *with negative increment of MEL and positive increment of demand*</u>

These cases refer to the conditions where there is a significant decrease in the maximum declared capacity from one period to the next together with an increase in the demand. These market conditions can be problematic especially when the market is already short but under normal conditions they can just reflect a forecasting mistake on the participants' side.

Market variables are not affected by these conditions. A clear example is the effect that these conditions have over the market length, represented by NIV. Figure 6.8 shows on the x-axis NIV's values, on the left y-axis NIV's probability distribution for normal (blue line), and these specific unusual (red line) conditions. On the right y-axis the green line shows the difference in probability between the normal and the unusual conditions. By observing this figure one can notice an increase in the probability of short market conditions. However, the highest probability increase is just 0.02 and corresponds to the smallest values of short market conditions.

These market conditions are therefore not carried forward for further analysis.

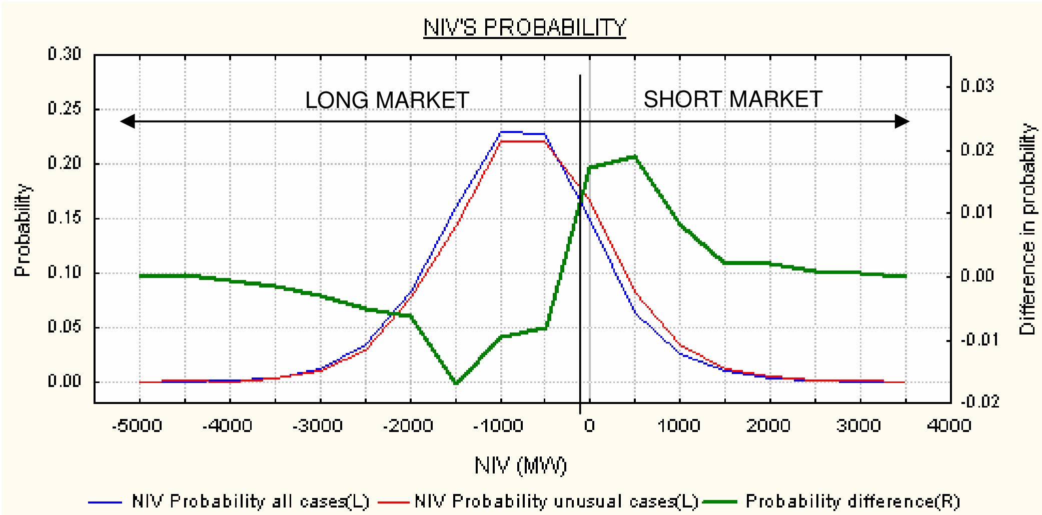


Figure 6.8 NIV's probability distribution for usual and unusual cases

$\dfrac{\Delta MEL}{\Delta Demand}$ *above the higher threshold*

In this context there is a large increase in the available capacity along with an increase in the demand. However the declared capacity increase is larger than the increase in the demand. These conditions are more likely to happen on Mondays 5:30 am (period 11) and they not have any significant impact on the market variables. These cases are thus not considered as unusual events worthy of further analysis.

6.6 Characterization of unusual events

6.6.1 Objectives

In the previous section we have selected the meaningful variables and cases that trigger unusual market conditions. The next step, and the aim of this analysis, is to describe these unusual conditions using probability theory and statistical modelling. The scope of the analysis is therefore to determine the likelihood of these unusual events, their duration and the mean waiting time between specific events.

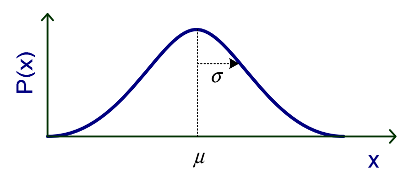
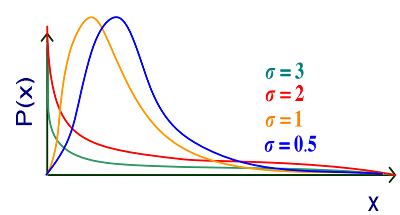
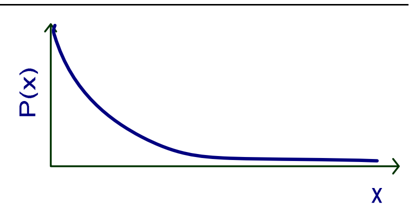
6.6.2 Analysis of trigger variables under unusual conditions

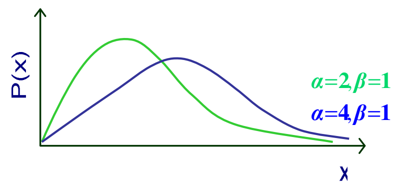
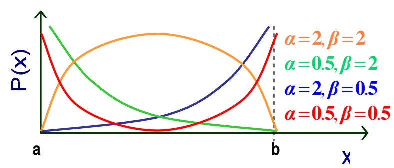
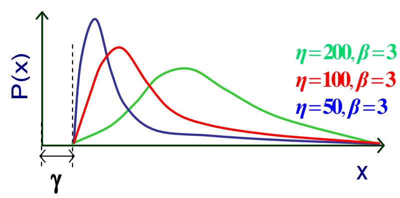
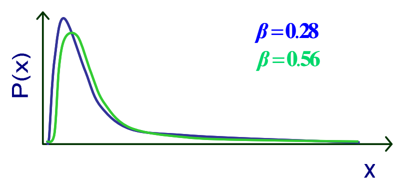
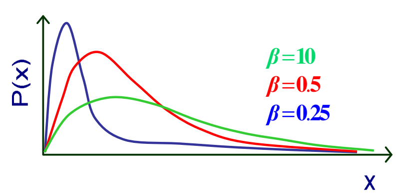
The main goal of this analysis is to find an independent probability distribution which is a good model for each trigger variable.

Non-parametric robust techniques are applied to obtain a parametric model that provides the likelihood of occurrence for each event. Non-parametric techniques are used because they do not rely on a specific distributional assumption. They are robust because they perform well under different distribution consideration.

The distributions considered are: normal, log-normal, exponential, gamma, beta, Weibull, log-normal, extreme value and Rayleigh. Table 6.5 briefly describes the main characteristics of each of these distributions.

Table 6.5 Probability distributions

NAME	PROBABILITY DENSITY FUNCTION	EXAMPLE
Normal	$f(x)=\frac{1}{\sqrt{2\pi}\cdot\sigma}e^{-\frac{(x-\mu)^2}{2\cdot\sigma^2}}$ Where: μ is the mean σ is the standard deviation and shape parameter	
Log-Normal	$f(x)=\begin{cases}\frac{1}{\sqrt{2\pi}\cdot\sigma\cdot(x)}\cdot e^{-\frac{(\ln(x)-\mu)^2}{2\cdot\sigma^2}} & ,x\geq 0\\ 0 & ,x<0\end{cases}$ Where σ is the shape parameter	
Exponential	$f(x)=\begin{cases}\frac{1}{\beta}\cdot e^{-\frac{x}{\beta}} & ,x\geq 0\\ 0 & ,x<0\end{cases}$ Where β is the shape parameter	

NAME	PROBABILITY DENSITY FUNCTION	EXAMPLE
Gamma	$$f(x)=\begin{cases}\dfrac{1}{\beta^{\alpha}\Gamma(\alpha)}\cdot x^{\alpha-1}e^{-\frac{x}{\beta}} & ,x>0\\ 0 & ,x\le 0\end{cases}$$ Where α is the scale parameter β is the shape parameter	
Betta	$$f(x)=\begin{cases}\dfrac{\Gamma(\alpha+\beta)}{\Gamma(\beta)\Gamma(\alpha)}\cdot x^{\alpha-1}(1-x)^{\beta-1} & ,a<x<b\\ 0 & ,x\le a, x\ge b\end{cases}$$ Where α and β are the shape parameters	
Weibull	$$f(x)=\begin{cases}\dfrac{\beta}{\eta}\left(\dfrac{x-\gamma}{\eta}\right)^{\beta-1}\cdot e^{-\left(\frac{x-\gamma}{\eta}\right)^{\beta}} & ,x\ge 0\\ 0 & ,x<0\end{cases}$$ Where γ is the location parameter β is the shape parameter η is the scale parameter	
Extreme value	$$f(x)=\frac{1}{\beta}e^{\frac{x-\alpha}{\beta}}\cdot e^{-e^{\frac{x-\alpha}{\beta}}}$$ Where α is the location parameter β is the scale parameter	
Rayleigh	$$f(x)=\begin{cases}\dfrac{x}{\beta^{2}}\cdot e^{-\frac{1}{2}\left(\frac{x}{\beta}\right)^{2}} & ,x\ge 0\\ 0 & ,x<0\end{cases}$$ Where β is the shape parameter	

The first step is to determine the location and shape parameters for each of the considered distributions. Non-parametric quantile (Q-Q) and probability (P-P) graphs are used for this purpose. A goodness-of-fit test is then applied to determine which of the distributions has the optimum fit. There is a wide range of goodness-of-fit tests ((Embrechts et al., 1997, Palutikof et al., 2001). They can be based on a test statistic that determines the probability of the null hypothesis (i.e. that the population distribution of the data sample is the same as the hypothesized distribution) like the chi-squared, the Anderson-Darling and the Kolmogorov-Smirnov test; or they can be based on probability plots like the L-moment diagrams ((Zafirakou-Koulouris et al., 1998). In our analysis the Kolmogorov-Smirnov test is used since it can be used for all probability distributions, and its performance does not depend on the sample size (it is an exact test).

6.6.2.1 Quantile and probability plots

Quantile-Quantile plots

Quantile-quantile (Q-Q) plots are used to determine the location and scale parameters for a family of distributions, as well as to check for the fit of a theoretical distribution to the observed data.

Given the set of data $x_1,..,x_n$, supposed these are governed by a distribution function $F_{\mu,\sigma}(x) = F((x-\mu)/\sigma)$ where μ and σ are the location and shape parameters. Thus $F{=}F_{0,1}$ is the standardised form of this distribution.

To produce a Q-Q plot the N observed data points are sorted into ascending order ($x_1 \le x_2 \le ... \le x_n$). These observed values, which correspond to $\hat{F}_n^{-1}(q)$, are plotted in one axis of the graph against $F_n^{-1}(q)$:

$$(F_n^{-1}(q_i), \hat{F}_n^{-1}(q_i)) = (F_n^{-1}(q_i), x_{i:n}), \text{ for } i = 1,..n\text{; with } q_i = i/(n+1)$$

The Q-Q plot is presented as a scatterplot with a linear interpolation, the intercept and slope of which provide the location and shape parameters. This can be explained from the relation ship between $\hat{F}_n^{-1}(q)$ and $F_n^{-1}(q)$ so that:

$$\hat{F}_n^{-1}(q_i) \approx F_{\mu,\sigma}^{-1}(q_i) = \mu + \sigma F^{-1}(q_i) \tag{6.1}$$

If the scatterplot differs consistently from the linear approximation then the initial hypothesis for the distribution function has to be rejected.

Probability-Probability plots

Probability-probability (P-P) plots are used to determine whether a specific frequency distribution, with defined location and shape parameters, fits the frequency distribution of a set of data $x_1,..,x_n$.

The observed cumulative distribution function is plotted in a scatterplot against the theoretical cumulative distribution function, so that each point corresponds to:

$$(F(x_i), \hat{F}(x_i)) \text{ for } i= 1,..n$$

If the theoretical cumulative distribution models well the observed distribution, then all points in this plot fall onto the diagonal line.

6.6.2.2 The Kolmogorov-Smirnov test

The Kolmogorov-Smirnov (K-S) test is used to decide if a sample comes from a population with a specific distribution (Conover, 1999).

Considering a data sample ($x_{1,...,}x_n$) consisting of n events with a cumulative distribution $S_n(x)$ and the hypothesis of a cumulative distribution function $F(x)$, the value D_n is calculated:

$$D_n = \max_{1<i<n} \left| S_n(x_i) - F(x_i) \right| \qquad (6.2)$$

The hypothesis regarding the distributional form is rejected if the test statistic, D_n, is greater than the critical value. There are several variations of these critical values in the literature that use somewhat different scaling for the K-S test statistic and confidence intervals. The software used to perform the K-S test provides the relevant critical values.

6.6.2.3 Results

The presented modelling techniques are applied to the trigger variables selected in section 6.4.3 in order to obtain the equations for their probability density function.

First the Q-Q graphs (included in appendix 2) provide the scale and shape parameters for all the considered distributions; among those, the ones showing a better fit are selected and plotted in P-P graphs (figures 6.9, 6.11 6.13, 6.15, 6.17 and 6.19). In each graph the x-axis represent the theoretical cumulative distribution and the y-axis the actual cumulative distribution. The numbers that follow the distribution name represent the location and shape parameters for that case.

Then the Kolmogorov-Smirnov test is used to select the distribution that provides the optimum fitting. These results are included for each case in tables 6.6 to 6.11.

The expressions of the fitted probability distributions are presented in equations 6.3 to 6.8.

Finally, the fitted probability density function is used to compare the observed and expected probability of the different variable values. These results are presented in figures 6.10, 6.12, 6.14, 6.16 and 6.18.

DFE below the lower threshold

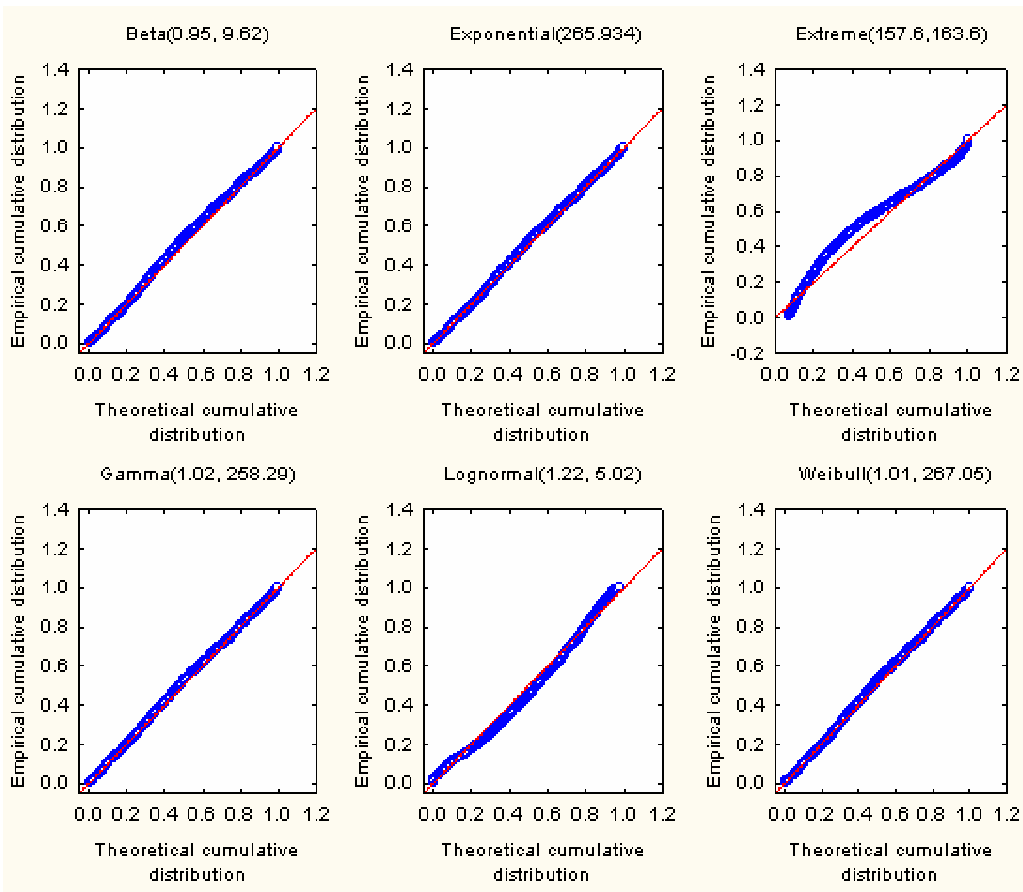


Figure 6.9 Probability-Probability graphs for DFE below the lower threshold

Table 6.6 Kolmogorov-Smirnov test

Distributions (Param.1,Param.2)	Parameter 1	Parameter 2	Kolmogorov-Smirnov D
Exponential (threshold, scale)	644	265.9336	0.020483
Weibull (scale, shape)	267.0461	1.0098	0.023182
Gamma (scale, shape)	258.2903	1.0296	0.024474
Log-Normal (scale, shape)	5.0246	1.2270	0.061039
Extreme Value (location, scale)	801.6470	163.5832	0.094964
Normal (location, scale)	909.9336	267.3657	0.160866
Rayleigh (threshold, scale)	644	266.6101	0.307780

The Kolmogorov-Smirnov test shows that DFE below the lower threshold events are best modelled by an exponential distribution. From the considered distributions the one giving the worst fit is the Rayleigh distribution.

