MODELING AND ANALYSIS OF A DECENTRALIZED ELECTRICITY MARKET: AN INTEGRATED SIMULATION / OPTIMIZATION APPROACH

by

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To my wife…

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ABSTRACT

MODELING AND ANALYSIS OF A DECENTRALIZED ELECTRICITY MARKET: AN INTEGRATED SIMULATION / OPTIMIZATION APPROACH

In this study, it is aimed to investigate electricity market restructuring and deregulation and understand the implications of a competitive power market based on hourly biddings. An alternating current (AC) transmission network with line capacity and production technology based constraints formed a basis for the analysis of electricity prices, availability and supply security. For this purpose an agent based simulation model (to mimic and oversee the biddings) and a nonlinear network flow optimization model (to oversee and optimize the electricity flows, while enforcing supply, demand, capacity and other technological constraints) are developed and integrated. The model is designed such that it can be used for market design as well as investment planning, being capable to identify the most appropriate electricity production technology, size, and region.

The transmission network, on which the scenario analysis are carried out, includes 30 bus, 41 transmission lines, nine generators, and 21 power users. The scenarios examined in the analysis covers various settings of transmission line capacities, transmission fees, hourly learning algorithms, structural changes such as shift of demand between nodes, introduction of new generator to selected nodes and their combinations. Results provide insight into key behavioral and structural aspects of a decentralized electricity market under network constraints.

ÖZET

ELEKTRİK ENERJİSİ SERBEST PİYASASININ MODELLEME VE ANALİZİ: BÜTÜNLEŞİK BENZETİM / ENİYİLEME

Bu çalışmada bağımsız elektrik üreticilerinin saatlik fiyat teklifleri vermesi prensibi altında elektrik piyasasının yeniden yapılandırması, yeniden düzenlemesi ve rekabetçi piyasa ortamı dinamiklerinin incelenmesi amaçlanmıştır. Kurulan optimizasyon modelinde hat kapasitesi ve üretim teknolojisi tabanlı kısıtları olan dalgalı akım iletim ağları, elektrik fiyatları, emre amadelik ve arz güvenliği analizi için temel oluşturmaktadır. Bu doğrultuda vekil tabanlı benzetim modeli ile doğrusal olmayan ağ akış eniyileme modeli geliştirilmiş ve bütünleştirilmiştir. Benzetim modeli çerçevesinde bağımsız üreticilerin de saatlik elektrik satış teklifleri üretilmekte, fiyat oluşumu ve sistemin takibi yapılmaktadır. Optimizasyon modeli çerçevesinde ise elektrik talepleri, serimin yapısı ve kapasitesi göz önüne alınarak, elektrik satış teklifleri ile ilgili iletim maliyetleri ile birlikte maliyetler minimize edilecek şekilde değerlendirilmekte ve kabul edilen tekliflerin ağ üzerinde akışları belirlenmektedir.

Senaryo analizlerinin yapıldığı iletim ağı 30 bağlantı noktası, 41 iletim hattı, 9 elektrik santrali ve 21 güç kullanıcısından oluşmaktadır. Analizde incelenen senaryolar, düğümler arası talep yapısı değişimi veya seçili düğümlere yeni elektrik santrali veya bunların bileşimi gibi yapısal değişiklikler, iletim hattı kapasiteleri, iletim ücretleri, saatlik satış teklifleri hazırlama algoritmaları için değişik ayarlamaları içermektedir. Sonuçlar, ağ kısıtları altında dağınık elektrik piyasasının kilit davranışları ve yapısal yönlerine ışık tutmaktadır.

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Art_{tj}	Daily acceptance rate at time t using markup j
b_{km}	Susceptance of branch km
B_{km}	$1/x_{km}$ for branch km
BR	set of all distinct branches km
$Exp(Art_{tj})$	Expected acceptance rate at time t using markup j
$Exp(Prf_{tj})$	Expected time t daily profit of markup j
$Exp(Prf_{tj})$	Expected daily profit at time t of markup j
$Exp(Rwd_{tj})$	Expected reward of markup j at time t
c_i	Bid of generator i
g_{km}	Conductance of branch km
I	Total number of generators
I_k	Set of generators located at node k
j	interval index (the markup number)
J	Total number consumers
J_k	Set of consumers located at node k
K	Total number of transmission grid nodes(buses)
km	Branch connecting node k and m
$Line_{km}$	Total power flowing on branch km
$Line_{max\ km}$	Thermal limit for flow on branch km
N	Total number of distinct network branches
P_{Genk}	Total real power injection at node k
P_{Gi}^{L}	Lower real power limit for generator i
P_{Gi}^{U}	Upper real power limit for generator i
P_{km}	Total real power flowing between k and m
P_{Lj}	Real power load withdrawn by consumer j
P_{Loadk}	Total real power withdrawal at node
$P_{NetInjectk}$	Total net real power injection at node k
Pol_j	probability of using a markup j
Prf_{tj}^{i}	Profit associated with markup j at hour i and iteration for day t

Prf_{tj}	daily profit at time t using markup j
Q_{Genk}	Total reactive power injection at node k
Q_{Gi}^{L}	Lower reactive power limit for generator i
Q_{Gi}^{U}	Upper reactive power limit for generator i
Q_{km}	Total reactive power flowing between k and m
Q_{Lj}	Reactive power load withdrawn by consumer j
Q_{Loadk}	Total reactive power withdrawal at node k
$Q_{NetInjectk}$	Total net reactive power injection at node k
Rank(j)	Rank of the markup j
S_0	Base apparent power in three phase MVAs
Sp	*Search Propensity*
t	Day time
tc_{km}	Transmission fee of line km
$Util_j$	Perceived utility using markup j
V_0	Base voltage in kVs
V_{Bk}	Voltage value at node k
V_k	Voltage magnitude at node k in kVs
V_k^U	Upper voltage level for node k
V_k^L	Lower voltage level for node k
x_{km}	Reactance of branch km
δ_1	Reference node 1 voltage angle
δ_k	Denote the voltage angle at node k
AC	Alternating Current
BSS	Balancing and Settlement System
CLF	Constrained Load Flow
CPU	Central Processing Unit
EMCAS	Electricity Market Complex Adaptive System
EML	Electricity Market Law
HHI	Hirschman-Herfindal Index
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers

IPP	Independent Power Producer
KKT	Karush-Kuhn-Tucker
LP	Linear Programming
MINOS	Modular IN-core Optimization System
MIP	Mixed Integer Programming
MVAR	Mega Volt Ampere Reactive
MW	Mega Watt
MWh	Mega Watt Hour
NBGB3	New Big Generator on Bus 3
NBGB6	New Big Generator on Bus 6
NGB21	New Generator on Bus 21
NGB28	New Generator on Bus 28
NSGB3	New Small Generator on Bus 3
NSGB5	New Small Generator on Bus 5
NSGB6	New Small Generator on Bus 6
NETA	New Electricity Trading Arrangements
NLP	NonLinear Programming
OECD	Organization for Economic Co-operation and Development
OPF	Optimal Power Flow
PURPA	Public Utility Regulatory Policies Act
QP	Quadratic Programming
SFE	Supply Function Equilibrium
SO	System Operator
SP	Search Propensity
SPLTB5	Split of generator on Bus 5
SUMT	Sequential Unconstrained Minimization Technique

1. INTRODUCTION

Electricity is an extremely flexible form of energy, and has been adapted to a huge and growing number of uses. The invention of a practical incandescent light bulb in the 1870s led to lighting becoming one of the first publicly available applications of electrical power. Due to its' ease of use, electricity has penetrated to wide ranging set of industrial and commercial uses (such as electric motor drive, welding, chemical reactions, high temperature processes) and residential use (such as space and water heating, cooking, appliances). Electricity is also employed within telecommunications, and indeed the electrical telegraph, demonstrated commercially in 1837 by Cooke and Wheatstone, was one of its earliest applications.

Between 1973 and 2007, world electricity production increased from 6130 TWh to 19,845 TWh. The average annual growth rate during that time span was 3.5%. In 1973, 72.9% of electricity production was generated in countries that are currently members of the Organization for Economic Co-operation and Development (OECD). According to International Energy Agency (IEA), in 2007, 54.0% of electricity production was generated in OECD countries (IEA, 2009). The increasing share of non-OECD electricity production reflects the higher growth rate, which has prevailed in these countries since 1973. In the last 34 years, electricity production has increased at an average annual rate of 5.1% in non-OECD countries, while in OECD countries the average annual growth rate during the same period has been 2.6% (IEA, 2009). This trend is expected to continue for upcoming decades.

Since electricity is a vital commodity for any modern economy, most countries have specially designed laws, by laws, organizations and frameworks overseeing the generation, transmission, distribution and consumption of electricity. In addition, the concerned facilities (such as power generation plants and transmission/distribution system) are either partially owned or tightly regulated by the state. The immediate concern of the state is continued and reliable availability of electrical energy at reasonable prices. Electricity prices fell in real terms for most of the industry's first century of existence, but rising fuel prices, problematic nuclear programmes and other problems led to increasing prices in many countries starting from the middle of the 1970s. Since then, the trend in favor of deregulation as a means of improving economic performance and supply stability started in numerous countries.

As first starters, the Public Utility Regulatory Policies Act (PURPA) of 1978 required utility firms to buy electricity from 'qualifying facilities' of co-generators and small power plants in the US. In the same year, Chile set up a wholesale market pool in which generators would sell their power to retailers, introducing a law in 1982 permitting large end users to choose their retailer and negotiate their prices freely. In 1990, the industry in England and Wales was restructured and privatized. The Electricity Pool was established as the setting for competition between generators, while the plan was that all electricity consumers would be able to choose a supplier by the year 1998. Norway founded electricity pool in 1991 and gave customer a choice for supplier selection. The pool than extended incorporating Sweden in 1996 making it the first multi-national electricity market named as Nordic pool (Carisson, 1999).

For the case of electricity, unlike any other form of commodity trading, generation must closely match the demand on a continuous time scale. The fact that electricity cannot be stored easily raises the need of generation, as it is demanded. The result of failing to do so leads to economic disruptions and / or in blackouts like the Northeast Blackout in summer 2003 (Minkel, 2005). Therefore, independent of the market design, a System Operator (SO) is an inevitable integral part of the regulatory infrastructure especially in deregulated market environment. One single system operator is needed to manage and control the physical operations to balance the demand and supply, while facilitating and overseeing fair competition. Degree and form of liberalization does not change this reality and must be obeyed in any sense (Al-Sunaidy and Green, 2006).

As stated by Haas and Auer (2006), effective competition may be achieved in a deregulated electricity market if the following six prerequisites are met (Haas and Auer, 2006).

- Separation of the grid from generation and supply;
- Wholesale price deregulation;

- Sufficient transmission capacity for a competitive market and non-discriminating grid access;
- Excess generation capacity developed by a large number of competing generators;
- An equilibrium relationship between short term and long term financial instruments that marketers use to manage spot-market price volatility;
- An essentially hands-off government policy that encompasses reduced oversight and privatization.