Therefore the fitted probability density function for DFE events below the lower threshold is given by the equation:

$$f(x) = \frac{1}{265.93} e^{-\left(\frac{-644-x}{265.9}\right)}, \quad x < -644 \qquad (6.3)$$

Using equation 6.3, the following figure shows the difference between the observed and the obtained probability for the different DFE values.

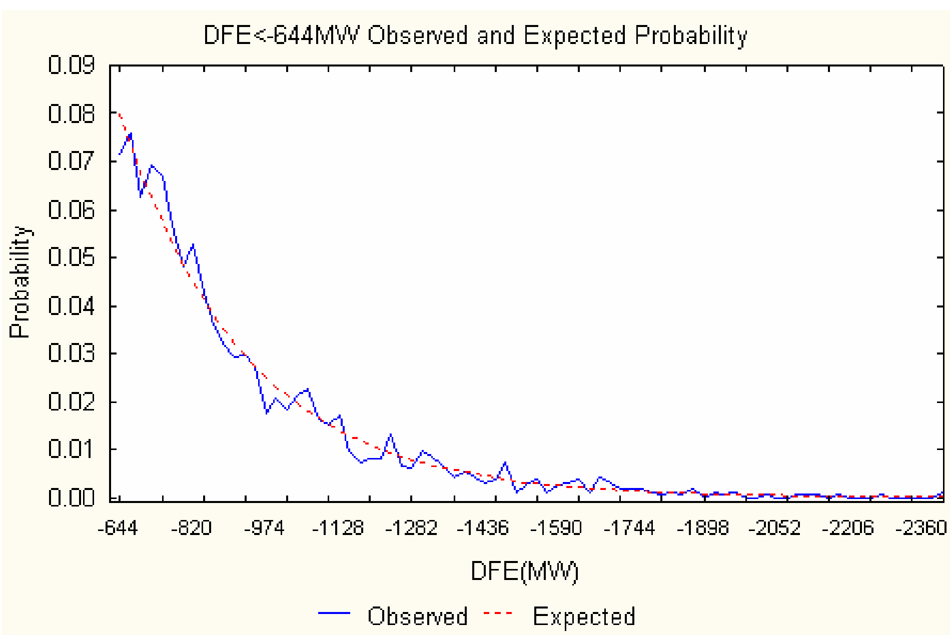


Figure 6.10 Obtained and observed probability

DFE above the higher threshold

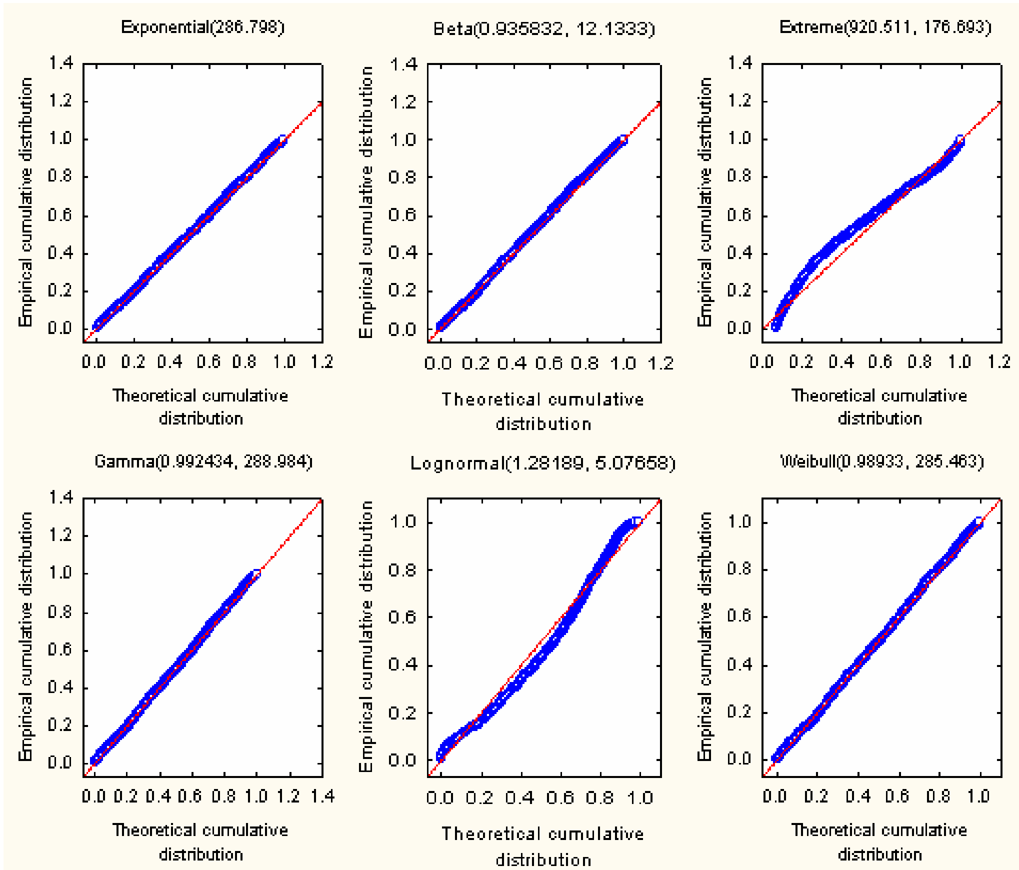


Figure 6.11 Probability-Probability graphs for DFE above the higher threshold

Table 6.7 Kolmogorov-Smirnov test

DISTRIBUTIONS (PARAM.1,PARAM.2)	PARAMETER 1	PARAMETER 2	KOLMOGOROV-SMIRNOV D
Exponential (threshold, scale)	750	286.798	0.014451
Gamma (scale, shape)	288.984	0.9924	0.015035
Weibull (scale, shape)	285.463	0.9893	0.017093
Log-Normal (scale, shape)	5.077	1.2819	0.075873
Extreme Value (location, scale)	920.511	176.6925	0.089657
Normal (location, scale)	1036.798	308.3887	0.177030
Rayleigh (threshold, scale)	750	297.740	0.300036

The Kolmogorov-Smirnov test shows that, as in the previous case, DFE above the higher threshold events are best modelled by an exponential distribution. From the considered distributions the one giving the worst fit is the Rayleigh distribution.

Therefore the fitted probability density function for DFE events above the higher threshold is given by the equation:

$$f(x) = \frac{1}{286.8} e^{-\left(\frac{x-750}{286.8}\right)}, \quad x > 750 \tag{6.4}$$

Using equation 6.4, the following figure shows the difference between the observed and the obtained probability for the different DFE values.

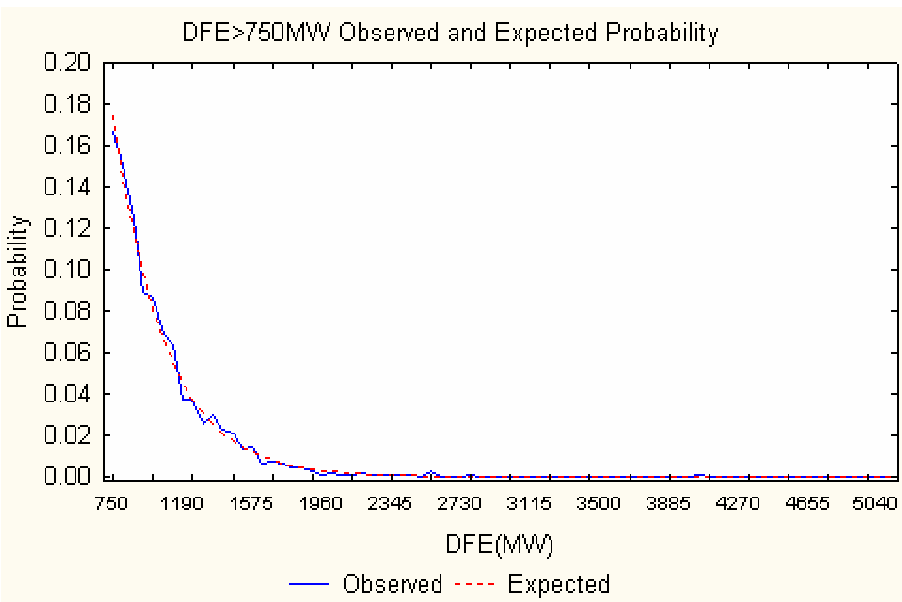


Figure 6.12 Obtained and observed probability

Plant loss

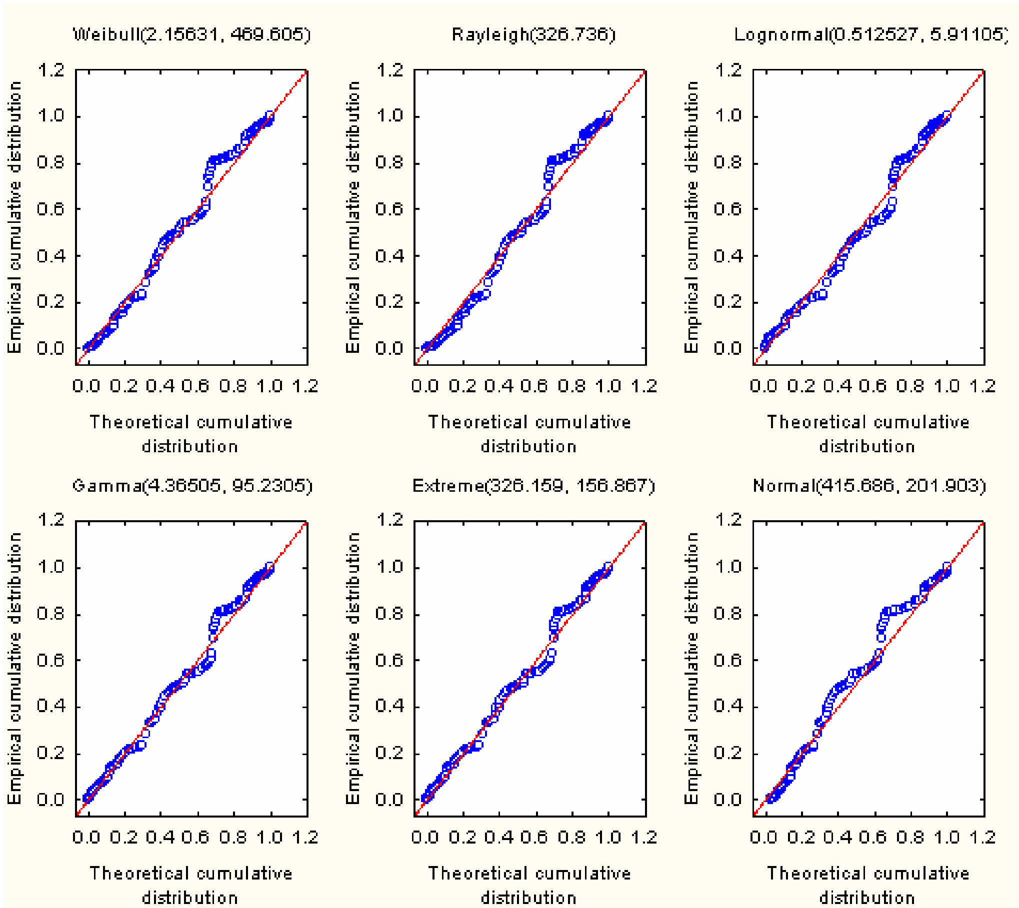


Figure 6.13 Probability-Probability graphs for plant loss

Table 6.8 Kolmogorov-Smirnov test

DISTRIBUTIONS (PARAM.1,PARAM.2)	PARAMETER 1	PARAMETER 2	KOLMOGOROV-SMIRNOV D
Extreme Value (location, scale)	326.1587	156.8665	0.087073
Gamma (scale, shape)	95.2305	4.3650	0.091621
Log-Normal (scale, shape)	5.9110	0.5125	0.104594
Rayleigh (threshold, scale)	0	326.7363	0.112589
Weibull (scale, shape)	469.6052	2.1563	0.120783
Normal (location, scale)	415.6856	201.9032	0.140618
Exponential (threshold, scale)	0	415.6856	0.284301

According to the results of the Kolmogorov Smirnov test plant loss events are best modelled by the extreme value distribution. In this case is the exponential distribution the one that offers the worst fit. The results for the D statistic are in this case significantly greater than in the previous ones, indicating a worse quality of the fitting.

The fitted probability density function for plant loss events is given by the equation:

$$f(x) = \frac{1}{156} e^{\frac{x-326}{156}} \cdot e^{-e^{\frac{x-326}{156}}} \quad (6.5)$$

Using equation 6.5, figure 6.14 shows the difference between the observed and the obtained probability for the different values of plant loss events.

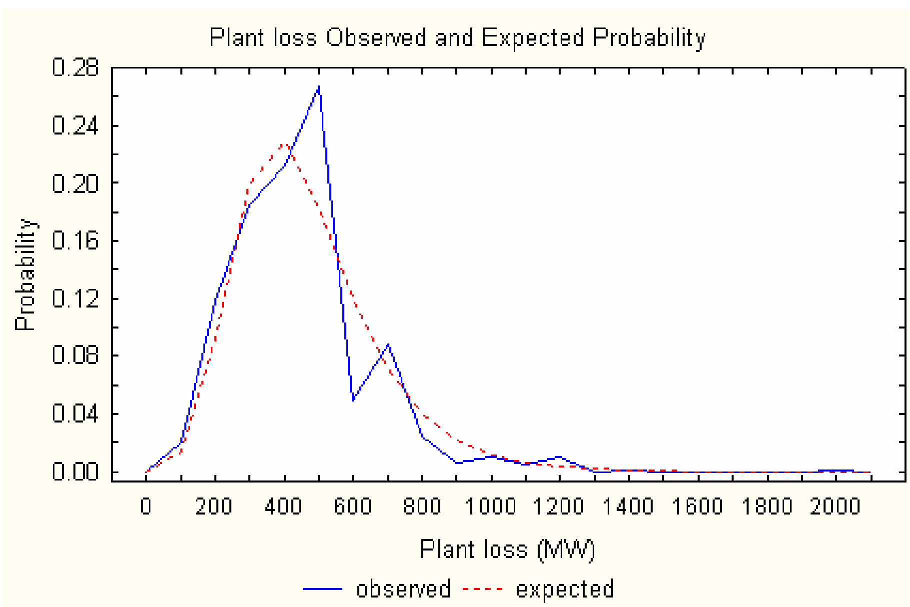


Figure 6.14 Obtained and observed probability

REM below the lower threshold

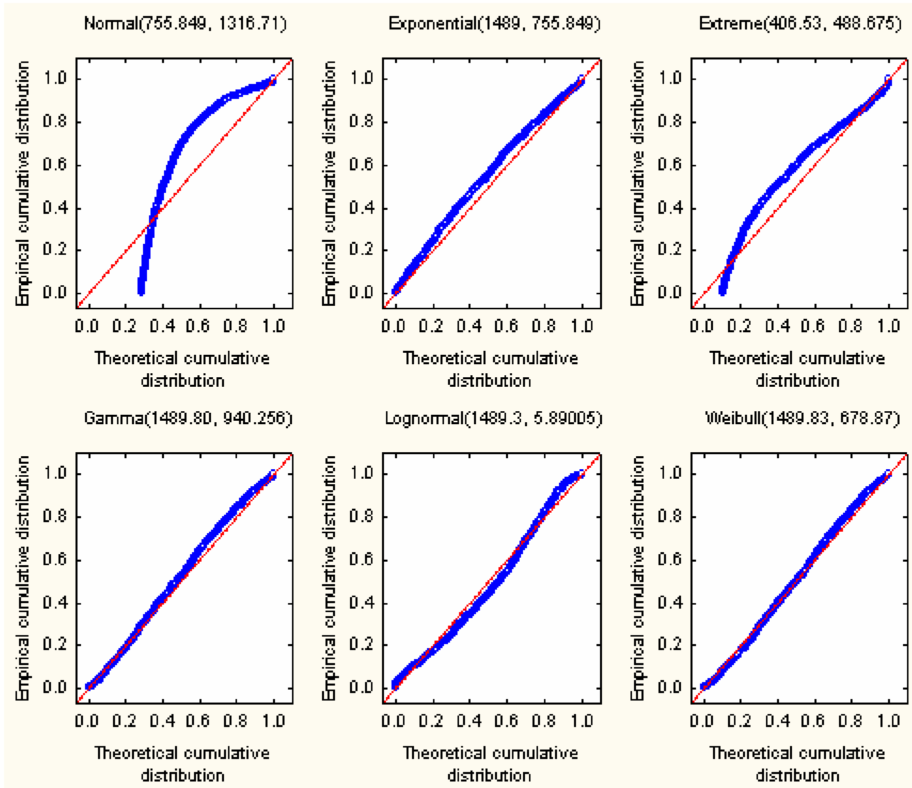


Figure 6.15 Probability-Probability graphs for REM_below the lower threshold (<-1489MW)

Table 6.9 Kolmogorov-Smirnov test

DISTRIBUTIONS (PARAM.1,PARAM.2)	PARAMETER 1	PARAMETER 2	KOLMOGOROV-SMIRNOV D
Weibull (scale, shape)	678.870	0.839	0.037298
Gamma (scale, shape)	940.256	0.804	0.051453
Log-Normal (scale, shape)	5.890	1.370	0.065495
Exponential (threshold, scale)	1489	755.849	0.066489
Extreme Value (location, scale)	1895.530	488.675	0.111850
Normal (location, scale)	2244.849	1316.706	0.283027
Rayleigh (threshold, scale)	1489	1073.275	0.476506

The Kolmogorov-Smirnov test shows that REM below the lower threshold events are best modelled by a Weibull distribution. From the considered distributions the one giving the worst fit is the Rayleigh distribution.

Therefore the fitted probability density function for REM events below the lower threshold is given by the equation:

$$f(x) = 1.23 \cdot 10^{-3} \left(\frac{-1489 - x}{678.8} \right)^{-1.839} \cdot e^{-\left(\frac{-1489 - x}{678.8} \right)^{0.839}} \quad , x < -1489 \qquad (6.6)$$

Using equation 6.6, figure 6.16 shows the difference between the observed and the obtained probability for the different REM values.

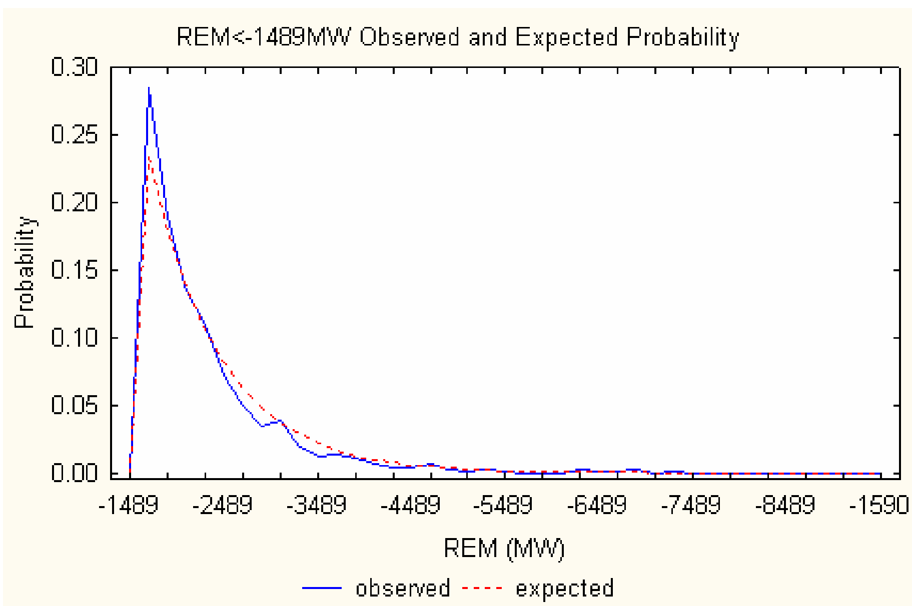


Figure 6.16 Obtained and observed probability

<u>REM above the higher threshold</u>

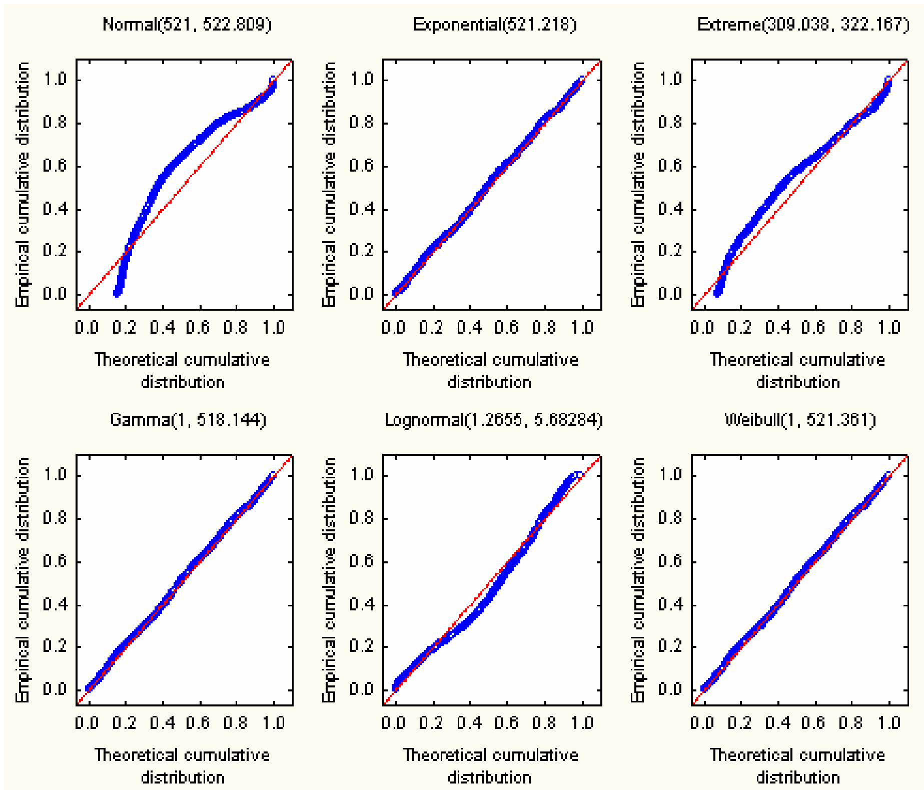


Figure 6.17 Probability-Probability graphs for REM above the higher threshold (>1574MW)

Table 6.10 Kolmogorov-Smirnov test

DISTRIBUTIONS (PARAM.1,PARAM.2)	PARAMETER 1	PARAMETER 2	KOLMOGOROV-SMIRNOV D
Exponential (threshold, scale)	1574	521.2175	0.016683
Weibull (scale, shape)	521.3613	1.0006	0.016684
Gamma (scale, shape)	518.1445	1.0059	0.017216
Log-Normal (scale, shape)	5.6828	1.2655	0.083138
Extreme Value (location, scale)	1883.038	322.1674	0.085596
Normal (location, scale)	2095.218	522.8088	0.159486
Rayleigh (threshold, scale)	1574	521.9244	0.299005

The Kolmogorov-Smirnov test results show that the exponential distribution is the one that gives the best fit for REM events above the higher threshold. Weibull distribution also offers a similar goodness of fit and as in previous cases the Rayleigh distribution is the worst fitting distribution.

The expression of the Weibull probability density function for REM events above the higher threshold is given by:

$$f(x) = \frac{1}{521.21} e^{-\left(\frac{x-1574}{521.21}\right)}, \quad x > 1574 \tag{6.7}$$

According to equation 6.7, figure 6.18 shows the difference between the observed and the obtained probability for the different REM values.

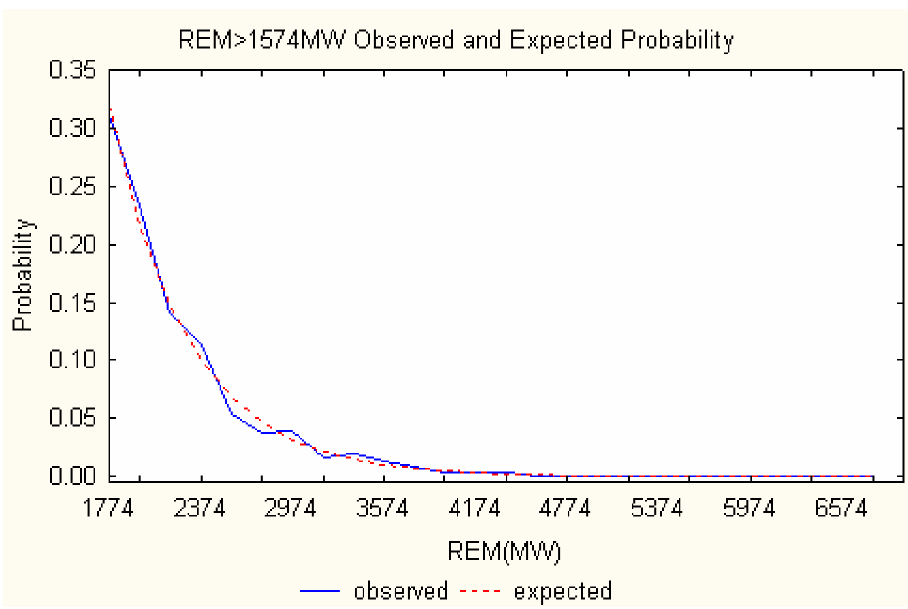


Figure 6.18 Obtained and observed probability

$\frac{DFE}{GCIV}$ with negative DFE and short market at gate closure

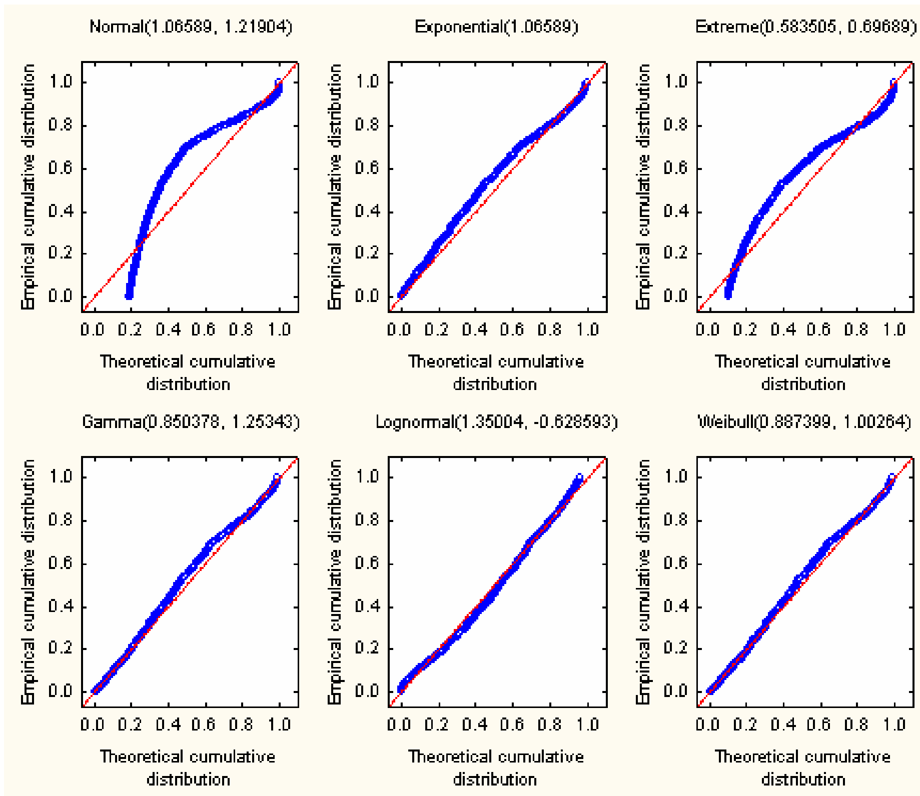


Figure 6.19 Probability-Probability graphs for $\frac{DFE}{GCIV}$ with negative DFE and short market at gate closure

Table 6.11 Kolmogorov-Smirnov test

Distributions (Param.1,Param.2)	**Parameter 1**	**Parameter 2**	**Kolmogorov-Smirnov D**
Weibull (scale, shape)	1.002636	0.887399	0.046199
Log-Normal (scale, shape)	-0.628593	1.350036	0.050270
Gamma (scale, shape)	1.253432	0.850378	0.055375
Exponential (threshold, scale)	0	1.065891	0.077503
Extreme Value (location, scale)	0.583505	0.696890	0.131355
Normal (location, scale)	1.065891	1.219037	0.198037
Rayleigh (threshold, scale)	0	1.144737	0.383224

The Kolmogorov-Smirnov test results show that the Weibull distribution is the one that gives the best fit for events defined by a negative $\frac{DFE}{GCIV}$ with negative DFE and short market at gate closure. Normal and Rayleigh distribution are the worst fitting distributions. The fitted probability density function for $\frac{DFE}{GCIV}$ with negative DFE and short market at gate closure is given by:

$$f(x) = 0.87\left(\frac{-x}{1.002}\right)^{-0.12} \cdot e^{-\left(\frac{-x}{1.002}\right)^{0.887}} \quad , x < 0 \qquad (6.8)$$

Using equation 6.8, figure 6.20 shows the observed and expected probability values for the different values of $\frac{DFE}{GCIV}$ events.

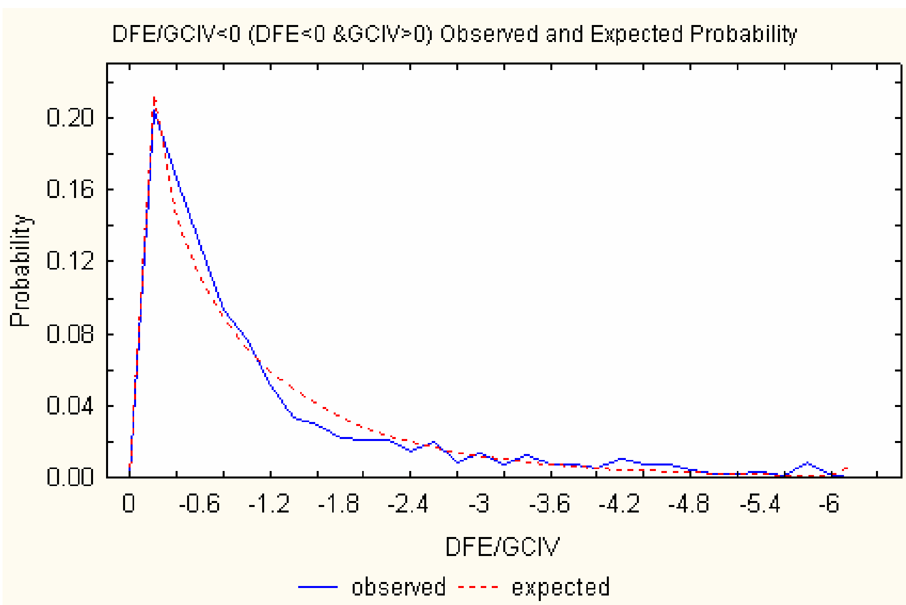


Figure 6.20 Obtained and observed probability

6.6.2.4 Conclusions

The main conclusion derived from these results is that unusual market events do not present a common behaviour. This is reflects the diversity of the events considered in this analysis (plant loss, large DFE errors…). There is not a unique probability distribution that fits all the considered conditions but the nature and the parameters of the fitted probability distributions vary from one case to another. Moreover, the goodness of fit differs from one case to another.

While exponential and Weibull distribution are the ones that best model continuous variables (DFE, REM and $\frac{DFE}{GCIV}$), the extreme value distribution is the best choice for the non-continuous plant loss variable. However it is also the plant loss event the one that gives the worst fit with a 0.08 value for the D Kolmogorov-Smirnov statistic (compared with a D= 0.014 in the DFE above the higher threshold case).