Even if the above conditions are met, the efficiency and effectiveness of the market is still not guaranteed. Various market designs are being implemented to overcome possible inefficiencies and random behavior of a deregulated electricity market. The trend towards liberalization has encouraged the research community to investigate new market designs and tools and develop decision analysis support models adapted to new market concept. Those support systems should be designed to deal with the highly complex, nonlinear, network constrained technical structure of the system, while also addressing the behavioral complexity of the market.

In decentralized electricity markets, many key decisions are made by multiple, self-oriented power companies. Bidding, operating level, capacity expansion, and financing decisions plays crucial role in market formation. Decision making of market participants is guided by price signal feedbacks and by an imperfect foresight of the future market conditions. Competitors unknown actions / reactions are very much important. Combined forces of supply & demand, rather than the historical costs of the underlying assets determine electricity prices. In such an environment, decision makers need to better understand both the short & long-term dynamics of the electricity market, including impacts/advantages of supply and demand; electricity generation technology selection; electricity generation capacity (size) selection; distribution network structure; location of suppliers and customers. Centralized Planning (and overall optimization) is no longer effective (may not even be possible).

Still, Decision Makers (individual power companies or a regulating authority) need answers to questions such as:

- At what price should generators price their output in order to balance market share, solvency, short term profitability and long term expectations?
- Which types of plants will be more attractive in a decentralized, competitive environment?
- How will competitors react against certain behavioral trends?
- What is the impact of transmission infrastructure and costs on electricity prices and generator profits?
- How can a Regulator ensure that competitive and stable prices prevail in the market?

Simulation & Optimization Modeling could provide most fitting tools for these purposes. Simulation models can mimick the hourly bidding and related activities inherent in a decentralized electricy market. Optimization modeling can mimick a "minimum price contract awarding" policy usually adopted by the regulatory authority, while taking transmission network infrastructure, costs and limitations into consideration. By means of such decision tools, iInvestors & regulators have a opportunity to better understand possible consequences of different decisions that they may make, under different policies and market conditions.

As more detail about the current literature is given in next section, one will see that most of the electricity market models developed omits the network structure, AC power constraints, and local market power. Those approaches mainly treat the market as a regular commodity market widely addressed in the economic literature; hence, in parallel to regular commodity markets, they mainly deal with the general market structure / operation problems.

In this study a mathematical model is developed to investigate and better understand the implications of a competitive and regulated power market (under transmission line and production technology based constraints) on electricity prices, sustainability, availability, and supply security. An integrated simulation/optimization approach is used in the modeling and analysis of the decentralized electricity market. The primary electricity supply/demand issue tackled is the "a day ahead hourly market balancing" based on the available AC network, estimated demand profiles and supply bids offered by the available electricity providers. For this purpose an integrated agent based simulation model and linear and nonlinear network flow optimization models are developed such that they can mimic bidding and oversee / optimize electricity flows, while enforcing technological and other constraints. In the simulation model generators try to maximize their profits under the existing market conditions and technical constraints, while their decision making mechanisms are designed in a way to benefit (learn from) their previous actions. The SO is structured such that demand is satisfied with minimum cost of generation and transmission. The SO oversees a predefined set of power generators and a power transmission network, while pursuing cost minimization through generation scheduling and power flow decisions. The characteristics and capacities of the generators and transmission lines are represented through two alternative optimization models (one linear and one non-linear).

Within this framework, various hourly and daily bidding strategies are developed and further policy analysis is carried out with various number of market parameters such as demand heterogeneity, supplier number, size and distribution over network. Besides, new generators are introduced to various locations in the network to see the possible effects over price formation and agent behavior.

The current study is an attempt to close the gap in the literature in electricity market modeling with the self-learning autonomous agents over a transmission network. The network is treated such that full AC OPF constraints are implemented with an exact solution approach. Additionally, the study attempts to use such modeling scheme for possible placement of new generators and their effects on the prices. Regarding the placement of the new entrant, various technological configurations are implemented to better understand the effect of selected technologies. Other novel features of the model are the introduction of hourly bidding strategies and transmission fee strategies, which are compared and investigated through scenarios.

In the next section, various studies related to electricity market modeling, optimum power flow, and Turkish electricity market deregulation are summarized. The differences between the selected studies and the current study are highlighted and alternative approaches are commented.

The third section explains the structure and design of the simulation / optimization model. Detailed description of each agent, including the learning mechanism of the generator agents is provided. The SO behavior, including the optimization procedure and formulation used by the SO, is described. The network structure is also introduced in this section; in this regard, generation facility placement, demand nodes, and other related technical details related to the network are given. Additionally, how data is generated and used and the flow of simulation are described in detail. Lastly, two approaches for the modeling of network structure are introduced and formulation related to each approach are given.

The fourth section focuses on the scenario analysis and the results obtained. Model results, according to the network modeling approaches, are classified and comparisons are made to see the effect of parameters on the price formation.

Last section concludes the study and compares the outcomes of the study with the current literature.

2. LITERATURE SURVEY

In this section, previous studies related to the modeling of liberalized electricity markets, which are relevant to the scope of the study are introduced and briefly discussed in the framework of four subsections. In the first subsection, the literature on general electricity market modeling is outlined. In the second subsection, the literature and previous work on agent based modeling within electricity markets are presented. The studies on the optimum power flow, solution methods and possible impacts on the liberalized electricity markets are discussed in the third subsection. These issues (which are addressed as power flow problems in the literature) are very much related to the current study since the scheduling of the generators and the flow of AC electric power through the transmission network to the demand buses are at the heart of the developed simulation / optimization model.

2.1. Electricity Market Modeling

Research developments in electricity market modeling follow three main trends: optimization models, equilibrium models and simulation models. Optimization models focus on the profit maximization problem for one of the firms competing in the market, while equilibrium models represent the overall market behavior taking into consideration competition among all participants. Simulation models are an alternative to equilibrium models when the problem under consideration is too complex to be addressed within a formal equilibrium framework. The different mathematical structures of these three modeling trends establish a clearer division. Their various purposes and scopes also imply distinctions related to market modeling, computational tractability, and main uses (Ventosa et al., 2005). Figure 2.1 shows a schematic representation of the market models classification.

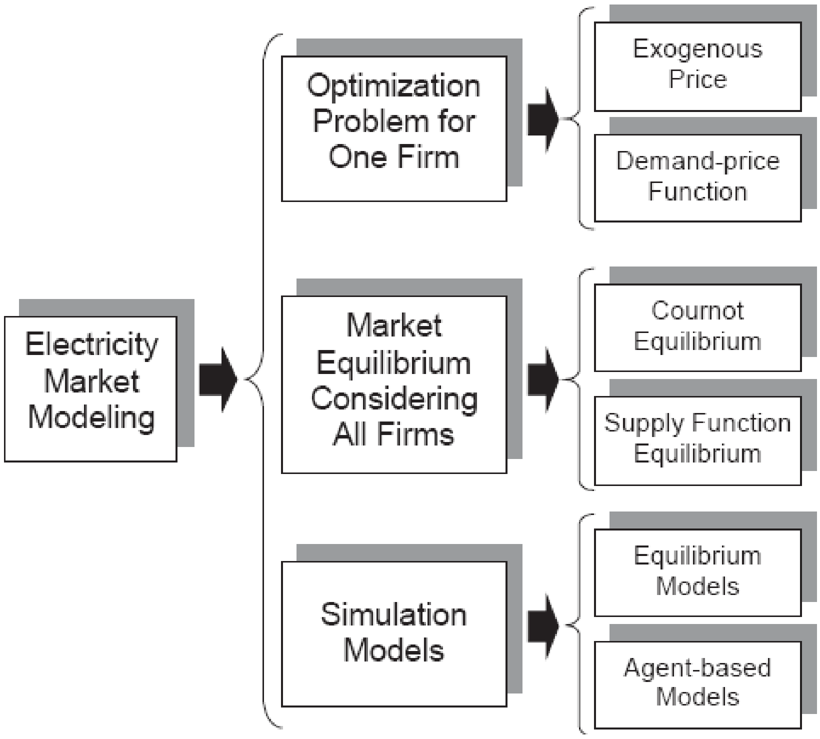

Figure 2.1.Schematic representation of electricity market modeling trends (Ventosa et al., 2005).

Single-firm optimization models take into account relevant operational constraints of the generation system owned by the firm of interest, as well as the price clearing process. According to the manner in which this process is represented, these models can be classified in two types: price modeled as an exogenous variable and price modeled as a function of the demand supplied by the firm of study. The model proposed by Gross and Finlay (1996) is a good example for such deterministic exogenous price models. It is shown that the firm's optimization problem can be decomposed in to a set of sub-problems, one per generator, resembling the Lagrangian Relaxation approach (Gross and Finlay, 1996). Another interesting study solves self commitment problem of a generation firm using stochastic exogenous price, (Rajaraman et al., 2001). Their problem is formulated based on Gross and Finlay (1996) approach, which is solved using backward Dynamic Programming.

Approaches that explicitly consider market equilibrium within a traditional mathematical programming framework are grouped into the equilibrium models category. There are two main types of equilibrium models. The most common type is based on

Cournot competition, in which firms compete in quantity strategies; where as the most complex type is based on Supply Function Equilibrium (SFE), where firms compete in offer curve strategies. Although approaches differ about the strategic variable (quantities vs. offer curves), both are based on the concept of Nash equilibrium—the market reaches equilibrium when each firm's strategy is the best response to the strategies actually employed by its opponents. Borenstein and his friends employed this theoretical market model (instead of the traditional Hirschman-Herfindal Index (HHI)) to analyze the Californian electricity market power (Borenstein et al., 1995). Borenstein and Bushnell extended this approach by developing an empirical simulation model that reaches at Cournot Equilibrium iteratively: the profit maximizing output of each firm is obtained assuming that production of the remaining firms remains fixed (Borenstein and Bushnell, 1999).

Equilibrium models are based on a formal definition of equilibrium, which is mathematically expressed in the form of a system of algebraic and/or differential equations. This imposes limitations on the representation of competition between participants. The fact that power systems are based on the operation of generation units with complex constraints only contributes to complicate the situation. Simulation models are an alternative to equilibrium models when the problem under consideration is too complex to be addressed within a formal equilibrium framework.

Simulation models typically represent each agent's strategic decision dynamics by a set of sequential rules that can range from scheduling generation units to constructing offer curves that include a reaction to previous offers submitted by competitors. The great advantage of a simulation approach lies in the flexibility it provides to implement almost any kind of strategic behavior. Static models seem to neglect the fact that agents base their decisions on the historic information accumulated due to the daily operation of market mechanisms. In other words, agents learn from past experience, improve their decision-making and adapt to changes in the environment (e.g., competitors' moves, demand variations or uncertain hydro inflows). This suggests that adaptive agent-based simulation techniques can shed light on features of electricity markets that static models ignore.