A common feature for all the continuous variables is that the probability peaks for values close to the threshold and decreases as the variable increases. However, the plant loss follows a different pattern: its probability increases until it reaches a maximum around 500MW (which can be considered the size of a large coal typical unit (National Grid Transco et al., 2004, ELEXON, 2005)) and decreases thereafter. Despite these differences in the probability distributions, all the results show the rarity of extremely large events.

6.6.3 Events duration

6.6.3.1 Duration criteria

This part of the analysis is concerned with the length of the sequence of consecutive events, that is, the duration of the events. The mathematical analysis of the duration of an event is defined as follows.

Consider a variable X, being $(x_{1,\ldots,}x_n)$ a series of observations over time, and define x_{max} as the threshold value that defines the occurrence of the event. A new auxiliary binary variable Y is defined as:

$$y_i = 1 \quad \text{if} \quad x_i \geq x_{\max}$$
$$y_i = 0 \quad \text{if} \quad x_i < x_{\max} \quad \text{for } i = 1, \ldots, n \qquad (6.9)$$

An event of duration j in X is defined as a subsequence of $(x_{i+1,\ldots,}x_{i+j})$ of $(x_{1,\ldots,}x_n)$ such that

$$y_i = 0, \quad y_{i+1} = \cdots = y_{i+j} = 1, \quad y_{i+j+1} = 0 \qquad (6.10)$$

where $y_i = y_n = 0$.The same criteria can be defined for x_{min} . Figure 6.21 illustrates the concept of the auxiliary variable y as well as the duration criteria.

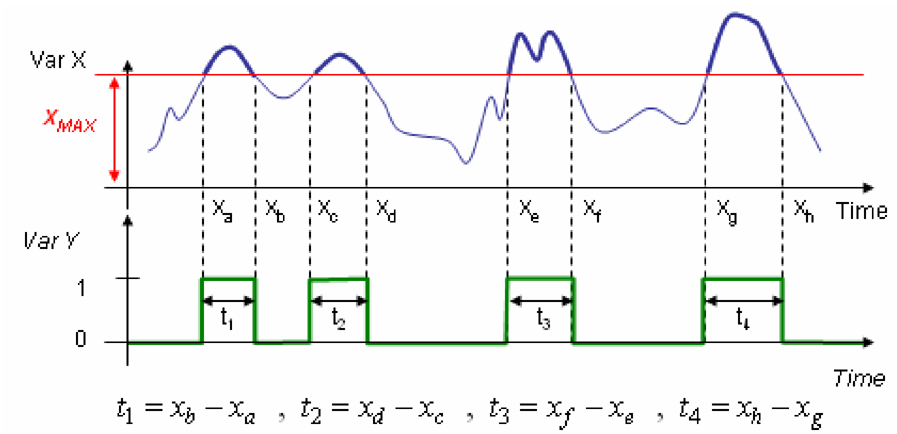


Figure 6.21 Events duration criteria

This definition refers to the case of a unique event. However this analysis considers a multidimensional scenario were different events can occur simultaneously (DFE and REM, DFE and plant loss, REM and GCIV/DFE and so on). For this case, we consider X^1, X^2,..., X^m variables with distributions in time

$$X^1 = (x_1^1, \ldots, x_n^1)$$
$$X^2 = (x_1^2, \ldots, x_n^2)$$
$$\vdots \qquad \vdots$$
$$X^m = (x_1^m, \ldots, x_n^m)$$

The corresponding thresholds for each variable are $x_{\max}^1, x_{\max}^2 \ldots, x_{\max}^m$.The auxiliary binary variable Y is defined as:

$$\begin{aligned} y_i &= 1 \quad \text{if} \quad \exists\, \mathrm{p}\ x_i^p \geq x_{\max}^p \\ y_i &= 0 \quad \text{if} \quad \forall\, \mathrm{p}\ x_i^p < x_{\max}^p \quad \text{for } i = 1, \ldots, n \end{aligned} \tag{6.11}$$

An event of duration *j* is defined by the variable Y according to equation 6.10. For the sake of simplicity, the events refer only to those defined by a maximum threshold; nevertheless, there is an analogous definition for the duration of the events identified by a minimum threshold. Figure 6.22 presents the concept of event duration for a multidimensional scenario with 2 variables *X* and *Z*.

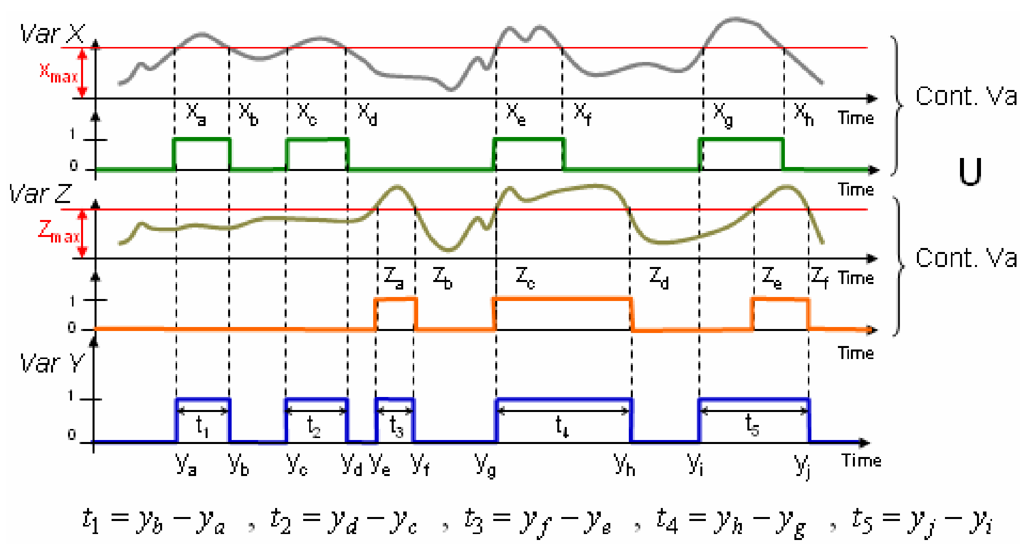


Figure 6.22 Events duration criteria for multidimensional scenario

6.6.3.2 Results

In this case only continuous variables are included. Since there is no available data to determine a plant recovery, plant loss is considered as an instant event with no duration.

First each event is independently considered. The following figure shows, for each variable, its duration histogram. The x-axis represents the duration, expressed in periods resolution, and the y-axis the frequency (i.e. the number of observances).

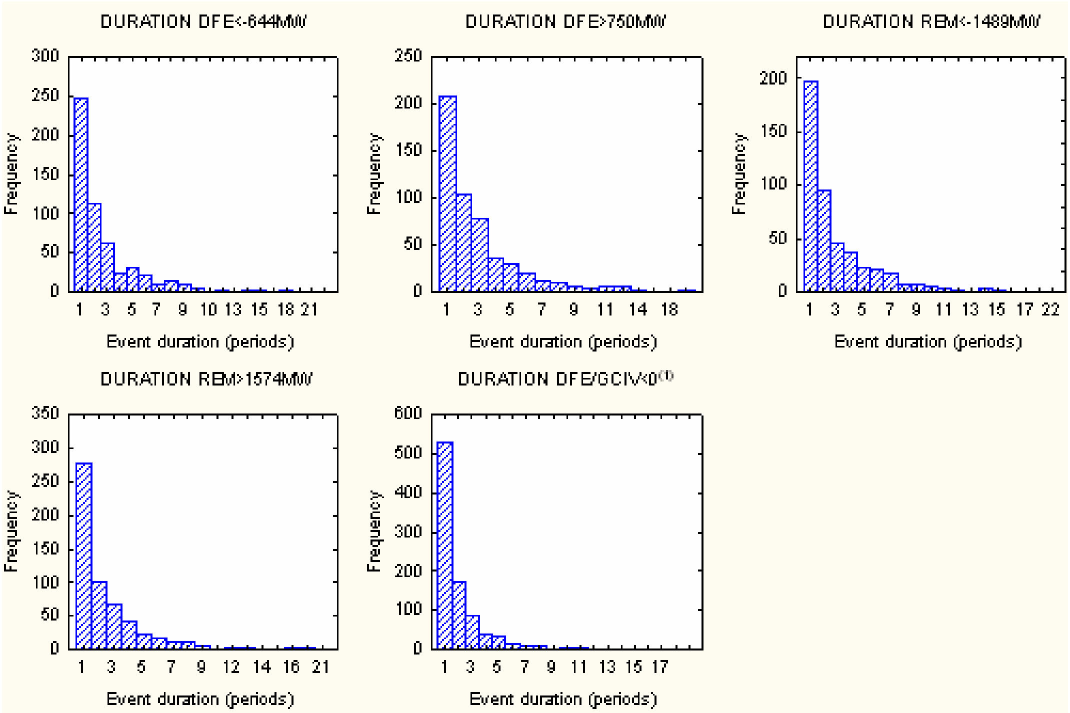


Figure 6.23 Event duration for continuous variables (note (1) DFE<0 and GCIV>0)

The mean duration as well as the 10 and 90 percentiles of the duration distribution for each event are presented in Table 6.12

Table 6.12 Event duration description

VARIABLE	MEAN DURATION	10 PERCENTILE	90 PERCENTILE
DFE<-644MW	2.96	1	7
DFE>750MW	3.06	1	7
REM<-1487MW	2.58	1	5
REM>1574MW	3.02	1	7
DFE/GCIV<0	2.09	1	4

In a multidimensional scenario an event is defined is a case when either DFE or REM are above or below their corresponding lower or higher thresholds or DFE/GCIV is negative. The results for the duration under these conditions are presented in Figure 6.24 and Table 6.13.

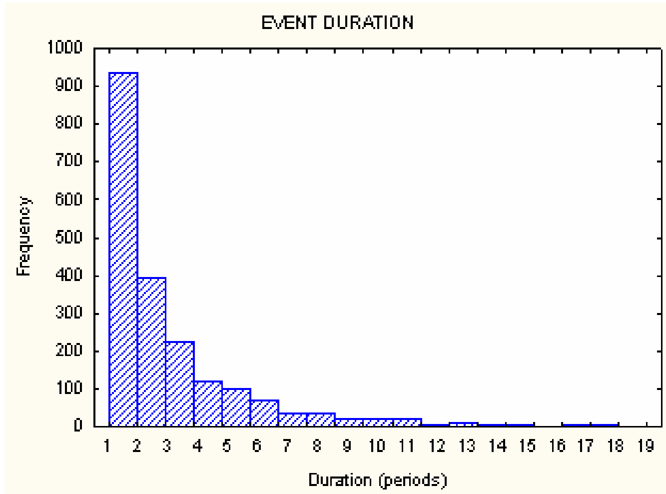


Figure 6.24 Event duration for multidimensional scenario

Table 6.13 Event duration description

MEAN DURATION	10 PERCENTILE	90 PERCENTILE
2.84	1	6

6.6.3.3 Conclusions

The results for the independent events show that these conditions have an approximate duration of 1.5 hours (3 periods). The cases where the demand forecast greatly exceeds the actual demand are the conditions that have a longer duration.

Another important observation, for the case of the DFE and REM, events is the consideration of the total energy that they represent (i.e. the average excess over the threshold times the duration of the event). Figure 6.25 shows, for each case, the histogram where the x-axis is the magnitude of the event in MWh and the y-axis the number of observations. This figure shows that events that exceed 1000MWh are extremely rare in any case.

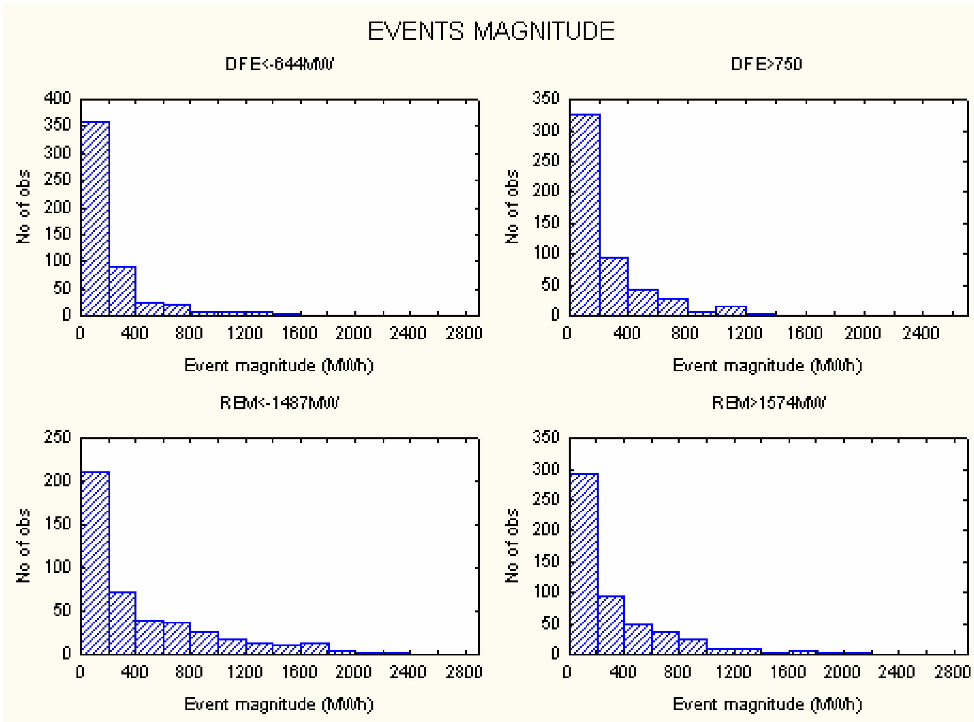


Figure 6.25 Events total magnitude

The duration of events in the multidimensional scenarios, does not differ greatly from the independent event consideration. This reflects how events of different nature usually are not linked in time but they happen either simultaneously or separately by at least one unit of time.

6.6.4 Time between events

6.6.4.1 The return period

The return period, also called recurrence interval, is the mean waiting time between events. The reciprocal of the return period is the exceedance probability of the event, that is, the probability that the event (set by a threshold u) is equaled or exceeded in any defined period of time. The return period is usually found in hydrologic frequency analysis to estimate how often events of a given magnitude will occur.

However, the return period does not determine when an event will occur, but it just informs about the likelihood of an event. In this way, a T-hour event is an event that over a long period of time (longer than T hours) has an average time of occurrence of T hours.

For engineering applications (Castillo, 1988), where the failure of a component is associated with the occurrence of an event, the return period can also be understood as the mean lifetime of this component.

Following the structure of the events duration analysis, this analysis considers first each event independently, and then analyses the return period considering the possible occurrence of all the events. Figure 6.26 describes the multidimensional approach for the calculation of the mean time between events.

In this analysis all events are examined, including not only continuous variables but also the plant loss which is treated as an instantaneous event.

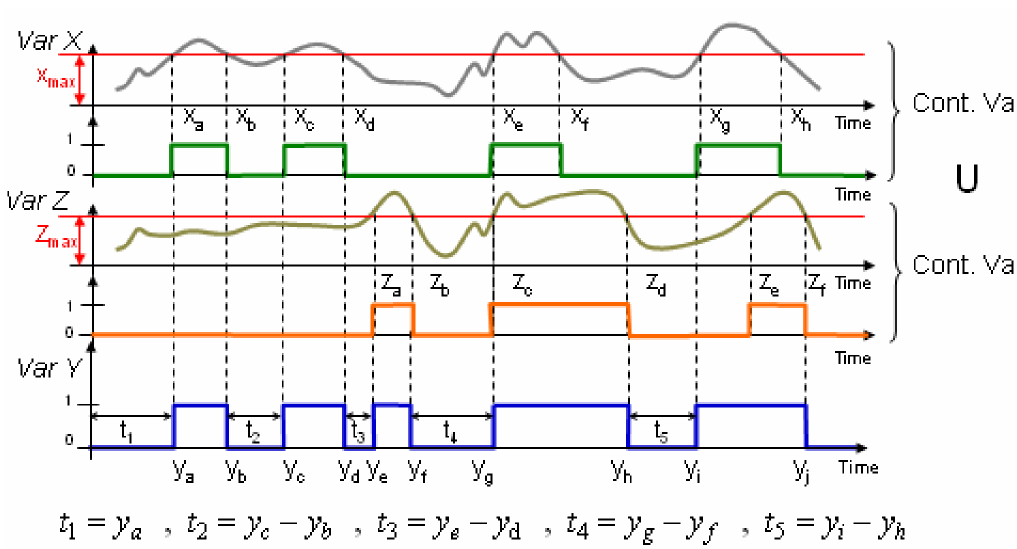


Figure 6.26 Time between events for multidimensional analysis

6.6.4.2 Results

The following figure presents the histograms for the time between events independently for each of the cases. The x-axis represent time between events in periods resolution and the y-axis is the frequency or number of observances.

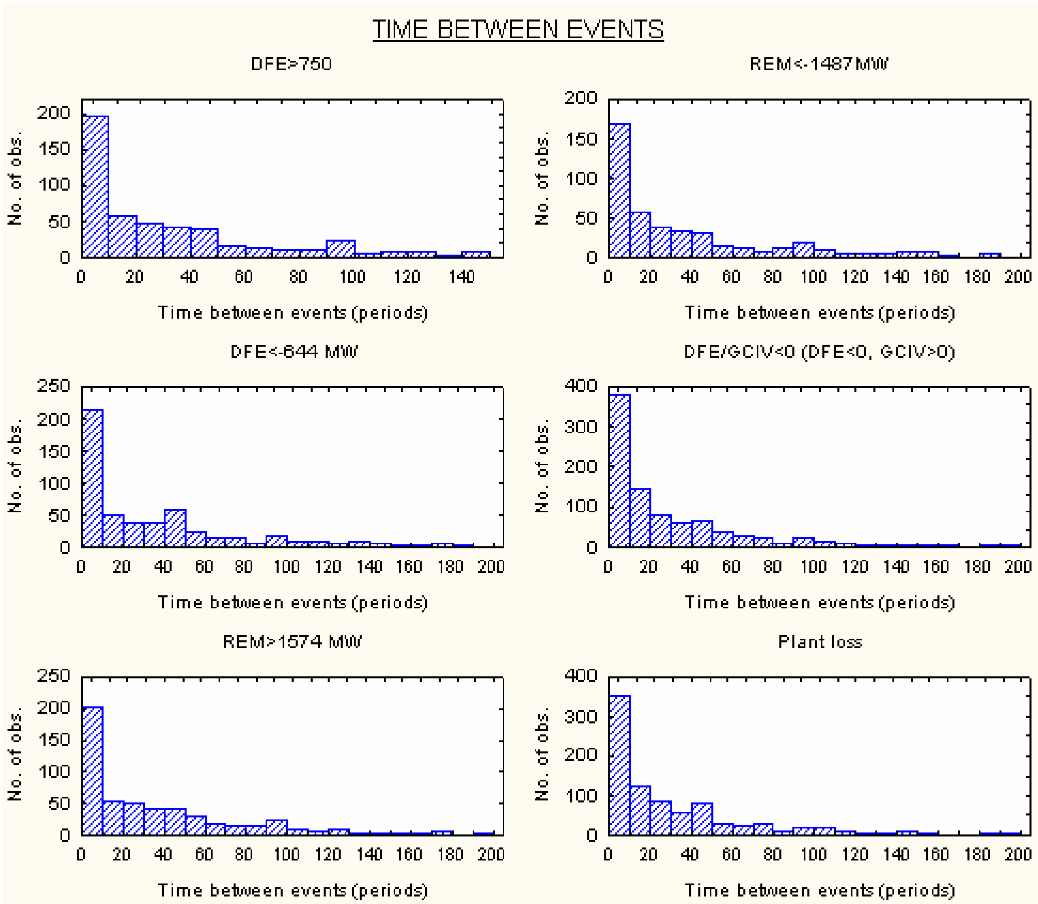


Figure 6.27 Time between events (singular events).

The statistical analysis of the time between events determines the mean time between events and therefore the T-hour return period. In this analysis the T-hour period is just half the value of the mean time between events expressed in market periods resolution.

Table 6.14 shows for each variable, its return period (T-hour), its mean, minimum and maximum times between event, as well as the standard deviation (in market periods resolution).

Table 6.14 Return period and time between events (TBE) for each event.

	T-HOUR	MEAN TBE	MIN. TBE	MAX. TBE	STD DEVIATION
DFE<-644 MW	24.7	49.38	1	619	74.28
DFE >750MW	26.23	51.46	1	699	81.09
Plant loss	16.5	33.1	1	259	40.82
REM<-1486	29.4	58.81	1	740	99.23
REM>1574	24.4	48.85	1	509	69.38
DFE/GCIV	14.89	29.78	1	263	37.25

For the multidimensional scenario, where the occurrence of all the events is considered, Figure 6.28 shows the histogram of the time between events with time between events in period resolution (x-axis), and number of observations (y-axis). Table 6.15 presents similar results to Table 6.14 but for the multidimensional case.

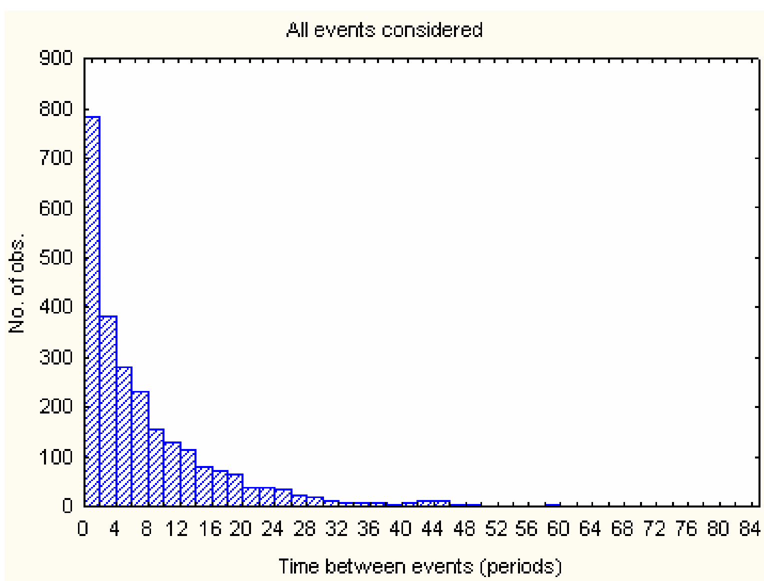


Figure 6.28 Time between events for multidimensional scenario.

Table 6.15 Return period and time between event (TBE) multidimensional scenario.

	T-HOUR	MEAN TBE	MIN. TBE	MAX. TBE	STD DEVIATION
ALL	4.42	8.82	1	120	10.46

6.6.4.3 Conclusions

When considering each event independently we can notice significant differences between the different return periods. According to this, DFE/GCIV events are most likely to happen followed by plant loss events; REM events are the most unlikely to occur (less than a daily event). These results complement with the previous event duration results. In this way the combination of duration and time between events helps to determine an average time sequence of the events.

The multidimensional scenario clearly differs from the single event conditions. The time between events decreases significantly to 4.42 hours. This result is partly due to the consideration of outages (not included in the duration analysis) and also due to the already mentioned characteristic two or more events do not occur in a consecutive manner.

As a general conclusion, it is observed that the multidimensional perspective transforms unusual events into "frequent" events. On average more than 5 events of a different nature happen in the market every day. However, the duration results for the multidimensional context do not greatly differ from those obtained for single events which also suggest that events occurrences are not consecutive.

6.7 Consequences analysis

6.7.1 Objectives

Up to this point, this study of unusual events has been focussed on their probability, frequency and duration. This section establishes the link between the causes and effects. In this way, the analysis of unusual events is expanded to define their consequences in the market. The market reaction is documented by considering the effect that unusual conditions have over balancing mechanism variables and imbalance prices.

This study is designed to give a global perspective on the effect of unusual events:

- The analysis considers that an event can have an impact on several variables and combines one-dimensional and multidimensional perspectives. The market reaction is evaluated using multiple variables, and considers first the impact of a single event and then, if possible, a combination of events.

- The response is evaluated in both its total magnitude (i.e. actual value of the variables) and also its relative value (i.e. deviation from moving averages).
- The analysis of consequences covers not only the static reaction of the market at the time of the event but also the dynamic behaviour of the variables prior and after the event.

The analysis of consequences of unusual events under NETA is difficult because of their relatively high frequency due to their way they have been defined, and the global nature (i.e. a unique value for the whole market) of the passive variables. The events proximity presents a complication for the dynamic analysis, since it is difficult to determine if the reaction of the market is still driven by a previous event. Moreover, the aggregated characteristic of the analysed variables can mask, in some cases, a local reaction to an event.

Input-output analysis has been applied to evaluate the economic impact of unscheduled events (Cochrane, 1999). However, this approach is linear and static; moreover it is based on the relation between production and demand, which is not applicable in the context of NETA and its data structure. Dynamic analyses are based on ARIMA time series techniques (ARIMA interrupted time series analysis) (McDowall et al., 1987); they analyse if an unscheduled event has an impact on the behaviour of the time series. This technique distinguishes the possible impacts of three major types of events: permanent abrupt, permanent gradual and abrupt temporary. The events causing the impact on the series are represented in the first two cases by a step function, and in the third one by a pulse function. The frequency and duration characteristics of most of the events considered in this analysis do not fall into any of these categories (only plant loss events can be modelled as a pulse). The fact that some of the affected passive (e.g. NIV) variables cannot be modelled by ARIMA also precludes the use of this technique.

Another major problem in the development of an effective line of analysis is the lack of extensive historical records.

To overcome these problems the analysis of the consequences uses ANOVA/MANOVA techniques. These techniques allow identifying if the differences between groups are significant. In this analysis, the groups are defined by the trigger values (usual or event conditions) and the effect of this imposed cluster are analysed in the passive (dependant) variables.

6.7.2 ANOVA/MANOVA analysis

The purpose of the ANalysis Of VAriance (ANOVA) technique and its multivariate extension MANOVA is to test differences between groups. ANOVA is a univariate procedure used to assess group differences on a single metric dependent variable (for example the sales of a product (metric variable) between customer groups (non metric variable)). MANOVA is a multivariate procedure that assesses group differences between two or more metric variables simultaneously (e.g. the sales in a range of products (metric variables) between customer groups).

The analysis of differences between groups is achieved by analyzing the variance, that is, by segmenting the total variance into the component that is due to true random error (i.e., within-group variability) and the components that are due to differences between means (i.e. between group variability). These variance components are then tested for statistical significance, and, if significant, the null hypothesis of no differences between means is rejected, and the alternative hypothesis (that the means of the population are different from each other) is accepted.

6.7.2.1 ANOVA

The variability analysis in the univariate case, with k groups and $n_{total} = n_1 + n_2 + ... + n_k$ observations, is based on the calculation of the F statistic. This is the ratio between the within groups estimate of variance (MS_W) and the between groups estimate of the variance (MS_B).

$$F - \text{statistic} = \frac{MS_B}{MS_W} \tag{6.12}$$

The MS_W is also known as the error variance, and it is based on the deviations of individual records from their group mean. It is comparable to the standard error of the t-statistic (equation 5.7).

The MS_B is based on the deviations of the group means over the overall mean. Under the null hypothesis all group means are equal (i.e. $\mu_1 = \mu_2 = ... = \mu_k$). The greater the differences between groups the higher the value of MS_B.

If the value of the *F* statistic exceeds its critical value then the null hypothesis is rejected and we can conclude that there is a significant difference between groups. The F_{crit} is determined from the *F* distribution with (k-1) and (n_{total}-k) degrees of freedom at a specified level of significance α.

ANOVA designs are based on the analysis of a unique measured variable (dependent variable). However, there can be one or more independent variables or factors with different groups defined among them. For instance, in the analysis of the sales volume of a product possible differentiating factors could include costumers' gender (male, female); costumers' age (under 30, over 30 years old), and costumers' incomes (lower than £20K, between £20K and £40K and over £40K). *Multifactor ANOVA* analysis makes it possible to check the relevance of each factor including the variability that each of them represent (e.g. one could determine if the sales volumes of the product differ significantly between males, under 30 years old with an income lower than £20K, and females over 30 years old with an income lower than £20K). Figure 6.29 describes the difference between one factor analysis and multifactor analysis for the volumes of sales example.

In all the analysis described to this point the observations of the dependent variable belong to different groups of subjects (e.g. males and females, under 30 years old, over 30 years old, etc.). In this case the independent variable is considered a between-groups factor. However, it is possible to have repeated measurements of the same variable (e.g. sales in winter, spring, summer and autumn) on the same subject. In this case, the factor is a repeated measures factor or within-subjects factor. *ANOVA repeated measures* analysis allows a dynamic analysis of the dependent variable.

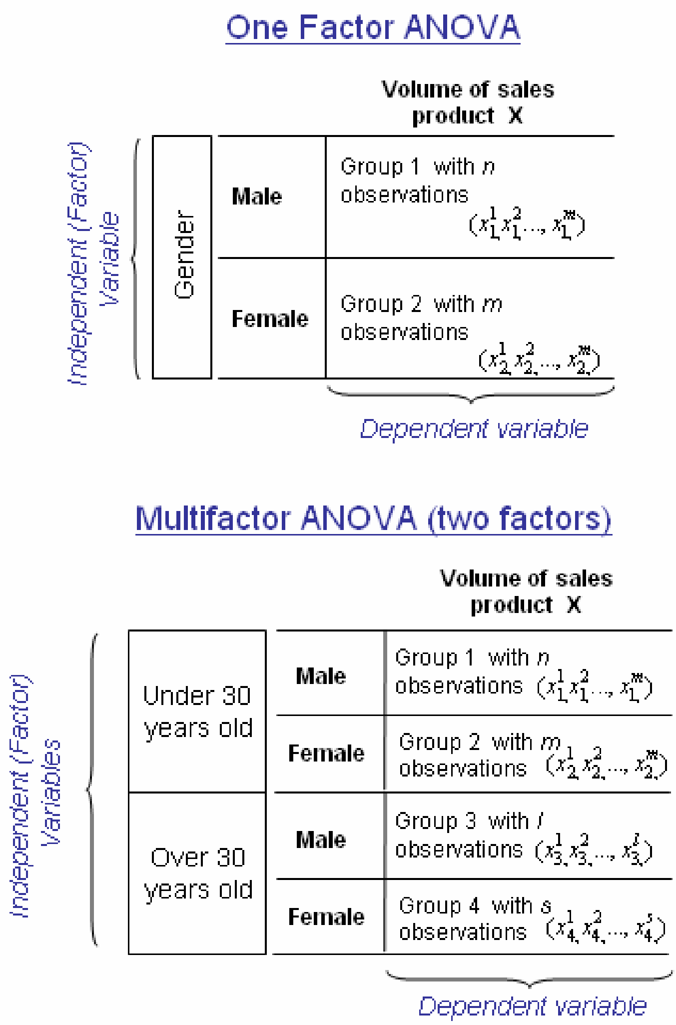


Figure 6.29 One factor and multifactor ANOVA

Further complex multifactor analysis can include of between-groups and repeated measures factors (i.e. between and within factors).

6.7.2.2 MANOVA

The multivariate analysis of the variance is used to determine differences between groups in multiple dependent variables (e.g. the volumes of sales of a range of products). Thus the null hypothesis is the equality of vectors of means on multiple dependent variables. The unique aspect of MANOVA analysis is the combination of the multidimensional measurements for statistical differences between groups into a unique value that maximizes the differences across groups.

As ANOVA could be considered an extension of the *t*-statistic, MANOVA can be considered an extension of the Hotelling's T^2.

Hotelling's T^2 provides a statistical test of the combination of the dependent variables that produces the greatest group difference. Considering a two-group case with n dependant variables, C is defined as a combination of the dependent variables of the form

$$C = W_1 Y_1 + W_2 Y_2 + \cdots + W_n Y_n \qquad (6.13)$$

where Y_i is the the i^{th} dependent variable and W_i its corresponding weight. For any set of weights the *t*-statistic can be calculated. From all the possible weights combinations there is one that maximizes the value of the *t*-statistic. The value of Hotelling's T^2 is the square of the maximum *t*-statistic. In other words, if there is a discriminant function for the two groups that produces a T^2 over its critical value, then the two groups are considered different across the mean vector.