2.2. Agent Based Approaches on Electricity Market Modeling

Bower and Bunn present an agent-based simulation model in which generation companies are represented as autonomous adaptive agents that participate in a repetitive daily market and search for strategies that maximize their profit based on the results obtained in their earlier policies and actions. Each company expresses its strategic decisions by means of the prices at which it offers the output of its plants. Every day, companies are assumed to pursue two main objectives: a minimum rate of utilization for their generation portfolio and a higher profit than that of the previous day. The only information available to each generation company consists of its own profits and the hourly output of its generating units. As usual in these models, the demand side is simply represented by a linear demand curve (Bower and Bunn, 2000). Such a setting allows the authors to test a number of potential market designs relevant for the changes that have recently occurred in the England and Wales wholesale electricity markets. In particular, they compare the market outcome that results under the pay-as-bid rule to that obtained when uniform pricing is assumed. Additionally, they evaluate the influence of allowing companies to submit different offers for each hour, instead of keeping them unchanged for the whole day. The conclusion is that daily bidding together with uniform pricing yields the lowest prices, whereas hourly bidding under the pay-as-bid rule leads to the highest prices.

Bunn and Oliveira (2001) in their follow up study developed a simulation platform that represents, with much more detail, the way that market clearing in New Electricity Trading Arrangements (NETA) was designed to function. This platform modeled the interactions between the Power Exchange and Balancing Mechanism; while considering that generators may feature different types of technologies. Besides, an active demand side, including suppliers is included. Also, they have developed learning processes for generators where each player selects a policy to use in the model by interacting with its opponents. (Bunn and Oliveira, 2001). In a later work, they adapted and extended this simulation platform to analyze if two particular generators in the Competition Commission Inquiry had gained enough market power to operate against the public interest (Bunn and Oliveira, 2003).

Researchers at Argonne National Laboratory in Chicago developed the Electricity Market Complex Adaptive System (EMCAS) model (North et al., 2002). Like the above-mentioned simulation models developed at the London Business School, the EMCAS model is an electronic laboratory that probes the possible effects of market rules by simulating the strategic behavior of participants. EMCAS agents learn from their previous experiences and modify their behavior based on the success or failure of their previous strategies. Genetic algorithms are used to drive the adaptive learning of some agents, and pool, bilateral contract and ancillary services markets are included.

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

Bin and his friends developed an agent simulation model to compare the market characteristics under different pricing methodologies (Bin et al., 2004). They use reinforced learning algorithms for generators to improve their bidding strategies under repetitive bidding for maximizing firm profit. They tested the uniform clearing price method, the pay as bid pricing method and the electricity value equivalent pricing method. They found that the electricity value equivalent pricing method is the most promising one with investment expansion compensation and low-level price variations.

The study published by Guerci and his friends focuses on modeling power exchanges in a multi-agent interacting framework with reduced behavioral assumptions (Guerci et al., 2005). A model of the day ahead market session of the Spanish Power Exchange using real demand data with simulated seller strategies is proposed. The number of sellers is defined at the first stage and the quantity of goods is distributed over the population of agents according to several initial distributions. A Clearing-house mechanism matches the cumulative demand and supply curves in order to determine the market-clearing price. The resulting price time-series are statistically tested to verify the validity of the model.

Bunn and Martoccia developed a detailed market micro simulation of agent bidding behavior to provide insights into the evolution of generator market power in the electricity pool of England and Wales (Bunn and Martoccia, 2005). The study supports the evolving story of unilateral market power dominance being manifest by the UK National Power in the early years that was constrained by regulatory oversight until 1996. As market concentration declined in the later years situation gradually turned into coordinated, tacit collusion. Furthermore, the analysis reinforces the view that simple market concentration measures, such as the Herfindahl- Hirschman Index (HHI), do not give a reliable diagnostic aid to the potential exercise of market power in the wholesale electricity sector.

2.3. Optimum Power Flow Literature

The application of optimization techniques to power system planning and operation problems has been an area of active research in the recent past. Optimal Power Flow (OPF) is a generic term that describes a broad class of problems. Generally, optimization of a specific objective function is carried out while constraints dictated by operational and physical particulars of the electric network must be satisfied simultaneously. OPF formulations aim to minimize the operating cost of thermal resources subject to satisfying constraints represented by bus active and reactive power balances in terms of voltages and phase angles (Momoh et al., 1999a).

A variety of optimization techniques has been used to solve OPF problems. Techniques used in literature can be classified as follows:

i. Nonlinear programming techniques ;
ii. Quadratic programming (QP) techniques;
iii. Newton-based solution of optimality conditions;
iv. Linear programming techniques;
v. Mixed integer linear programming techniques;
vi. Interior point methods.

Nonlinear programming (NLP) deals with problems involving nonlinear objective and constraint functions. The constraints may consist of equality and/or inequality formulations. Several methods such as Sequential Unconstrained Minimization Technique (SUMT), Lagrange multiplier based and the Modular In Core Optimization System (MINOS) augmented concept have been used to solve OPF problems . This class of models is developed with the assumptions of nonlinear objectives and constraints. Carpentier first introduced a generalized, nonlinear programming formulation of the economic dispatch problem, including voltage and other operating constraints (Carpentier, 1962). Dommel and Tinney developed a NLP method to minimize fuel cost and active power losses using the penalty function optimization approach (Dommel and Tinney, 1968). This NLP method checks the boundary on using a Lagrange Multiplier approach, and is capable of solving large size power system problems up to 500 busses. In a more recent study , Ponrajah and Galiana presented a continuation method (homotopy method) to solve nonlinear programming optimization problems(Ponrajah and Galiana, 1989). This method is used to solve a minimization of fuel cost function problem, which has a quadratic objective function and linear constraints. The method is tested on 6-, 10-,30-, 1 18-bus systems and compared to MINOS 4.0. A survey of most commonly found applications revealed that about 8% of OPF formulations employed general purpose packages applied for both real-time on-line and off-line operational problems (Momoh et al., 1999a).

Several QP methods have been used to solve OPF type of problems focusing on loss, voltage economic dispatch issues (Momoh et al., 1999a). The very first study published by Reid and Hasdorf presented a QP method to solve QP formulation problems (Reid and Hasdorf, 1973). The method employs Wolfe's algorithm specialized to solve the economic dispatch problem (which does not require penalty factors or the determination of the gradient step size). The CPU time required was very reasonable; however, the time increased as the system size increased. The method did not integrate the power flow as constraint and economic dispatch; therefore, they have to be solved separately, which can affect the central processing unit (CPU) time required. In a more recent work Aoki and followers presented a method which is an efficient, practical and definitive algorithm for dealing with constrained load flow (CLF) problems (Aoki et al., 1987). The method has a procedure for control variable adjustment, and the CLF problem is treated as a sequence of nonlinear programming problems. A Quasi-Quadratic programming problem formulation is employed. The algorithm satisfies nonlinear constraints and the MINOS technique is used. This method was tested on a 135-bus real-scale system of the Chougoku Electric Power Company. This method's constraints in order of priority are reactive power, voltage magnitude, and transformer tap ratios and employs a predetermined priority order of bringing in the reactive power constraints as they affect the objective function.

In the third category, the necessary conditions of optimality commonly referred to as the Kuhn-Tucker conditions are obtained. In general, these are nonlinear equations requiring iterative methods of solution. The Newton method is favored for its quadratic convergence properties. The earliest papers using Newton method for OPF are published by Rashed and Happ (Happ, 1974, Rashed and Kelly, 1974)

Linear programming (LP) addresses problems with constraints and objective function formulated in linear forms. Approximately 25% of the papers reviewed solve OPF problems using LP based techniques (Momoh et al., 1999a). The objective functions (including voltage, loss, economic dispatch and/or reactive power) are linearized to enable an LP formulation. One of earliest study using a linear programming approach to determine an economical schedule that is consistent with network security requirements for loading plants in a power system is developed by (Wells, 1968). The cost objective and its constraints are linearized and solved using the simplex method. This represented an experimental algorithm to implement a scheme for selecting and updating variables at the buses. Primarily, this is a decomposition approach based on Dantzig and Wolfe's algorithm. For deeper aspects of the use of LP based techniques for OPF problems one should see the article published by Alsac and his friends (Alsac et al., 1990).

Mixed Integer Programming (MIP) is a particular type of linear programming where some of the variables are restricted to be integers. Integer programming, and mixed integer programming, like nonlinear programming have extremely demanding computational requirements and the number of integer variables deployed is an important indicator of the difficulty for solving an MIP. One should look at the review article published by Momoh and his friends for further details of MIP implementations in OPF literature (Momoh et al., 1999b).

Even though the interior point method was devised in the early to mid-I980s, its application to power system optimization problems began with a delay. In the OPF literature, first Clements and his friends applied interior point methods to power systems(Clements *et al.*, 1991). Clements presented a nonlinear programming interior point technique for solving power system state estimation problems and featuring detection and identification of bad data. Their approach used a logarithmic barrier function interior point method to accommodate inequality constraints, and Newton's method to solve the Karush-Kuhn-Tucker (KKT) equations. This method was tested on 6-, 30-, 40-, 55-, and even up to 118- bus systems with favorable results.

Another interesting study that uses OPF to investigate market concentration in an electricity network is done by Lye and his friends (Lye et al., 2005). They show that the HHI lacks the capability of measuring market power on a bus to bus basis; they suggest an alternative methodology based on line congestion for measuring market power bus to bus basis.

Yong and Lassester introduced new concepts of generation sets and load sets to model the behavior of power supply and load distribution in the new retail wheeling market (Yong and Lasseter, 1999). They formulate an OPF offering the flexibility of choosing generators by consumers and other liberalized market flexibilities (which are usually unavailable in conventional OPF formulations). Formation of this OPF problem, in which the public interests are maximized, is demonstrated over a IEEE-14 bus system.

2.4. The Turkish Electricity Market

In 2001, Turkish Electricity Market Law (EML) came into force aiming for establishing a financially strong, stable, transparent, and competitive electricity market based on bilateral contracts. The Balancing and Settlement System (BSS) was put into practice in November 2004, in order to create a market where uncontracted generation can be traded. The actual implementation of the BSS started on August, 1st 2006. Özkıvrak argues that both the privatization and deregulation efforts in 1980s and 1990s and the restructuring efforts in 2001 have remained in background with the only target of ensuring funds urgently for needed investments in the electricity sector (Özkıvrak, 2005). The author also points out that the privatization and deregulation efforts prior to the 2001 Law resulted in State dominance in the sector. Besides, the author claims that there are also several important problems, inhibiting competition (e.g., there is no access supply, there is high losses in the distribution, the metering-communication control infrastructure is not established completely yet). The privatization process is also seen as a barrier for an efficient electricity market by the author which is supported by another study published by (Cetin and Oguz, 2007).

As also reported by (Erdogdu, 2010) the BSS has been criticized from its beginning as transferring excessive profits to private generation companies. The author claims that, current BSS not only undermines the healthy development of the electricity market in Turkey, but also prevents power plant investments due to uncertainties it created. Erdogdu points out that even if the current state of the BSS may have avoided power cuts so far; no meaningful competition has developed in the Turkish wholesale market yet. The author claims that a significant amount of work still lies ahead to reach a structure in which generators, suppliers, customers and other actors in the market can all freely negotiate, each taking their own view of the prices, risks, opportunities and threats forming a competitive market as a whole..

Bagdadioglu and Odyakmaz also discuss the BSS and claim that artificially determined shadow prices, in other words, prices that are determined by the intervention of the government or the SO in line with central planning and shaped according to populist concerns, send misleading signals to the market and increase downward pressure on generation expansion (Bagdadioglu and Odyakmaz, 2009). They suggest the implementation of a cash-based balancing and settlement mechanism. Authors claim that current trend in price differences, between the market and regulated wholesale prices (reflecting also the profit margin), encourage generators and wholesalers to reduce their direct, bilateral agreement customers in favor of selling to the market. This trend seems to be inappropriate in terms of the market design: not only does it create additional cost because of demand forecast deviation for distribution companies, but such distortions also cause delays in investment decisions.

Bagdadioglu and Odyakmaz also point out the problems in electricity power measuring. According to the authors, power metering infrastructure, especially for low voltage electricity, has been observed unsatisfactory (Bagdadioglu and Odyakmaz, 2009). The development of metering infrastructure is very important for the success of market implementation reforms. Solution of this situation require both legislative measures and financial investment. They finally argue that the implementation of market and regulatory reforms exhibits serious divergences from the initial design of the regulatory framework and market system (Bagdadioglu and Odyakmaz, 2009). The authors claim the differences are mainly due to the lack of commitments, contributions, and participation on the public and government side. They suggest that improving coordination between public authorities, private market participants and regulatory authority together with full commitment should be the dominant act for the success of Turkey' s electricity market reforms.

Another study published by Bahçe and Taymaz compares the welfare implication of privatization of the distribution networks by comparing two extreme cases, a pure regional distributional monopoly case and a representative pure "free" consumer case, with a benchmark case of administered price regulation (Bahçe and Taymaz, 2008). They developed a simulation model of the Turkish electricity system, and used the data on generation and distribution costs. They found substantial welfare losses occurring if the distributional companies behave as regional monopolists. They suggest that the best way to regulate distributional monopolies is to put price cap upon distribution price, while leaving sell prices of generators unregulated. They also argue that the idealistic case is to make all consumers free for directly contracting the suppliers; they end up with technological needs and consequences such as metering, network balancing, and real time pricing.

3. DESIGN AND STRUCTURE OF SIMULATION MODEL

In this section, the components of the integrated simulation / optimization model are presented in six sub sections. In the first section power user, Independent Power Producer, power generator, power transmission operator, power transmitter, and SO agents' objectives are described and the structural forms embedded are explained in detail together with the various parameters related to each agent. In the second subsection each agents' behavioral algorithm related state charts, triggering processes and the related information flow within the agents are presented. In the third subsection, the transmission network infrastructure is presented. The technical details about the transmission network and the generators including location in the network are given in this section. In the fourth subsection, information about the the demand data is given, including the load variations during the simulation period and the demand locations in the network. In the last part two modeling approaches regarding the transmission network are presented, which affect the decision process of the SO and the whole simulation model behavior.

3.1. Agents

3.1.1. Power User Agents

These agents form the demand side of the electricity market. Each tries to satisfy its demand with minimum cost. They primarily represent the independent power consumers or distribution companies in the electricity market. Each power user agent has its own real and reactive power demand level characteristics reflecting the local conditions they are bonded. The independent demand of a power user agent is reflected through a daily load curve (in hourly levels), which may also feature yearly or seasonal variations. At each time interval power user agents consume the power supplied by suppliers and/or power transmitter agents.

The overall electricity market simulation is designed to seek out ways to supply sufficient power to satisfy the demand of each power user agent. Demand is assumed to be deterministic and inelastic throughout the planning horizon. At hourly auctions, the SO tries to satisfy the demand of power user agents at minimum cost for maximizing the surplus of these agents. Inability to supply electricity to any power user agent at any time interval leads to power cuts at that region / consumer.

3.1.2. Independent Power Producer (IPP) Agents

These agents are the investors in the market whose objectives are to maximize their profits. Power Producer agents can invest in new power production facilities (with a choice of different technologies) in order to increase their production capacity with an aim to increase future profits. They offer bids consisting of a specific level of energy (in MWh units) at a specific price to the SO, at each time interval (each hour in base case), for each power plant in their portfolio or an aggregate price for the overall portfolio.

Each IPP agent has the following parameters; starting account balance and credibility, starting number of power generator agents owned and together with sizes and technologies, willingness to take risk, preferred profit margin and learning algorithm specific parameters.

Starting account balance represents (in million $ units) the amount of capital at the disposal of the investor. These funds may then be used for new investments throughout the simulation. Starting credibility is a parameter which reflects the easiness of finding credit for new investment projects and the amount of credit that can be found for that investor. Type, size and number of power generator agents (plants) at the start of the game is another parameter set of the IPPs. These parameters set the size of agent, market share and marginal cost of production of the related IPP at the start of planning horizon.

Each IPP submits its hourly bid to the SO, with bid contents based on its marginal cost of production, bidding strategy, desired profit margin, excess capacity of the market at that time interval and the effect of learning from the previous auctions. An IPP can bid distinctly for each power plant owned or can bid for aggregated portfolio which is exogenously determined at the start of the simulation. An IPP’s response to pool price and formation next bidding period’s price is mainly effected by the learning algorithm’s inherited. Throughout the planning horizon learning effect carries significant weight. The learning process depends on the realizations of the previous day's pool prices formed at the last pool auction, all previous pool auctions realized and the previous decisions made at the bidding process. Willingness to take risk is a discrete parameter describing the desired level of profit that a certain project should offer to be investable for an IPP.

3.1.3. Power Generator Agents

These are the power plants that actually produce the electricity. These agents are owned by the IPPs. They are primarily defined through the technological parameters according to the type of technology deployed. Parameters related to power plants agents are listed in Table 3.1.

Table 3.1.Parameters of power generator agents

Power generator agents parameters
Availability
Operating Costs
Setup Costs
Capacity
Maximum number of startups and shutdowns in a day
No load costs
Location
Construction time

Each parameter mentioned above varies significantly according to the technology selected. Availability is the technical availability of the equipment to convert the primary energy resource to electricity as percentage of total time over a year period. It varies from 99% for base load technologies to 95 % for flexible ones..

Operating costs are functions of the primary energy resources deployed according to technology used by power plant. Prices of primary energy resources used change the operating cost of plants as a function of the technology. Setup costs describe the needed investment to construct, test and prepare the plant for the final production stages. The corresponding setup cost is paid by the IPP at the time a new power plant is initiated. The setup cost is also a function of the capacity, technology and location parameters. Capacity parameter represents maximum power that the power generator agent can supply if it is fully deployed. Maximum number of start-ups and shutdowns in a day limits the number of start-ups and shutdowns during a day as a function of the technology selected. No load cost refers to the cost incurred by the power generator agent even when it is not scheduled for production. In physical terms, this parameter reflects the expenses necessary to keep the plant alive and ready for the next bidding period. Location parameter is related to the geographical placement of the agent. Construction time is the period between the decision for investment to fully functional and tested plant completion.

3.1.4. Power Transmission Operator Agent

This agent is the operator of the overall interconnection system. It is the owner of all transmission lines (power transmission agents). It has the parameters listed in Table 3.2.

Table 3.2.Parameters of power transmission operator agents

Power transmission operator agent
Account balance
Credibility
Profit Margin
Willingness to take risk

Since transmission system is a natural monopoly, it is the owner of the full transmission line network. It tries to maximize its profit according to parameters given. Profit expectations can be set to zero, if electricity transmission is seen as a public service. This agent may invest in new transmission line agents or increase the capacity of the current power transmitter agents according to transmission line loading and congestion level. It submits bids to the SO for each power transmitter agent individually (as price per MWh). The bidding price is a combination of the transmission cost (as determined by the power transmitter agent) and the desired profit margins.

3.1.5. Power Transmitter Agents

These are the agents that are actually transmitting the electricity produced by power generator agents to the power user agents. They transmit the electricity from one region to another, while charging a specific price per MWh transmitted.

Power transmitter agents' parameters are listed in Table 3.3. Voltage is used for electrical potential difference. Capacity is the amount of power that can be transferred throughout the line. Susceptance and conductance are technical parameters related to the technical properties of the transmission line measured in Siemens (as reciprocal of ohms (Ω)).

Table 3.3.Parameters of power transmitter agents

Power transmitter agents
Capacity
Susceptance and Conductance
No load cost
Operating cost
Setup Cost
Construction Time
Starting region
Ending region
Control stations and regions

No load cost refers to the cost incurred by the power transmitter agent even when it is not scheduled for transmission. In physical terms, this parameter reflects the expenses necessary to keep the transmission line up and ready for the next bidding period. Operating cost is the cost of transmitting one MWh of electricity per period (including transmission losses). Setup cost is the cost incurred by the Power Transmission Operator Agent to initiate a new transmission line (agent) or to increase the capacity of an existing line (agent).Construction time is the period between the decision for investment to fully functional and tested operating line completion.

Starting region and ending region are the transmitter lines' starting and ending nodes in the network where loading from power generators can be made and power user agents can pull electricity from the line. Control stations and regions represents the intra stations that can perform power loading and balancing.

3.1.6. The System Operator (SO)

The SO is the central planner agent that tries to satisfy the demand of power user agents at minimum cost. Central planner considers the independent power producers' bid prices, quantities and power plant locations; available transmission line capacities, bid prices from the power transmitter operator agent; and power user agents' demand quantities and regions, it then tries to find an optimum combination of active power generator agents, quantities to be generated and power flows (trough the existing network) to minimize the total cost of electricity. The related power purchase and routing decisions (over the duration of the planning horizon and on a scenario basis) lie at the heart of the aggregated simulation / optimization model.

3.2. Behavioral Algorithms

In this subsection, the agents introduced in previous section will be elaborated in more detail. Information about the internal structure of the agents is given including their behavioral algorithms, related state charts, triggering processes and the information flow within the agents.

3.2.1. Power User Agents

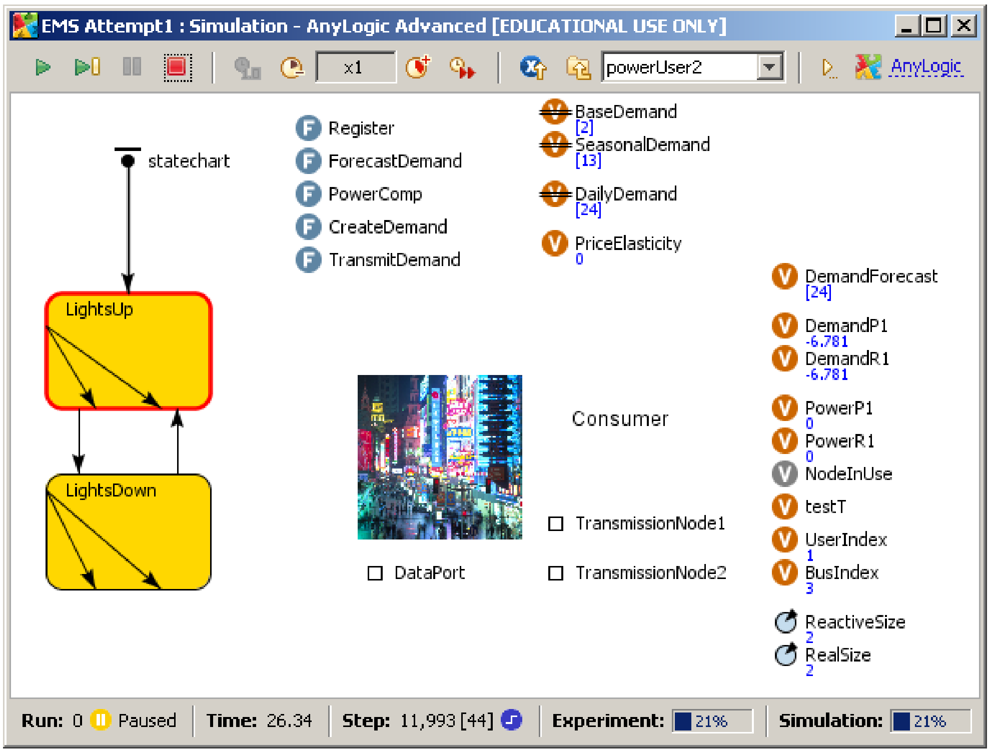

Figure 3.1. Structure of Power User Agents

The Internal structure of a Power User agent can be seen in Figure 3.1. This screen is the main interface of the agent for configuration.