The critical value of T^2 is determined from an F distribution with n and $N_1 + N_2 - 2 - 1$ degrees of freedom (where n is the number of dependent variables and N_1, N_2 the number of observations in each group). The tabulated value for F_{crit} is obtained at a specified level of significance α. Then the value of T^2_{crit} is calculated as follows:

$$T^2_{crit} = \frac{n(N_1 + N_2 - 2)}{N_1 + N_2 - p - 1} \times F_{crit} \qquad (6.14)$$

Following the described approach, MANOVA analysis can be considered as multivariate analysis of ANOVA. Thus, the objective is to find the set of weights that maximizes the ANOVA F value of the combination of dependent variables for all the (k) groups defined by the factor variable. From this maximum F value, the greatest characteristic root (gcr) is computed

$$gcr = \frac{(k-1)F_{\max}}{N - k} \qquad (6.15)$$

If the value of the *gcr* exceeds its critical value then the null hypothesis of equivalent group mean vectors can be rejected.

Other commonly used parameter to test overall significance in MANOVA is the Wilk's lambda. Wilk's lambda examines if groups differ without considering their linear combination and therefore is easier to calculate. A more detailed description of the MANOVA analysis formulas falls out of the scope of this thesis, but for a detailed description of the matricial equations the interested reader can refer to (Milliken and Johnson, 1992, Milliken and Johnson, 2000, Harris, 2001).

As described for ANOVA, complex designs with multiple factor variables can also be considered in MANOVA analysis. Moreover, between and within groups (i.e. repeated measures) multifactor MANOVA can also be defined.

6.7.2.3 ANOVA/MANOVA for unusual events analysis

ANOVA and MANOVA analysis have been applied for the consequences analysis of unusual events. The adaptation of these techniques is achieved by the variables selection and transformation. In this way ANOVA and MANOVA analysis can determine if the variables' behaviour differs between normal and event conditions. These techniques can also be understood as an imposed cluster analysis; the clusters do not originate from the similarities between values of the dependent variables, but an external variable (i.e. the trigger variable) defines the clusters membership. Therefore cases are assigned to groups according to the events condition (i.e. event or no event) and the goodness of the artificial cluster is confirmed with the rejection of the nulls hypothesis.

In this way, the ANOVA/MANOVA factors, independent or grouping variables are the trigger variables and the dependent variables are the passive variables.

MANOVA analysis provides a univariate measurement of the event significance for the whole set of passive variables that represent the market activity.

ANOVA/MANOVA *repeated measures* structure allows analysing the dynamic reaction of the passive variables to an event by considering the increments and decrements of each dependent variable before and after an event.

Another important aspect to validate the use of ANOVA/MANOVA is to verify that the main assumptions of the analysis are met by the considered data structure. The main assumptions are (Harris, 2001, Lindman, 1974, Hair et al., 1984, StatSoft, 2004):

- Normality assumption. The dependent variable should be normally distributed within groups. Overall, the F-test is remarkably robust to deviations from normality (Hair et al., 1984, StatSoft, 2004).
- Homogeneity of variances. The variances in the different groups are assumed to be identical. However, Lindman (Lindman, 1974) shows that the F statistic is quite robust against violations of this assumption. There is a special case where the F statistic is very misleading. This is when the means are correlated with variances across cells of the design. This is usual in the presence of outliers. It is important to remark that our analysis conditions are not affected by this condition. Although the existence of an event is, for some variables, determined by its extreme values, these are only defining the group creation (independent variable). Therefore, the dependent variable, where the F statistic is calculated, is not affected by the presence of outliers.

6.7.3 Data preparation and transformation

6.7.3.1 Dependent variables

The dependent passive variables are selected using a criterion that strikes a compromise between a precise market representation and dimensionality issues. From the initial quantitative approach the variables carried forward in the variance analysis are: Accepted Offer Volume (AOV), Accepted Bid Volume (ABV), Demand, GCIV, NIV, SBP and SSP. Note that demand values are not expected to be affected by the unusual conditions considered in this analysis, rather they can be used to define the usual conditions when the events occur.

Each of these variables is transformed to produce other related dependent variables:

- Deviation from moving average. The moving average is computed over a window of 8 periods ($\overline{x}_i = (Mov.average(x))_i = (x_{i-7} + x_{i-6} + \ldots + x_i)/8$). The variable is transformed as follows

$$x_i^{t1} = \overline{x}_i - x_i \tag{6.16}$$

- Period to period variable change. For each variable value and each period, the period-to-period increment and decrements are calculated for two periods before that period and two periods after that period. In this way, not only the future impacts of an event are considered but also backward impacts to the past (before the event). This process is illustrated in Figure 6.30. Four dependent variables are generated:

$$\begin{aligned} x_i^{t2} &= x_{i-2} - x_{i-1} \\ x_i^{t3} &= x_{i-1} - x_i \\ x_i^{t4} &= x_i - x_{i+1} \\ x_i^{t5} &= x_{i+1} - x_{i+2} \end{aligned} \tag{6.17}$$

Therefore each variable produces 5 more dependent variables that added to the actual (non transformed) variable value make a total of 42 dependent variables to be considered.

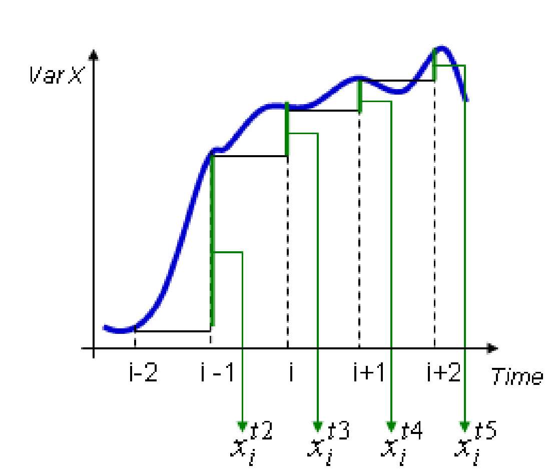


Figure 6.30. Dependent variable period to period transformation

6.7.3.2 Independent (factor) variables

The independent factor variables are the trigger variables as well as time for the MANOVA repeated measures analysis.

The coding factors defined for these variables are show in Table 6.16.

Table 6.16 Independent variable factor codes

VARIABLE	EVENT	CODE
DFE	>750 MW	1a
	<-644 MW	1b
	-644MW<DFE<750 MW	0
Plant loss	>0	2
	=0	0
REM	>1574 MW	3a
	<-1489 MW	3b
	-1489<REM<1574 MW	0
$\frac{DFE}{GCIV}$	$\frac{DFE}{GCIV}$ <0; when DFE<0 and GCIV >0	4
	Any other case	0

6.7.3.3 Analysis structure

The analysed scenarios are determined by the independent variables. In addition to the one-factor analyses it is possible to consider the consequences of multiple events (e.g. DFE above the higher threshold combined with Plant loss events). This is achieved through multifactor between groups analyses. Table 6.17 shows the feasible factors combinations with the symbol "✓" and those that could not be computed, due to lack of data for those conditions, with the symbol "✗". A maximum of two factors are combined since the available data does not allow further complex designs (e.g. there are not enough cases in which simultaneously occur plant loss, DFE value above its higher threshold and REM value below its lower threshold to establish any significant conclusion of the market reaction to those conditions).

Table 6.17 Feasible factors combinations

	DFE (0,1a,1b)		
Plant loss (0,2)	✓	Plant loss (0,2)	
REM (0,3a, 3b)	✓	✓	REM (0,3a, 3b)
$\frac{DFE}{GCIV}$ (0,4)	✗	✗	✗

Each of these one factors and multifactor are considered for the following analysis:

- MANOVA of actual values for AOV, ABV, Demand, GCIV, NIV, SBP and SSP.
- MANOVA of deviation of moving average variables including AOV, ABV, Demand, GCIV, NIV, SBP and SSP.
- Repeated measurements ANOVA for AOV, ABV, Demand, GCIV, NIV, SBP and SSP.

For multidimensional MANOVA analysis, the STATISTICA™ software used in this analysis calculates not only the multidimensional significance (significance of the overall market reaction) but also carries out the one dimensional analysis for each of the dependent variables and determines the statistical significance of the results.

6.7.4 Results

The results are presented separately for each event or combination of events (described in Table 6.17). This chapter includes the results with tables and graphs only for the DFE events and the combination of DFE with plant loss. For the rest of the events, only the conclusions derived from the results are included in this chapter. The whole set of tables are included in Appendix 3.

6.7.4.1 DFE Events

The Table 6.18 presents the results that quantify the significance of the market reaction to the conditions defined by a trigger variable(s). This is defined by the overall multivariate significance test for both the analysis of the actual variable values and the analysis of the variables' deviations from their moving averages. These significance tests refer to two different estimation coefficients: the Roy´s gcr and the Wilk´s lambda. For each test the coefficient value, its corresponding F and its significance when compared with the critical value are included. "✓" indicates that the value is significant, and "×" indicates that the value is not significant. For all the cases the higher the value of the coefficients the more pronounced the differences between the groups. Therefore, the more significant is the market reaction. It is important to note that the market reaction is evaluated as a whole so a unique value is obtained for all the dependent variables and all the groups defined in the specific event (e.g. a unique value for DFE event for all the dependent variables).

Table 6.18 Multivariate test of significance for DFE events

	MULTIVARIATE RESULTS					
	ACTUAL VALUES			DEVIATION FROM MOV. AVERAGE		
TEST NAME	*Value*	*F (Fcrit=2,9)*	*Sig.*	*Value*	*F (Fcrit=2,9)*	*Sig.*
Roy´s gcr	0.19647	820.30	✓	0.063581	265.3952	✓
Wilk´s Lamdba	0.80846	468.31	✓	0.930615	152.8060	✓

The following table presents the significance of the separate reaction of each dependent variable to a DFE trigger event. This is the univariate test of significance for each dependent variable. The table contains parallel results for the actual variable values and their deviation from moving averages. The table shows for each variable the within groups estimate of variance (MS_W), the between groups estimate of the variance (MS_B), and the F- statistics with its significance. As in the previous high values of the F coefficient are interpreted as significant differences between event and no event conditions.

Table 6.19 Univariate results of significance for DFE events

DEPENDENT VARIABLE	UNIVARIATE F RESULTS							
	ACTUAL VALUES				DEVIATION FROM MOV. AVERAGE			
	MS_B	MS_W	F (Fcrit=2,9)	Sig.	MS_B	MS_W	F (Fcrit=2,9)	Sig.
AOV	52871726	147343	358.8	✓	6857029	62687	109.4	✓
ABV	2.39E+08	4.72E+05	506.3	✓	4.54E+07	142815	318.5	✓
Demand	1.21E+10	3.80E+07	318.3	✓	3.28E+06	6.92E+06	47.5	✓
GCIV	1.19E+08	8.51E+05	140.1	✓	16422101	240744	68.2	✓
NIV	4.04E+08	7.33E+05	551.0	✓	6. 36E+07	194497	327.1	✓
SBP	68093	5167	13.1	✓	71792.7	4025.6	17.8	✓
SSP	2354.7	63.3	37.2	✓	84.0	39.2	2.1	×

The next two tables (Tables 6.20 and 6.21) unfold the dependent variables statistics for each trigger variable conditions (e.g. usual conditions, DFE below the lower threshold and DFE above the higher threshold). The first table refers to actual values of the passive variables and the second to the deviation from their moving averages.

Table 6.20 Market variables (actual values) group statistics for DFE events

DEPENDENT VARIABLE	ACTUAL VALUES MARKET CONDITIONS					
	Usual conditions (0)		DFE<-644 MW (1b)		DFE>750 MW (1a)	
	Mean	Std Error	Mean	Std Error	Mean	Std Error
AOV	308.68	2.32	546.03	13.82	215.68	7.31
ABV	-1079.31	4.18	-803.84	17.58	-1544.49	20.98
Demand	33829.41	38.71	36320.53	139.99	37041.62	136.33
GCIV	-897.59	5.55	-1108.60	29.58	-579.93	25.59
NIV	-1061.22	5.17	-537.18	25.84	-1525.24	24.22
SBP	33.75	0.45	39.97	1.12	41.12	1.81
SSP	9.45	0.04	11.02	0.35	10.312	0.14

Table 6.21 Market variables (deviation from moving average) group statistics for DFE events

DEPENDENT VARIABLE	DEVIATION FROM MOVING AVERAGE MARKET CONDITIONS					
	Usual conditions (0)		DFE<-644 MW (1b)		DFE>750 MW (1a)	
	Mean	Std Error	Mean	Std Error	Mean	Std Error
AOV	-4.22	1.55	86.86	6.16	-21.70	6.17
ABV	7.39	2.35	94.77	9.29	-213.09	9.32

DEPENDENT VARIABLE	**DEVIATION FROM MOVING AVERAGE MARKET CONDITIONS**					
	Usual conditions (0)		*DFE<-644 MW (1b)*		*DFE>750 MW (1a)*	
	Mean	*Std Error*	*Mean*	*Std Error*	*Mean*	*Std Error*
Demand	-53.15	16.34	427.40	64.70	414.00	64.88
GCIV	2.63	3.05	-118.19	12.06	76.23	12.10
NIV	1.05	2.74	185.49	10.84	-206.75	10.87
SBP	-0.71	0.39	2.62	1.56	8.51	1.56
SSP	0.03	0.04	-0.09	0.15	-0.29	0.15

The significance of the difference in the variable dynamics for the events conditions when compared with the normal conditions is presented in Table 6.23. For this purpose, the table contains, for each dependent variable, the f-statistics for the increments and decrements between the two periods before the event and the two periods after the event. As in previous cases, a high value of the f-statistics mean a significant difference between normal and event conditions in the variable dynamics for that corresponding period.

Table 6.22 Repeated measurements univariate significance results

DEPENDENT VARIABLE	**REPEATED MEASUREMENTS UNIVARIATE SIGNIFICANCE RESULTS**							
	(t-2)-(t-1)		*(t-1)-t*		*t-(t+1)*		*(t+1)-(t+2)*	
	F (Fcrit=2,9)	*Sig.*	*F (Fcrit=2,9)*	*Sig.*	*F (Fcrit=2,9)*	*Sig.*	*F (Fcrit=2,9)*	*Sig.*
AOV	16.77	✓	13.40	✓	9.21	✓	15.34	✓
ABV	81.49	✓	63.79	✓	9.48	✓	35.49	✓
Demand	26.26	✓	46.57	✓	62.08	✓	23.92	✓
GCIV	23.82	✓	19.83	✓	58.55	✓	49.38	✓
NIV	67.33	✓	60.27	✓	19.81	✓	38.20	✓
SBP	2.39	×	0.65	×	0.17	×	1.02	×
SSP	1.85	×	2.94	✓	0.17	×	0.17	×

The results show that DFE events have an impact on the considered market variables. Both the overall significance test and the univariate test show a significant difference between the dependent variables values under normal conditions, events with DFE over the higher threshold and events with the DFE under the lower threshold.

For the events where the demand largely exceeds its forecast, there is a significant decrease of the ABV and a increase of the AOV. These events also have an effect over the market length both at GC (the market is longer due to the misleading value of the demand forecast) and after the BM (the overall market length becomes shorter than in normal periods). Imbalance prices are also affected by these events. SBP increases due to the increase of offer acceptances. SSP also increases despite the decrease in the accepted bids. A possible reason for this is that the total volume of accepted bids decreases but the ones which are accepted seem to have high acceptances prices.

For the events where the demand forecast largely exceeds its actual value, there is a decrease in the AOV and a very significant increase of the ABV. These events also affect the market length both at GC and even more significantly after the BM. In this last case the market length (NIV) increases to and average value of -1525MW (1.5 times the length in normal conditions). Imbalance prices also increase under these DFE conditions. Particularly significant is the increase of SBP (8.51 £/MWh increased from its moving average). As in the previous case, this may be due to the combination of a decrease in the total volume that weights the accepted offers, with very high prices of those accepted offers.

The BM variables dynamic analysis shows that the evolution of most of the variables over time is also affected by DFE events. Imbalance price dynamics are the only variables that do not present significant differences between normal and event conditions.

Figure 6.31 shows the dynamic evolution of those variables with significant results. In each graph the x-axis represent time increments and the y-axis the increments and decrements of the dependent variable. Therefore, positive values mean an average increasing variable behaviour and negative values a decreasing trend in the variable for that period. For all the graphs vertical bars denote 0.95 confidence intervals. For each graph, the blue line represents normal conditions, the red line conditions with DFE below its lower threshold, and the blue line conditions with DFE above its higher threshold.