This interface contains the "Ports" which are essential for interacting and communicating with other agents. The ports TransmissionNode1 and TransmissionNode2 are defined to distinguish between Real and Reactive power flows respectively. Communication between the Power User and the SO agents is featured via the DataPort where data exchange on load levels and other technical data occurs.

The communication between agents is the resultof a set of actions determined by how the agents behave in a dynamic environment. Behavioral aspects of the agents are implemented with the use of "Statecharts". The Power User Agents has two main states: one is "LightsUp" while the other one is "LightsDown". Transition between these two states is subject to the power flow level of the bus to which the agent is connected. If power flow is not enough to keep the voltage at the specified threshold levels, transition from "LightsUp" to "LightsDown" occurs. State change occurs. If power flow recovers the need of the buses, than a state change back to "LightsUp" occurs.

States may also have self transitions based on some conditions. The Power User agent has two self transitions per state. Each transition is subject to a message containing a keyword for a specific purpose. For example, the first transition in the "LightUps" state is subject to a message passed to the statechart containing the keyword "SendDemandForecast". When this message is received "ForecastDemand" function is called so that demand projections are made for the next 24 hours with a predefined methodology. Afterwards the "TransmitDemand" function is called and produced forecasting results are passed to the SO.

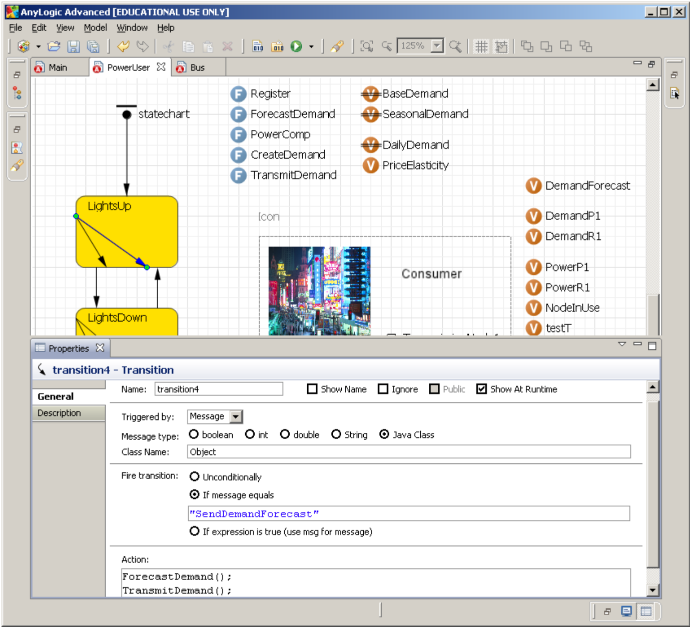

Figure 3.2. Self Transition example

The other self transition is conditioned on a message containing the keyword "Demand". When this message is received, the "CreateDemand" function is called so as to compute hourly demand and send it through power ports to the connected Bus.

The second state has currently only a single transition due to the implementation of constant price elasticity. However, the possibility to implement time based price elasticity with another transition remains. This is left as a potential improvement for future research.

3.2.2. Independent Power Producer (IPP) Agents

IPP Agents are the owners of the Power generator Agents. The internal structure of an IPP agent can be seen in Figure 3.3. The IPP interface includes two Data ports, namely "DataPort1" and "DataPort2". "DataPort1" features communication port of the IPP with the SO. "DataPort2" is the communication port of the IPP with the Power generator Agents owned.

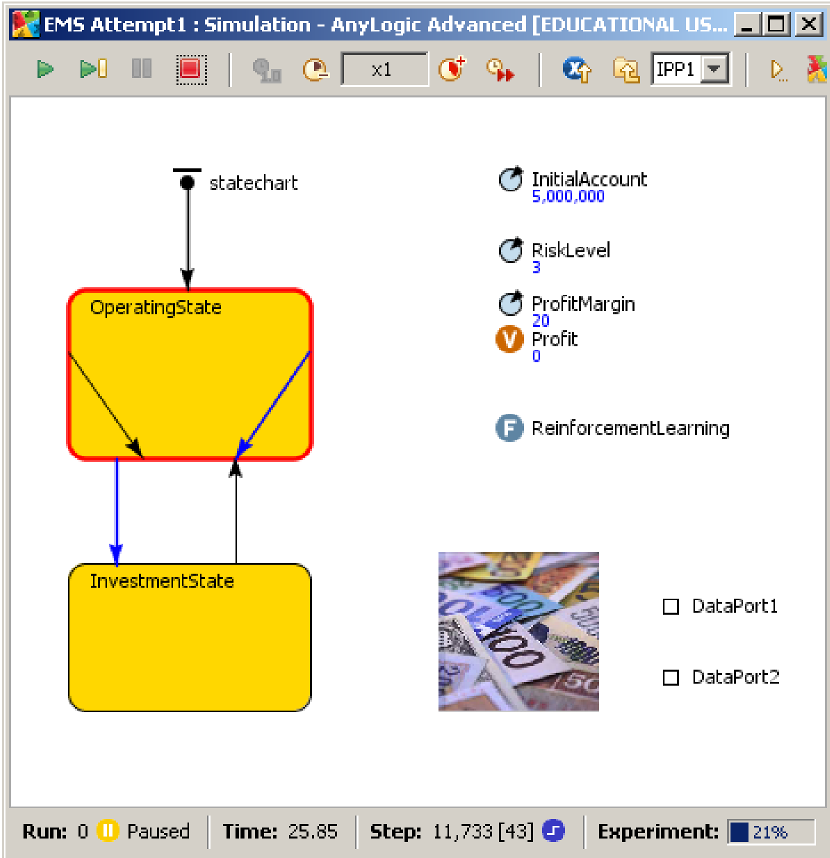

Figure 3.3. Structure of Independent Power Producer Agents

An IPP agent has two main states “OperatingState” and “InvestmentState”. “OperatingState” is the state where IPP performs daily system operations. “InvestmentState” is an undeveloped study area where investment on new projects would be considered.

The “OperatingState” has two self transitions. One on the left listen the port connected to the SO. When a triggering message is received, IPP sends related messages to Power generator Agents for bid computation and other related actions. And the bids are directly made from power generators to the SO. Thus each owned power generator agent bids hourly prices for its production. However, it is also possible for the IPP to bid one price for all of the owned Power generator agents. The self transition on the right occurs every 24h simulation time unit. It triggers the profit calculation for owned Power Producer agents. Thus, the financial position of an IPP is refreshed by this transition every simulation time unit (24 hours).

3.2.3. Power generator Agents

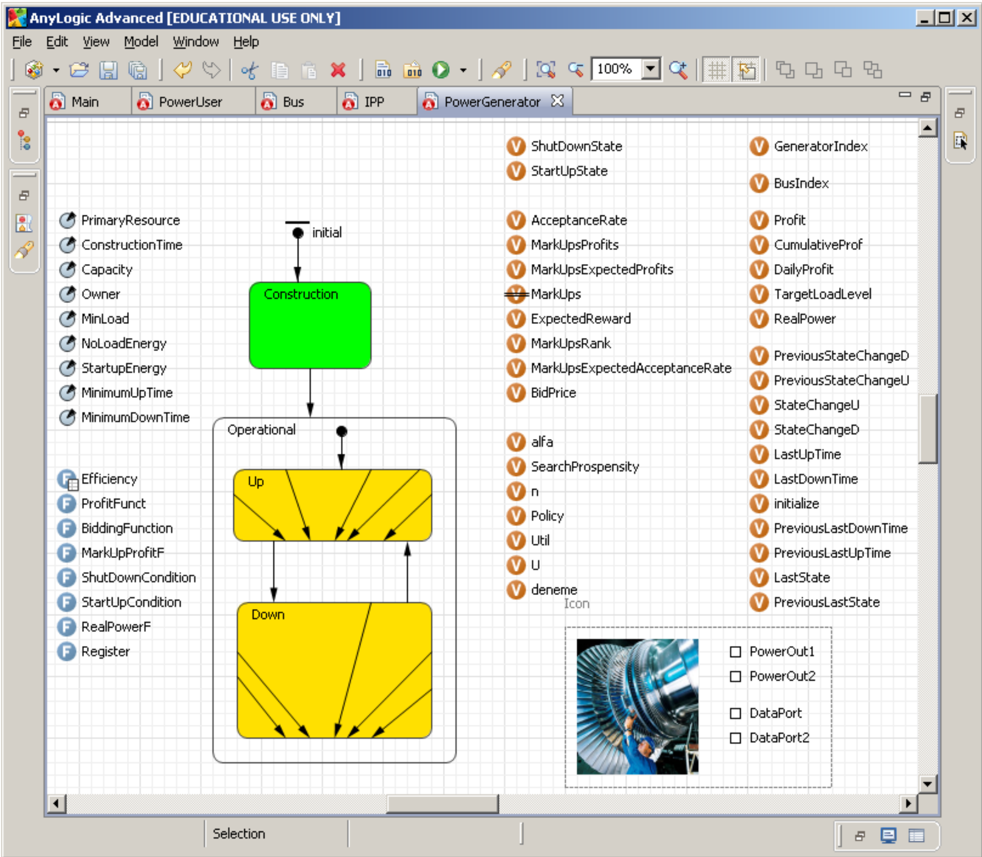

Figure 3.4. Internal Structure of Power generator Agent

Power generator Agent possesses one of the most internally complex structures. As can be seen in Figure 3.4. It includes two main states Construction an Operational. The Operational State has two sub states Up and Down.

There are two power and two data ports. The generator transmits real and reactive power components generated from PowerOut1 and PowerOut2 ports respectively. “DataPort” and “Dataport2” are used for communication with the conrolling IPP and the SO respectively.

The statechart of the Power generator Agent is the most complex part of the agent. When an agent is initialized, the first state is the “Construction” state. An agent will be residing in this state until the simulation time exceeds the construction period, which is a parameter of the agent itself. When the construction period ends, the Power generator agent transits to the Operational state. The Operational State is a hybrid state consisting of two sub states. When the Operational state is reached, first Up state is triggered. The transition between Up and Down states is determined by load levels scheduled and technical constraints such as minimum up and down times.

The up state has five transitions. The first transition is triggered by the received message “Operate”. It initiates the information flow for a predefined schedule. After completion of information flow, state variables are updated according to last states data. Thus, transition is triggered by the SO to make the agent ready for the next 24 hour interval.

The second transition is triggered by simulation time change. Within every unit simulation time, the profit realized is computed and shut down conditions are checked. If no load has been scheduled for generation for the next MinimumDownTime period, transition from Up state to Down state is triggered.

The third transition is related to agents’ synchronization. This transition is triggered by the message “Supply” sent by the SystemOperator. Then, the power produced is transmitted through the power ports to the connected bus.

The fourth transition is related to owner-utility relationship. Transition is triggered by the message sent by the controlling IPP. Cumulative profit up to this simulation time is sent to the controlling IPP and the cumulative profit variable is set “0” for further profit tracking.

Last but not least is the fifth transition. It is triggered by the message “Calculate” received from the controlling IPP. It activates the bidding price mechanisms and triggers the flow of generated bidding results to the SO. The bidding mechanism is an important part of the agent as it features various self-learning capabilities and options. A modified version of the self-learning autonomous algorithm purposed by Bower and Bunn (2001) is used throughout the simulation.

At each trigger, the agent calculates the *expected daily profit* and the *expected acceptance rate* for each one of the markups (price levels based on last pool prices) used at that specific iteration.

i. The expected daily profit is calculated using exponential smoothing of the profits earned on past trading days.

ii. The expected acceptance rate is calculated using exponential smoothing of the number of hours that a bid (offer) was accepted, for the specific markup, in the past trading days.

Thus, given the expected acceptance rate and the expected daily profit, each player calculates an *expected reward* for each markup. Then the agent computes a *utility function* values over the markups. In order to compute the utility function values, the agent ranks the markups by decreasing level of expected reward. The markup with the highest expected reward receives a higher perceived utility value. Finally, the agent transforms the utility function into a policy—an association between each markup and the percentage of bidding (offering) that markup in the next day's appropriate auction. The agent's policy is used to choose the price in the following day.

Let j=1...10 represent the interval index (the markup number) and t=1...K represent the day (time). Then, Prf_{tj} represents the daily profit at time t using markup j. $Exp(Prf_{tj})$ indicates the expected time t daily profit of markup j. Art_{tj} represents the daily acceptance rate at time t using markup j. $Exp(Prf_{tj})$ indicates the expected daily profit at time t of markup j. $Exp(Art_{tj})$ represents the expected acceptance rate at time t using markup j. $Exp(Rwd_{tj})$ represents the expected reward of markup j at time t. Rank(j) stands for the rank of the markup j. $Util_j$ and Pol_j stand for the perceived utility and the probability of using a markup j. At the end of the day, after receiving the feedback with the prices and quantities traded in each hour, the policy is calculated with the following algorithm:

First calculate the new expected daily profit and acceptance rate for the markups used.

Let Prf_{tj}^{i} represent the profit associated with markup j at hour i and iteration for day t, then the daily profit and the acceptance rate will be, respectively,

$$Prf_{tj} = \sum_{i=1}^{24} Prf_{tj}^{i} \tag{3.1}$$

$$Art_{tj} = \left(Number\ of\ bids\ \left(offers\right)\ accepted_{tj}\right) /\ 24 \tag{3.2}$$

Then, for each used markup j

$$Exp\left(Prf_{tj}\right) = Exp\left(Prf_{t-1\,j}\right) + \alpha * \left[Prf_{t-1\,j} - Exp\left(Prf_{t-1\,j}\right)\right] \tag{3.3}$$

$$Exp\left(Art_{tj}\right) = Exp\left(Art_{t-1\,j}\right) + \alpha * \left[Art_{t-1\,j} - Exp\left(Art_{t-1\,j}\right)\right] \tag{3.4}$$

Second, recalculate the expected reward for each markup. For every markup j

$$Exp\left(Rwd_{tj}\right) = Exp\left(Prf_{t\,j}\right) * Exp\left(Art_{tj}\right) \tag{3.5}$$

Third, rank the markups j by descending value of the expected rewards.

Four, calculate the perceived utility of each markup j,

$$Util_{j} = U * \left(\left(sp - n\right) / sp\right)^{Rank(j)-1} \tag{3.6}$$

where, for each agent, U , *sp (Search Propensity)*, and n equal 1000, 4, and 3, respectively. This approach is quite flexible enabling the construction of a wide variety of utility functions. After calculating the perceived utility from each markup, the agent transforms this utility function into a policy. Table 3.4 shows an implementation of utility function as an example for convenience.

Finally, calculate the “policy,” i.e., the probability of using each markup j. For this purpose, rule of proportionality is used: the probability of choosing a certain markup is directly proportional to the weight of that markup perceived utility in the sum of perceived utilities of all markups

$$Pol_j = Util_j / \sum_k Util_k \quad (3.7)$$

The power generator agents determine their bids through the above self reinforcement learning algorithm (adapted from Bower and Bunn 2001) and send them to the SO. In the simulation model, the "MarkUpProfile" module is constructed for deriving expected profit, acceptance rate and expected reward for each markup and the BiddingFunction module accomplishes policy formation, as outlined by the algorithm described above.

Table 3.4. Policy derivation example (Bunn and Oliveira, 2001).

Mark-up Categories	1	2	3	4	5	6	7	8	9	10
Exp_{tj}(Prf)	500	400	600	300	1000	700	800	850	750	900
Exp_{tj}(Art) (%)	100	94	98	80	85	70	65	70	60	55
Exp_{tj}(Rwd)	500	376	588	240	850	490	520	595	450	495
Rank(j)	5	9	3	10	1	7	4	2	8	6
$Util_j$	3.9	0	62.5	0	1000	0.3	15.6	250	0.1	1
Pol_j (%)	0.3	0	4.7	0	75	0	1.2	18.8	0	0.1

The Table 3.4 displays an example of policy derivation starting from the computed expectation values for each markup. Policy is build on ten different markups defined for the agent. *Exp(Prf)*, *Exp(Rwd),* and *Exp(Art)* represent, respectively, the expected profit , reward and the acceptance rate of each markup *j* at time *t*. *Rank(j)* orders the rewards from the highest to the lowest expected reward. *Util* represents the perceived utility an agent receives from a certain markup. *Pol* represents the probability of using a certain markup when bidding.

3.2.4. Power Transmission Operator Agent

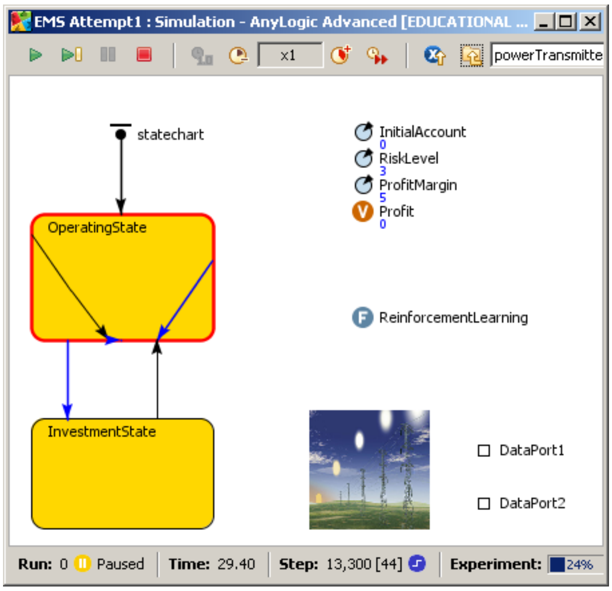

Figure 3.5. Internal structure of Power Transmission Operator Agent

A Power Transmission Operator agent's internal structure can be seen in Figure 3.5. Its' interface has two data ports; one for communication with the SO and the other for communicating with the controlling Power Transmitter Agents. There are two main states, namely, "OperatingState" and "InvestmentState". Currently the "InvestmentState" has no transitive action but offers a branch of study for further research.The "OperatingState" on the other hand has two self transitions. The first one is triggered every 24 hours. Its is to initiate the process of profit transfer from the owned Transmitter Agents. The second transition is triggered by the message "Operate" coming from the SO as a warning for schedule change. Then, the Operator Agent warns the owned Transmitter agents by sending a warning message to trigger the required processes.

3.2.5. Power Transmitter Agents

The Power Transmitter Agents' internal structure can be seen in Figure 3.6.

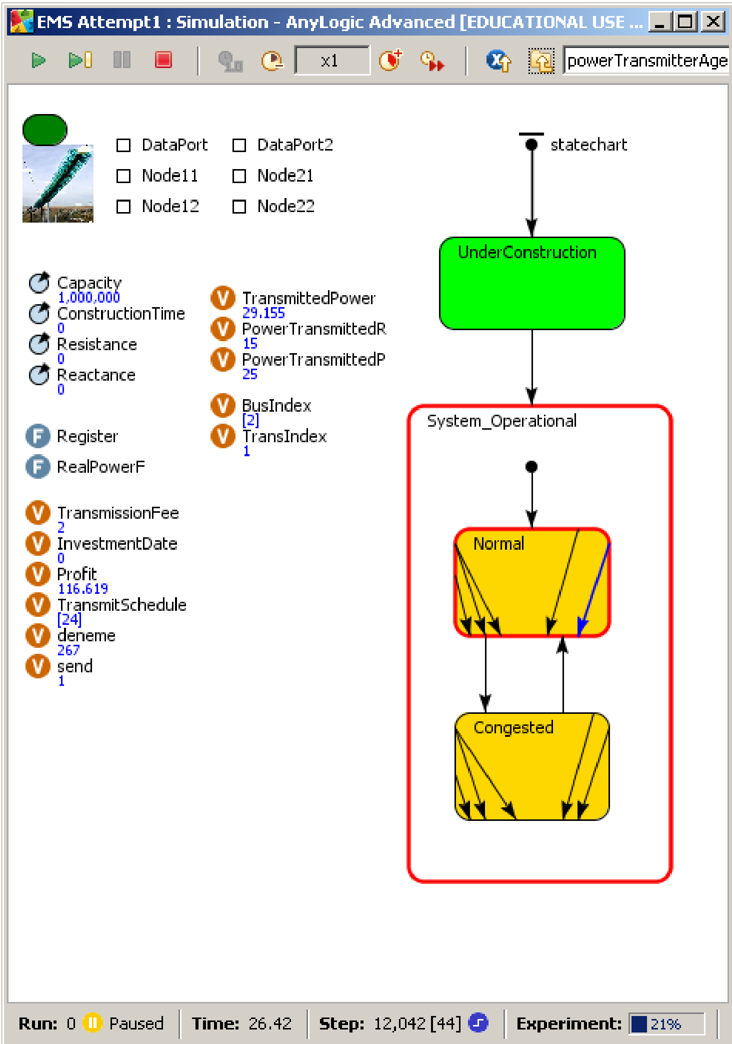

Figure 3.6. Internal Structure of Power Transmitter Agent

The Power Transmitter Agent is composed of six ports. two of which are data ports and the other four power transmission ports. "Dataport" and "Dataport2" are used for communication and message passing to the Power Transmission Operator and the SO agents respectively. Node11 and Node12 form the first terminal interface to connect to a Bus for Real and Reactive power components respectively. Node21 and Node 22 form the second terminal interface to connect to a Bus for Real and Reactive power components respectively.