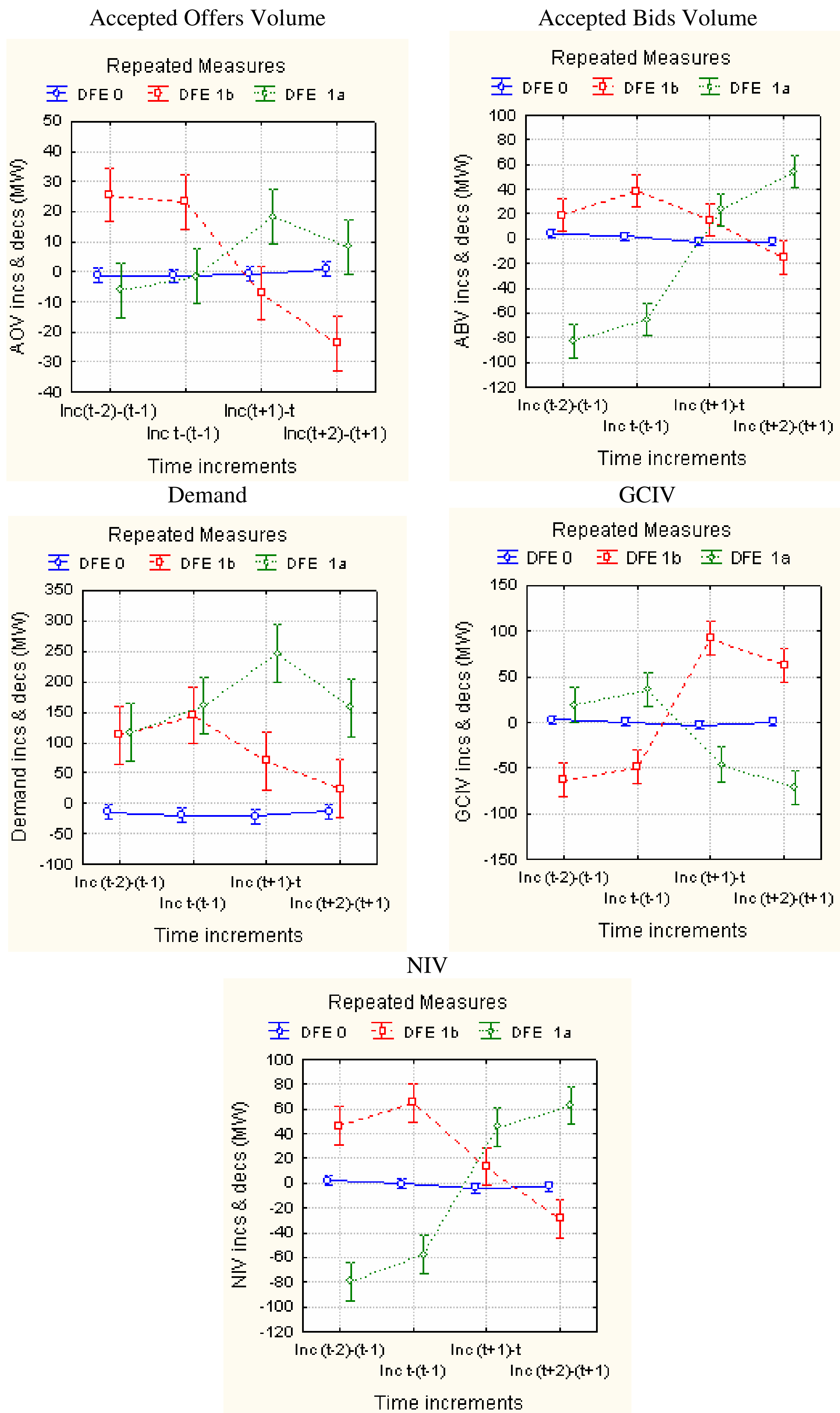


Figure 6.31 Variables dynamics for DFE events

6.7.4.2 Plant loss Events

The results for plant loss events are presented in Appendix 3 following a similar format to the one described for DFE events.

The results presented in Tables A3.1 to A3.5 show that plant loss events do not have a significant impact on most of the market variables included in this analysis. Only demand values are significantly affected by these events. Plant loss events register higher average demand than normal conditions. This may easily be due to the fact that in high demand conditions there are more units committed, so there is a higher probability of a plant loss event.

The lack of impact of plant loss events can also be explained from the combination of nature of the events together with the characteristics of the analysed data. Plant loss events are local events and the actions to remedy these conditions are in most cases local. Therefore, the local reaction can easily be masked in the global variables values used in this analysis. Moreover, the size of the plant loss events is relatively small, since its maximum value does not exceed 3% of the average demand.

6.7.4.3 REM Events

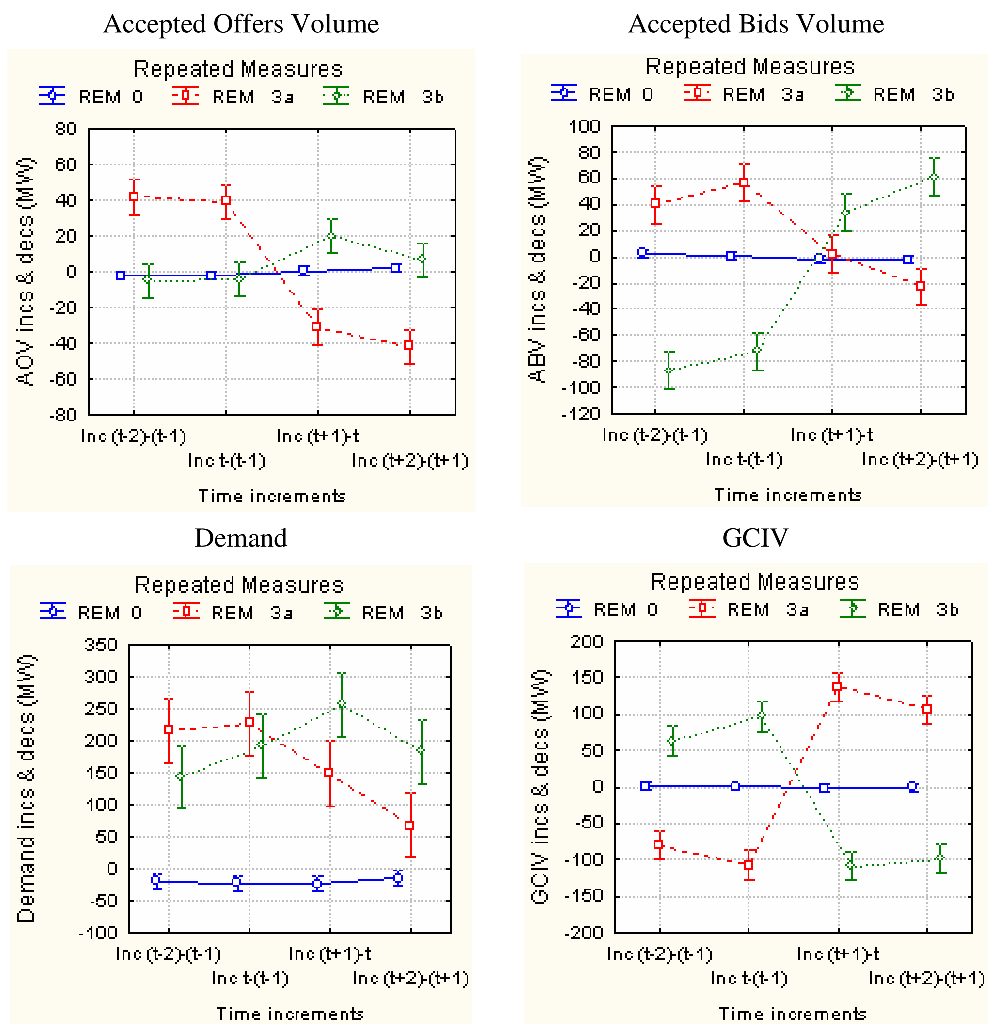
The results for REM events are presented in Appendix 3 following a similar format to the one described for DFE events.

The results presented in Tables A3.6 to A3.10 show that REM events have a significant impact on all the market variables.

REM events below the lower threshold refer to any PGCE not included in the DFE that creates an excess of over 1489MW in the system. Under these conditions there is a consequent decrease of the accepted offers, an increase of the accepted bids, and an increase of the Net Imbalance Volume (the market is even longer than under normal conditions). As for DFE, REM events also have an impact over imbalance prices.

REM events above the higher threshold refer to any PGCE not included in the DFE that creates a deficit of over 1574MW in the system. The consequent market reaction is an increase of the accepted offers, a decrease not only of the accepted bids but also in the market length represented by NIV. Imbalance prices also increase under event conditions.

The repeated measures analysis shows that the variables dynamics are also affected under REM events. Figure 6.32 shows the dynamics for those variables significantly impacted by REM events, with a similar structure that the one of Figure 6.31.



NIV

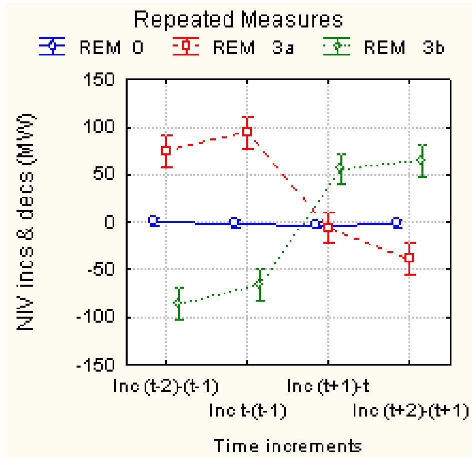


Figure 6.32 Variables dynamics for REM events

6.7.4.4 DFE/GCIV Events

The results for DFE/GCIV events are presented in Appendix 3 following a similar format to the one for the plant loss events.

DFE/GCIV events refer to condition when the demand exceeds its forecast and this one exceeds the declared generation at GC (short market conditions). As presented in Tables A3.11 to A3.15, these events significantly affect the market conditions. The volume of accepted offers significantly increases to an average value of 936MW (over 3 times the value of normal conditions), to compensate the error in the demand forecast. The volume of accepted bids is also reduced since, under these events, the need to decrease generation levels is significantly less. It is important to notice that the unusual long market conditions at GC are also maintained after the BM. In this way, NIV reaches a maximum average value of 222.2MW.

Figure 6.33 highlights the results obtained for these events conditions over the actual values of the dependent variables AOV, ABV, GCVI and NIV. In each graph the x-axis represents the event and no event conditions (following the coding described in Table 6.16) and the y-axis represent for each variable their means actual values. For all the graphs vertical bars denote 0.95 confidence intervals.

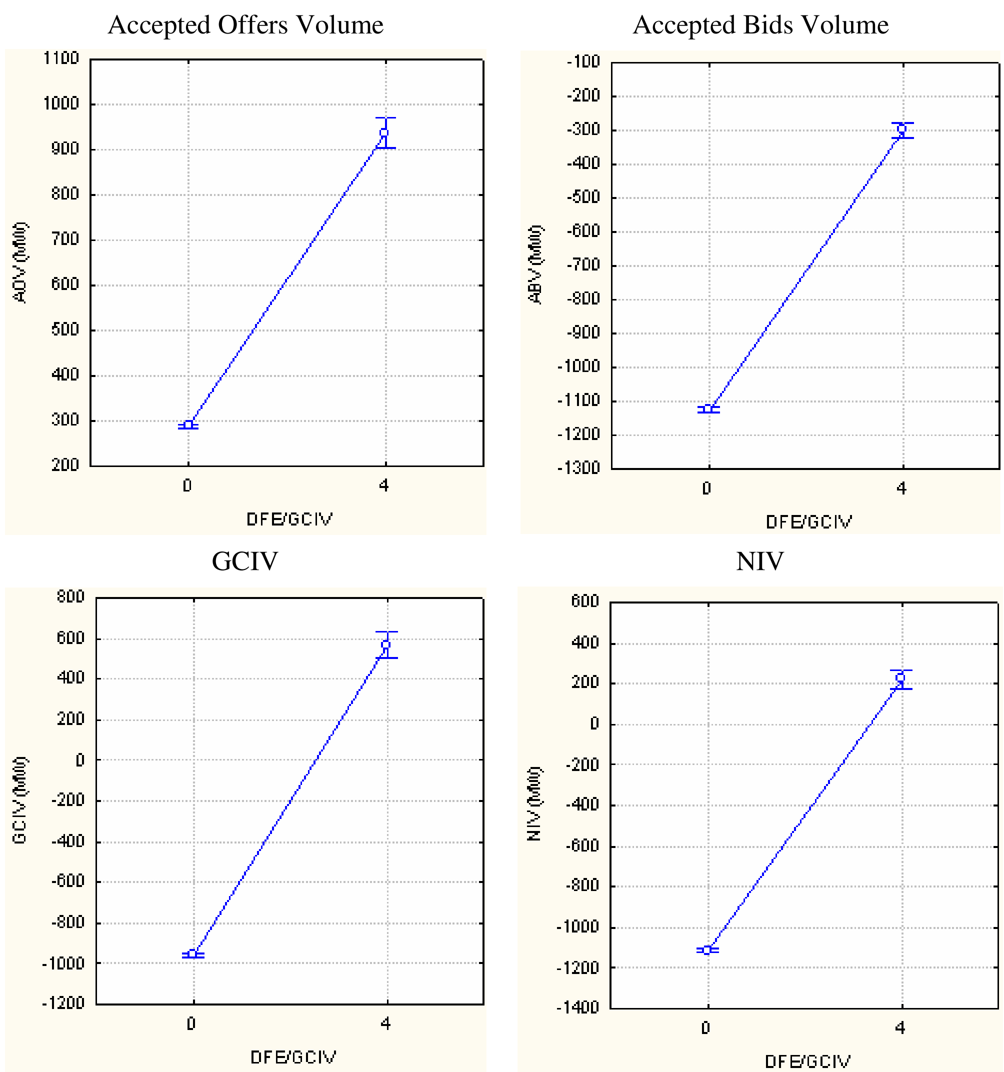


Figure 6.33 Actual mean variables $\frac{DFE}{GCIV}$ *events*

The dynamics of AOV, ABV, GCIV and NIV are significantly affected by $\frac{DFE}{GCIV}$ events. However, unlike previous events, the variables' dynamic is only significantly affected for the periods after the event.

6.7.4.5 DFE & Plant loss Events

The Table 6.23 presents the results that quantify the significance of the market reaction to the conditions defined by the combination of DFE and Plant loss events.

Table 6.23 Multivariate test of significance for the combination of DFE and plant loss events

	MULTIVARIATE RESULTS					
TEST NAME	ACTUAL VALUES			DEVIATION FROM MOV. AVERAGE		
	Value	*F (Fcrit=2,9)*	*Sig.*	*Value*	*F (Fcrit=2,9)*	*Sig.*
Roy´s gcr	0.000174	0.725	✗	0.000182	0.76038	✗
Wilk´s Lamdba	0.999763	0.496	✗	0.999743	0.53600	✗

The following table shows for each variable the within groups estimate of variance (MS_W), the between groups estimate of the variance (MS_B), and the F- statistics with its significance. As in previous cases high values of the F coefficient are interpreted as significant differences between event and no event conditions.

Table 6.24 Univariate results of significance for the combination of DFE and plant loss events

	UNIVARIATE F RESULTS							
DEPENDENT VARIABLE	ACTUAL VALUES				DEVIATION FROM MOV. AVERAGE			
	MS_B	MS_W	*F (Fcrit=2.2)*	*Sig.*	MS_B	MS_W	*F (Fcrit=2.2)*	*Sig.*
AOV	5.80E+04	28977	0.20	✗	1.14E+05	57065	0.91	✗
ABV	3.14E+05	1.57E+05	0.33	✗	1.51E+05	75330	0.53	✗
Demand	1.04E+08	5.21E+07	1.37	✗	2.13E+07	1.06E+07	1.54	✗
GCIV	3.28E+05	164091	0.19	✗	3.42E+05	171198	0.71	✗
NIV	3.38E+05	168815	0.23	✗	1.57E+05	78441	0.40	✗
SBP	4636	2318	0.45	✗	4317	2159	0.54	✗
SSP	20	9.79	0.15	✗	11	6	0.14	✗

The next two tables (Tables 6.25 and 6.26) unfold the dependent variables statistics for all the possible each trigger variable conditions. Each table is divided in two parts. The first part corresponds to usual conditions of plant loss events and the three possible conditions of DFE events (e.g. usual conditions, DFE below the lower threshold and DFE above the higher threshold). The second part of the tables corresponds to usual conditions of plant loos events and the three possible conditions of DFE events. The first table refers to actual values of the passive variables and the second to the deviation from their moving averages.