The state chart is composed of two main states, namely "UnderConstruction" and "System_Operational". Once the agent is initialized, it remains in the state "UnderConstruction" state for a prespecified period defining the construction time. After construction is finished than "System_Operational" main state is activated. This state has two sub states: Normal and Congested. Transition between these two states is dependent on the power flow levels between two terminals. If the power flow level is less than capacity, normal state will be active; else Congested state is activated.

Each sub state has five self transitions. The first transition is triggered by timeout, with the change of simulation time. It computes the total electricity transmitted from real and reactive powers levels transmitted between terminals. Next, the financial aspect of the transmission is computed. Second, transition is triggered by the message "SendFees" sent by the Power Transmission Operator Agent. Line specific fees and capacity limits are passed to the SO. The third transition is triggered by the "Operate" message. Then within 24 hours, the power flow schedule exchange between the SO and the Power Transmitter Agent starts. The fourth transition is triggered by the controlling agent with message "SendProfit", which initiates transfer of cumulative profit to the controlling agent. The fifth transition is triggered by the message "Transmit" sent by the SO. It initiates the procedures to transmit power through the terminals.

3.2.6. Bus Agents

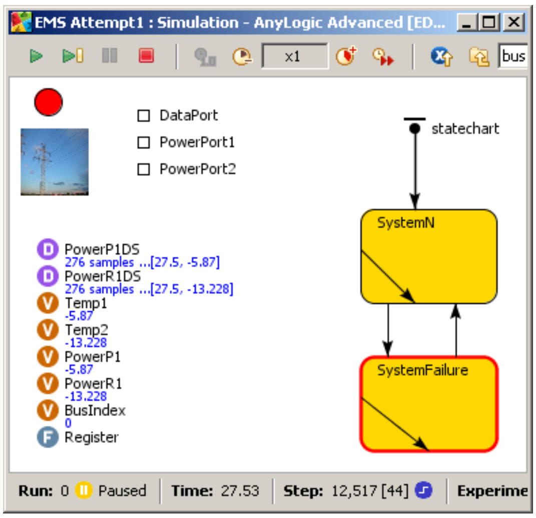

Figure 3.7. Internal Structure of Bus Agent

The Bus agent forms a platform where active power players like Power User Agents, Power generator Agents and Power Transmitter Agents interact and interchange power. A generator agent must connect to the network via a bus. Generators and consumers are connected to one bus while each terminal of transmitters is also connected to one bus. Each generator agent sends its real and reactive demand, generation or transmission to “PowerPort1” and “PowerPort2” respectively. The Bus agent behaves like a small power pool similar to a swimming to pool: we want to keep water level above “0” level with minimum deviation. If the power flow level at one bus is under the required level, none of the agent connected thon bus can operate normally, thus power failure occurs.

The Bus agent has two states: “SystemN” defines normal operating conditions, while the second stage is (as its name suggests) SystemFailure. If net power flow is semi positive (demand is satisfied) SystemN is activated, else SystemFailure is activated. In case of SystemN activation, all connected agents are warned about the situation. Two states have the same self transition which is triggered by the SO for system synchronization.

3.2.7. The System Operator

The SO’s internal structure can be seen in Figure 3.8. It has only one data port at the interface. All messages to the connected agents are passed through this port. There are two main states. One is DailyOperation and other is InvestmentOperationState. As the names suggest, operational decisions are given in the former state and the later one processes investment decisions in the system. The first self transition is the system synchronization. It is triggered by timeout: every 6 minutes system is rechecked and synchronized. The second self transition is also triggered by timeout. Every 24 hours the “Operate” message is send to the agents triggering the schedule information update for the generator agents. Then, for the formation of next 24 hours’ schedule, each generator agent is triggered to pass bids, fees and demands to the SO. The third self transition is based on the condition that all generator agents have passed the bidding information to the SO. When the third self transition is triggered, the optimization procedure is called and next 24 hours’ schedule is generated. When the second self-transition is triggered, the formed schedule is passed to the generator agents.

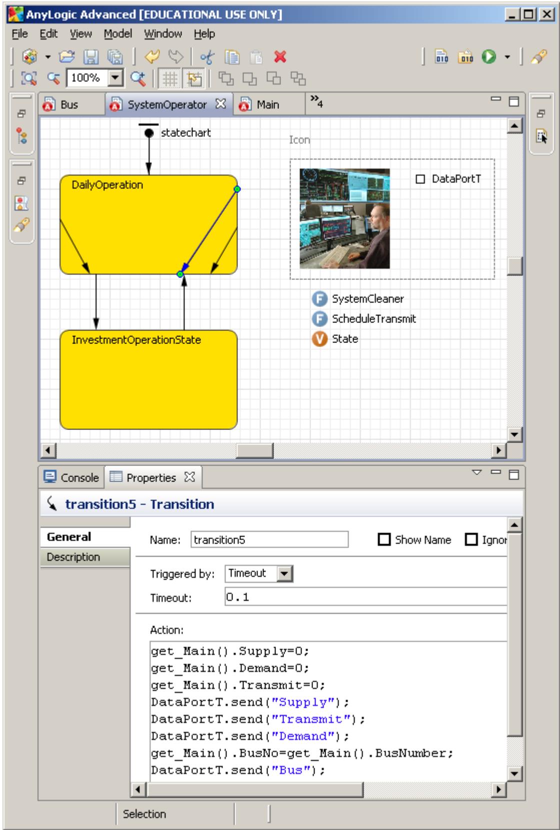

Figure 3.8. Internal Structure of SO and a self transition

3.3. Learning Capability Equipped Hourly Bidding Strategies

The profit maximization oriented hourly bidding strategies of generator agents are based on learning algorithms designed to take advantage of past experience and / or information and / or self strong points. The self reinforcement learning algorithm that is used for producing bidding strategies for the maximization of profit on a daily basis. This is obtained by determining the optimum increase or decrease of all prices for all time intervals, which is a single strategy for all day. There no distinction between if they are peak, transition or low demand time intervals. This approach has some disadvantages due to its nature. Generators are lacking the nature of time intervals, which lowers the profit levels that they can get without disturbing the profit levels of other time intervals. For the completeness of modeling, algorithms that permit the hourly base speculation due some specific property time interval, producer or any other related market variables, are developed. First algorithm that is considered is the *Price Tracking Algorithm*.

The motivation for this algorithm has been to enable the generator agents to see their relative power in the price formation procedure by comparing the prices they bid by the prices announced by the SO.

The Price tracking algorithm follows the steps listed in Table 3.5.

Table 3.5. The Price tracking algorithm

In every time interval (hour) = i
Price Gap (i) = Price (i) – Bid Price (i)
Take average and standard deviation of last 30 simulation time step
Look T value of the sample with 29 degree of freedom.
If T value is less than or equal to $T_{0.95,29}$ Then
*PriceTrackingEff=- PriceTrackingEffFact * T/$T_{0.95,29}$ + (1 + PriceTrackingEffFact)*
Else
PriceTrackingEff=1
Next time interval

As indicated, the multiplicative factor "*PriceTrackingEff*" is used to adjust the basic bid price. The "PriceTrackingEffFact" controls the magnitude of the adjustment. The algorithm tries to compare the bids submitted to the SO and prices announced by subtracting one from another. Then it forms an expectation based on 30 day sample history. Sample mean being close to zero levels triggers higher "*PriceTrackingEff*" value and bidding price is elevated accordingly. The effect of the algorithm would be seen in cases where a specific generator is dominant in supplying electricity as the highest bidder. This is very important in transient and peak time intervals due to technical constraints.

The second learning algorithm developed to support bidding strategies is the *The Market Share Algorithm* that focuses on the share of the generator agents on the spot market, at hourly time intervals. The underlying assumption is that a generator with a high share in the spot market can venture to add a markup to its marginal production cost. Accordingly, at every time interval, generator agents compare their scheduled load with the total demand of that time interval. If their share is greater (less) than the predefined level than a bid price markup is added (subtracted) to basic pricing strategy, affecting the bidding procedure.

Market Share algorithm follows the steps listed in Table 3.6.

Table 3.6. The Market Share Algorithm

In every time interval (hour) = i
Market Share (i) = Load (i)/ Demand (i) – 1 / Number of generators
*Expected Market Share (i) = Expected Market Share (i-1) + alfa * (Market Share (i) – Expected Market Share (i-1))*
*Market Share Effect (i) = (Expected Market Share (i))^3 * Market Share Effect Factor+1*
Next time interval

The important parameter of this algorithm is "*Market Share Effect Factor*" , which determines maximum price markup that a generator agent can add to its basic pricing strategy according to the market share level.

Third hourly algorithm, the "*Market Power Algorithm*", developed focuses on the *gap* between the demand, and physical capacity available. Then based on this gap, the generator compares this gap and its own production level in order to assess the importance of its generation in the production mix. If the ratio of generator's electricity generation level to the *gap* is at a significant level, than the generator's "market power" would allow some markup to its basic price level (thereby aiming to increase the profit at that time interval hour). The algorithm is summarized in Table 3.7.

Table 3.7. The Market power algorithm

In every time interval hour=i
Market Power (i)=generator Load (i) / (Physical Capacity – Demand(i))
*Expected Market Power (i) = Expected Market Power (i-1) + alpha * (Market Power (i) – Expected Market Power (i-1))*
Market Power Effect (i) = max(1, 1 / (1.2- Expected Market Power (i))$^{1/8}$)
Next time interval

Accordingly, the normal bid price formation is not affected until "*Expected Market Power*" reaches 20%. After the 20% threshold, bid price is increased through the multiplicative factor "*Market Power Effect*", which is dependent on the value of "*Expected Market Power*".

All learning algorithms addressing hourly bid price formation are applied at the 1000th hour of the planning horizon in order to give an opportunity for sufficient data accumulation necessary for self learning effects.

3.4. The Network

A transmission network system with 30 bus, 41 transmission lines, 9 generators, and 21 power users is used for model testing, execution, and scenario evaluation purposes. This particular network which is a well known Institute of Electrical and Electronics Engineers (IEEE) 30 bus test system that is real in terms of existence is adopted from (Shahidehpour et al., 2002) and offers a realistic market network with power users and generators. The network structure is displayed in Figure 3.9.