Table 6.25 Market variables (actual values) group statistics for the combination of DFE and plant loss events

DEPENDENT VARIABLE	**ACTUAL VALUES MARKET CONDITIONS**					
	Plant loss usual conditions (0)					
	Usual conditions (0)		*DFE<-644 MW (1b)*		*DFE>750 MW (1a)*	
	Mean	*Std Error*	*Mean*	*Std Error*	*Mean*	*Std Error*
AOV	308.3	2.4	547.0	14.0	215.2	7.4
ABV	-1080.6	4.2	-802.8	17.7	-1546.7	21.2
Demand	33766.9	39.3	36285.2	142.7	37017.7	138.6
GCIV	-897.8	5.7	-1107.1	29.7	-578.3	26.0
NIV	-1062.7	5.3	-536.4	26.2	-1528.1	24.4
SBP	33.6	0.5	39.9	1.1	40.7	1.8
SSP	9.4	0.0	11.0	0.4	10.3	0.1

DEPENDENT VARIABLE	**ACTUAL VALUES MARKET CONDITIONS**					
	Plant loss (2)					
	Usual conditions (0)		*DFE<-644 MW (1b)*		*DFE>750 MW (1a)*	
	Mean	*Std Error*	*Mean*	*Std Error*	*Mean*	*Std Error*
AOV	306.7	12.8	513.1	80.1	229.5	48.4
ABV	-1036.8	24.8	-840.4	125.9	-1478.5	131.6
Demand	35837.8	219.8	37586.9	657.8	37760.4	757.5
GCIV	-889.7	29.1	-1163.6	242.4	-630.3	154.7
NIV	-1013.3	30.9	-564.0	159.0	-1439.1	163.4
SBP	38.7	2.8	43.9	5.6	55.5	12.2
SSP	10.6	0.4	11.7	0.6	11.0	0.9

Table 6.26 Market variables (deviation from moving average) group statistics for the combination of DFE and plant loss events

Dependent variable	Deviation from moving average Market conditions					
	Plant loss usual conditions (0)					
	Usual conditions (0)		*DFE<-644 MW (1b)*		*DFE>750 MW (1a)*	
	Mean	*Std Error*	*Mean*	*Std Error*	*Mean*	*Std Error*
AOV	-3.66	1.6	86.67	8.0	-22.53	5.3
ABV	6.94	2.3	93.04	9.3	-212.59	11.2
Demand	-88.01	16.7	409.94	63.1	392.67	58.8
GCIV	3.37	3.0	-119.96	14.5	76.33	13.1
NIV	0.63	2.7	183.45	12.4	-207.05	12.1
SBP	-0.79	0.4	2.65	1.0	8.15	1.5
SSP	0.00	0.0	-0.10	0.3	-0.30	0.1

Dependent variable	Deviation from moving average Market conditions					
	Plant loss (2)					
	Usual conditions (0)		*DFE<-644 MW (1b)*		*DFE>750 MW (1a)*	
	Mean	*Std Error*	*Mean*	*Std Error*	*Mean*	*Std Error*
AOV	-21.98	9.1	93.76	50.5	3.13	30.2
ABV	21.86	14.3	156.58	65.4	-228.12	64.5
Demand	1066.36	101.0	1051.79	345.7	1054.74	355.0
GCIV	-21.10	16.6	-55.21	86.6	73.11	67.3
NIV	14.46	16.3	258.25	86.8	-197.79	66.5
SBP	1.74	2.5	1.71	4.5	19.38	6.9
SSP	0.78	0.3	0.27	0.9	0.15	0.5

The significance of the difference in the variable dynamics for the combination of plant loss and DFE events is presented in Table 6.27. As in previous cases, the table contains for each dependent variable the f-statistics for the increments and decrements between the two periods before the event and the two periods after the event.

Table 6.27 Repeated measurements univariate significance results

DEPENDENT VARIABLE	**REPEATED MEASUREMENTS UNIVARIATE SIGNIFICANCE RESULTS**							
	(t-2)-(t-1)		*(t-1)-t*		*t-(t+1)*		*(t+1)-(t+2)*	
	F (Fcrit=3,84)	*Sig.*	*F (Fcrit=3,84)*	*Sig.*	*F (Fcrit=3,84)*	*Sig.*	*F (Fcrit=3,84)*	*Sig.*
AOV	0.06	✗	0.32	✗	5.18	✓	6.7	✓
ABV	0.28	✗	0.52	✗	0.94	✗	0.14	✗
Demand	0.046	✗	0.03	✗	0.71	✗	1.15	✗
GCIV	0.13	✗	0.13	✗	0.81	✗	0.17	✗
NIV	0.5	✗	0.45	✗	6.16	✓	1.9	✗
SBP	1.22	✗	0.014	✗	1.7	✓	0.86	✗
SSP	0.38	✗	0.05	✗	0.82	✗	0.62	✗

All the results show that the combination of DFE and plant loss events does not have any significant impact on the market conditions. It is possible to attribute these results to the lack of market reaction to the plant loss event. It is important to mention that these results refer only to the multiple combination of events and they do not contradict those obtained for DFE or plant loss when considered independently.

6.7.4.6 REM & Plant loss Events

The results for the combination of REM and plant loss events are presented in Appendix 3 following a similar format to the one described for the combination of DFE and plant loss events.

The results presented in Tables A3.16 to A3.20 show that this combination of events does not have a significant impact on the dependent market variables.

As for the DFE and plant loss events combination this can be due to the lack of market reaction to plant loss events.

6.7.4.7 DFE & REM Events

The results for the combination of DFE and REM are presented in Appendix 3 following a similar format to the one described for the combination of DFE and plant loss events.

Despite of the strong effect that each of these events has over the market condition, the results presented in tables A3.21 to A3.25 show that their combination significantly reduces their effect over the market variables.

The overall significant test exceeds the threshold value of $F_{critical}$ showing that these conditions have an overall impact on the market conditions. However, the univariate results show a non significant reaction of NIV and SBP for the actual variable values, and also present a reduction in the significance of the reaction of ABV and the GCIV variables for the deviation from moving average analysis.

These results can be explained from two different perspectives. The first one is the compensating effect that the simultaneous combination of these events may have in some particular cases. For instance, the market reaction to DFE events below the lower DFE threshold is compensated with the market reaction to REM events below REM lower threshold. Another similar case is the combination of to DFE events above the higher DFE threshold with REM events above REM higher threshold. The second reason to explain the reduced significance of the events combination is the number of cases that verify the imposed conditions. In this way the number of cases that simultaneously combined DFE and REM events is significantly less than when considering each event independently. This can be observed in the high values obtained for the standard errors for this case. Low number of observances with high standard errors results in less significant differences between groups.

6.8 Conclusions

ANOVA/MANOVA techniques prove to be effective, flexible and customisable tools for the analysis of unusual events. The results allow evaluating not only the instant actual market reaction in absolute variables values, but also the market relative reaction in the form of variables deviations from their moving average. Moreover, the repeated measures analysis provides an insight of the variables evolution before and after the events.

When considering the effect over actual variable values, DFE events are the ones with the most significant impact over the market variables. However for the deviation of the variables from their moving average, both DFE and REM have similar significant results. Plant loss events are the event with less impact over the market variables.

The long market conditions have an effect over the market reaction and even modify what could be considered theoretical market reactions. For instance, in the event of demand greatly exceeding its forecast, under ideal 0MW market length conditions, accepted offers would be the variable that would counterbalance this forecast error. However, the long market conditions result in a market reaction driven by a more significant decrease in the bid acceptances than the increase in the offer acceptances. Therefore, ABV is the more affected variable for the events conditions.

The results also show that the BM provides the market with the mechanisms needed to correct unusual events. Therefore, a general conclusion of this analysis is the robustness of NETA.

CHAPTER 7

Conclusions and Future work

7.1 Conclusions

The introduction of competition and deregulation in electricity markets is not a simple change. In England and Wales the market shifted from a centralised Pool to NETA which was designed to encourage bilateral trading and to minimize centralised actions. This change created a wide range of challenges for all market participants, including the SO, to optimise their strategies in order to maintain or increase their revenues and profits. The changes resulted thus not only in new questions but also in the need to explore new ways to achieve their answers.

Another important characteristic of NETA was its prolific data generation. The analysis of this data provides the possibility of gaining better insight into the market behaviour. NETA is thus the perfect environment to test the combined application of data mining techniques and classical techniques to the analysis of electricity markets.

This thesis contributes to the development of new methodologies for the analysis of new structured electricity markets. To achieve this, the thesis unfolds in two different directions: the modelling and forecast of the market volume, and the analysis and characterization of unusual market conditions.

7.1.1 Forecasting the Net Imbalance Volume

The Net Imbalance Volume (NIV) represents the total net energy that the SO must buy or sell in the forward market or through the balancing mechanism to keep the system balanced. From the perspective of a system operator, it is a key market variable to forecast since knowing in advance NIV values allows the SO to purchase this energy on the forward market. This approach usually helps minimize the total balancing cost. From the participants' perspective, it is also a very important variable since its forecast can help them plan a competitive market position for the balancing mechanism.

The one-dimensional approach, described in Chapter 4, shows that traditional forecasting techniques do not provide a feasible solution for forecasting horizons longer than one-day ahead. However, the techniques used for the analysis of the series help uncover NIV's complex structure.

The introduction of other market variables expands the analysis of NIV to a multidimensional perspective. Exploratory classical techniques in combination with data mining provide the necessary tools to uncover non-linear relations between these variables and identify the best predictors for the variables to be forecast. The application of recently developed data mining techniques based on neural networks offers a much better performance than conventional forecasting techniques. However, to maintain a reasonable accuracy, these networks must be updated on a regular basis.

While the results presented in Chapter 5 demonstrate that the proposed approach yields forecasts that are useful, it is clear that the accuracy of forecasts of market variables is still much lower than the accuracy that one can achieve when trying to predict daily or weekly load profiles. However, the true measure of improvement when forecasting market imbalance volumes is not an abstract error index but the savings in balancing costs that this improvement makes possible. With a one-month-ahead time scale in particular, the 20% error reduction in the forecasted volume that the proposed method achieves makes possible a significant increase in the amount of energy that can be the traded in the forward market.

The analysis of unusual events in the England and Wales balancing mechanism opens a new line in the analysis of electricity markets. The analysis of unusual events is a complete analysis of both the causes that create the unusual conditions as well as the effects they have on the market operation.

From a methodological point of view, this thesis does not only presents a systematic approach for single events analysis but it also introduces a multidimensional perspective, considering multiple unusual market conditions that can coexist in time, and the effect that these conditions have over multiple market variables.

The analysis of the events has taken three different perspectives to define and characterise the events, to determine their duration and to calculate their average return period:

- The event characterisation results highlight the differences between possible events occurring in the market.
- The duration analysis results indicate that single events do not extend in average for more than 1.5 hours (3 periods); the extension of the duration analysis to the possible occurrence of multiple events reflect that events do not occur in a consecutive manner but they happen either simultaneously or separately by at least one unit of time.
- The return period analysis shows that unusual values of market variables, in the more realistic multiple event scenario, are not infrequent; in fact, during an average day 5 or more events of different natures can happen.

The first challenge of the consequences analysis is to find appropriate techniques to develop a well-founded and flexible methodology which considers single and multiple events as well as multiple dependent variables, and combines both the instantaneous and dynamic performance of the market variables. The second challenge is to overcome the practical restrictions that are imposed by the data sets. Due to young market conditions, there are not enough data to create a highly reliable reference model; also the existing data imposed simplifications on the analysis such as, the consideration of plant loss events as instantaneous events due to the unavailability of information regarding the units' back to service time.

All these difficulties are overcome by the adaptation of ANOVA/MANOVA analysis. This technique defines not only the market status for event conditions and its dynamics but also measures their significance when compared with normal market situations. The results prove that unusual market conditions affect the balancing mechanism variables that refer to the actions involved in counterbalancing the event's conditions. Moreover the prevalent and non-ideal long market usual conditions modify the theoretical reaction one could anticipate under balanced conditions. Nevertheless, the market design is robust and can absorb unusual events at least to the extent of the magnitude found in our data.

Finally as overall view, the newly developed techniques provide answers to some of the new questions that arise from the complex operation of liberalised electricity markets. Moreover, these techniques can also be adapted to other areas of market research.

7.2 Suggestions for future work

The recommendations for future work can be divided into groups: general recommendations and recommendations for other areas of analysis. The former presents possible ideas for the enhancement of the developed techniques and the later extends their use and application.

The first group of recommendations provides ideas for further research in the line of NIV forecasting and events analysis:

- The forecasting analysis has followed a point approach to NIV's forecast. This point forecast combines the deterministic and probabilistic approaches since it estimates the median value of NIV. However the probabilistic approach could be expanded to provide complementary probabilistic output and include consideration of probabilistic inputs. The former approach would estimate the uncertainty of the forecast with lower and upper boundaries as well with a prediction density. The latter would consider the uncertainties on the input variables.

- The presented forecasting analysis has been focused on the forecast of actual values of NIV. Combining the proposed multidimensional non-linear approach of this thesis with the line of analysis suggested by Zhou et al. (Zhou et al., 2004) for electricity prices modelling, a possible expansion of NIV forecast could include the residual analysis. Besides forecasting NIV volumes, it could be possible to predict the errors and to modify the forecast to improve the accuracy. However it is important to keep in mind that NIV is much more changing and noisy than other variables like electricity demand and prices. In the case of NIV, it remains to be shown how much the forecast can be iteratively updated using the error and how much the error volatility can have a positive impact on the final forecast.

- The next step in the events analysis would be to develop a methodology to forecast them. In events forecasting the aim is not to predict the value of a certain variable but to predict whether a certain event might take place in the future. In this way, point prediction techniques cannot be presented as an alternative since their performance is based on how well the prediction adapt to its real value, but in events forecast the objective is to detect the events and accurately locate them in time. Some work has been developed for univariate series for linear one-dimensional series to develop on-line alarm systems (Antunes and Turkman, 2002). However their possible application to a multidimensional non-linear framework opens a new path for analysis.

The second group of recommendations provides ideas for further research under the new BETTA framework:

- Expansion to participants' analysis behaviour. Differences in bidding strategies between participants can be analysed in terms of their generating portfolio, vertical integration, geographic location and other discriminant factors. Unsupervised clustering learning techniques can be used to analyse the bidding pattern of the market participants. This analysis would also allow discovering possible gaming strategies and detecting the exercise of market power. A further extension of this analysis could include the temporal evolution of the different patterns, and how participants react to external factor such as market rules changes.

- Risk analysis of bidding strategies. Following the line of analysis presented by McClay et al. ((McClay et al., 2002). The risk analysis would consider the different strategies that participants use to deal with volume uncertainty and imbalance prices. Instead of the contracting strategy simulation line proposed by McClay this analysis would follow a bottom up approach by examining the actual data derived from the participants' activity in the market to build up separate models for different strategies.
- Combination of global market and participants' analysis. The participants' analysis would provide a structured model of how they contribute to the creation of some global variables (e.g. NIV) and their possible strategies. This exploratory analysis could also help the understanding of this complex market variable from some of their own components.
- Advice price analysis. The advice price is the suggested price for the SO to trade volumes in the forward market. It is thus one of the components required to perform the trading advice, together with the advised volume (NIV forecast). The advice price is a function of the offers price, the bids price and the probability of reversal (i.e. the probability of the future trades requiring reversing actions in the balancing market). This analysis could combine the analysis of the elements that form the advice price to obtain an accurate method to calculate it. Both offers and bids prices could be modelled in the previously described participant's analysis. The probability of reversal is the random component of the advice price. The analysis of NIV residuals would give a better understanding of the reversal effect and would improve accuracy when calculating this probability of reversal. Being able to forecast the participants bidding strategies and a precise knowledge of the reversal probability value would improve the advice price assessment.

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