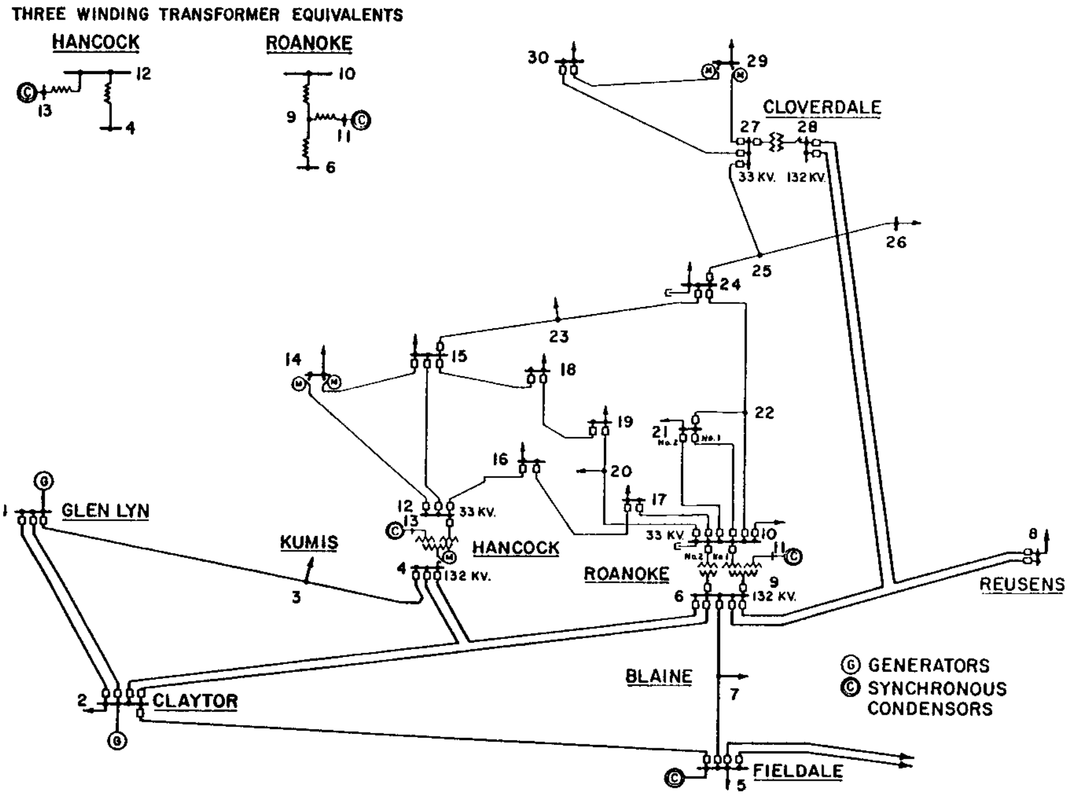

Figure 3.9. 30 bus network Shihidehpour et.al. 2002

The structure naturally gives advantages to some of the generators due to the bus they are connected. The generators that are far away from the power users may remain uncompetitive (due to transmission costs and local transmission constraints) even though they bid low prices. The shifting of generator locations in other scenarios will help to better understand the role of the transmission network structure. The number of generators and power users are satisfactory to form a market that is competitively structured in conventional economical measures. Network structure details can be found at Table 3.9.

Detailed information about generators can be seen in Table 3.8.

Table 3.8. Detailed generator information in 30 bus network

Generators	***Capacity (MW)***	***MinLoad (MW)***	***Reactive Limits Supply (MVAR)***	***Reactive Limits Consume (MVAR)***	***NoLoad Energy (MWh)***	***Startup Energy (MWh)***	***Minimum Up Time (MWh)***	***Minimum Down Time (MWh)***	***Primary Resource***	***Connected Bus***
Generator 1	133	0	111	74	10	2.058	3	2	Gas	30
Generator 2	45	0	38	25	5	0.882	1	1	Gas	24
Generator 3	45	0	38	25	5	0.882	1	1	Gas	11
Generator 4	177	0	124	89	10	2.94	4	2	Oil	2
Generator 5	133	0	111	74	10	2.352	3	2	Gas	8
Generator 6	133	0	80	53	10	2.352	3	2	Coal	5
Generator 7	222	0	133	89	20	5.88	5	3	Coal	1
Generator 8	177	0	124	89	10	2.793	4	2	Oil	13
Generator 9	177	0	124	89	10	2.793	4	2	Oil	15

Table 3.9. Detailed network structure of 30 bus network.

Branch No	From-to	R (p.u)	X(p.u)
1	1-2	0.0192	0.0575
2	1-3	0.0452	0.1852
3	2-4	0.057	0.1737
4	3-4	0.0132	0.0379
5	2-5	0.0472	0.1983
6	2-6	0.0581	0.1763
7	4-6	0.0119	0.0414
8	5-7	0.046	0.116
9	6-7	0.0267	0.082
10	6-8	0.012	0.042
11	6-9	0	0.208
12	6-10	0	0.556
13	9-11	0	0.208
14	9-10	0	0.11
15	4-12	0	0.256
16	12-13	0	0.14
17	12-14	0.1231	0.2559
18	12-15	0.0662	0.1304
19	12-16	0.0945	0.1987
20	14-15	0.221	0.1997
21	16-17	0.0824	0.1932
22	15-18	0.107	0.2185
23	18-19	0.0639	0.1292
24	19-20	0.034	0.068
25	10-20	0.0936	0.209
26	10-17	0.0324	0.0845
27	10-21	0.0348	0.0749
28	10-22	0.0727	0.1499
29	21-22	0.0116	0.0236
30	15-23	0.1	0.202
31	22-24	0.115	0.179
32	23-24	0.132	0.27
33	24-25	0.1885	0.3292
34	25-26	0.2544	0.38
35	25-27	0.1093	0.2087
36	28-27	0	0.396
37	27-29	0.2198	0.4153
38	27-30	0.3202	0.6027
39	29-30	0.2399	0.4533
40	8-28	0.0636	0.2
41	6-28	0.0169	0.0599

3.5. Compilation of the Demand Data

During the simulation runs, the demand levels deployed in Table 3.10 are used as the demands of consumer agents. The general demand pattern of the power users (which can be seen in Figure 3.10) is common,. and this is actually quite reflective of the demand pattern of Turkey for year 2002. The actual demand pattern of 2002 is displayed in Figure 3.11.

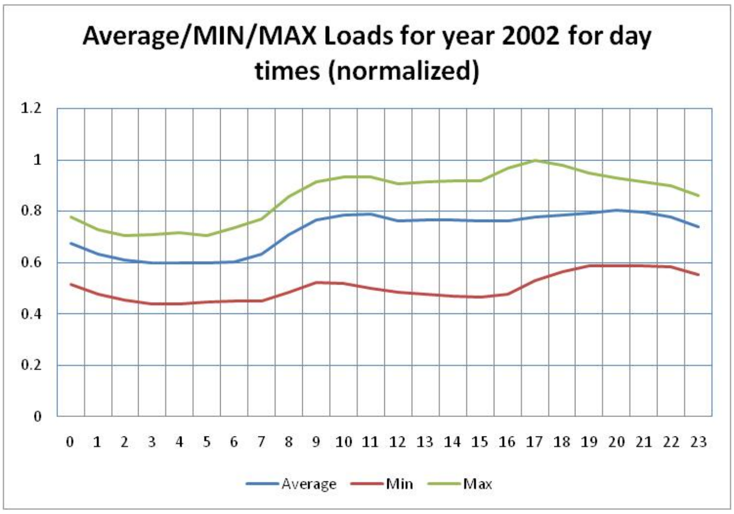

Figure 3.10.Descriptive information for demand profile of Power Users according to hours the day.

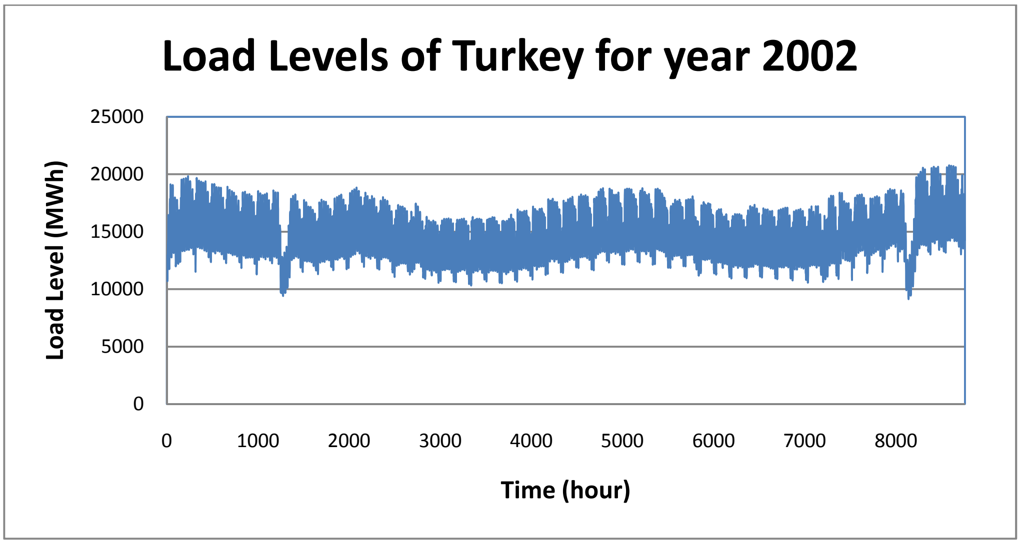

Figure 3.11.Load curve for Turkey for the year 2002

Table 3.10.Power users demand information and connected bus numbers

Power users	*Max Load (MW)*	*MinLoad (MW)*	*Connected Bus*
Power user 1	54	23	2
Power user 2	5	2	3
Power user 3	16	7	4
Power user 4	222	98	5
Power user 5	54	24	7
Power user 6	96	42	8
Power user 7	14	6	10
Power user 8	27	12	12
Power user 9	14	6	14
Power user 10	19	8	15
Power user 11	10	4	16
Power user 12	22	10	17
Power user 13	5	2	18
Power user 14	19	9	19
Power user 15	5	2	20
Power user 16	43	49	21
Power user 17	5	2	23
Power user 18	23	10	24
Power user 19	11	5	26
Power user 20	5	2	29
Power user 21	23	10	30

3.6. The Simulation Flow

Flow of the simulation model is based on the hourly biddings and the following market balancing effects. The operations flow of the hypothetic day ahead balancing market is as follows:

i. Hourly electricity demand forecasts of each power user for the next day is taken into consideration.
ii. Transmission operator agents submit their capacities and their transmission line fees for the next day;
iii. Generator agents send their capacity and bids for electricity price on hourly basis.
iv. With all data collected, the SO generates production and transmission schedule based on total cost minimization (actually forming an ordered list of all electricity plus transmission cost offers / options and accepting the smallest, then moving and accepting higher offers until the demand of the period is satisfied.

v. The accepted schedule is passed to the generators and transmission lines.
vi. Based on the list of accepted offers, generators deploy their learning processes and select the strategy for the next day and create fresh hourly bid prices.
vii. Daily generation, transmission and consumption activities are carried on;
viii. For the next day Step i is initiated again.

3.7. Modeling Approaches

In this study, two modeling approaches are used for the modeling of the underlying transmission network. These two approaches, namely the minimal cost network flow and the alternative current optimum power flow formulations primarily differ regarding their assumptions associated with the technical characteristics, needs and limitation of power flow on the given network structure. These assumptions affect the SO agent behavior in the simulation and influence generator agents' learning mechanisms there by affecting the simulation outcomes. Accordingly, the whole SO decision process relies on these assumptions that changes the way of handling the dispatch and distribution problem.

Electricity flows from power plants, through transformers and transmission lines, to substations, distribution lines, and then finally to the electricity consumer. The electric system is highly interconnected. The interconnectedness of the system means that the transmission grid functions as one entity. Power entering the system flows along all available paths, not just from Point A to Point B. The system does not recognize divisions between service areas, counties, states, or even countries. The current transmission grids includes not only transmission lines that run from power plants to load centers, but also from transmission line to transmission line, providing a redundant system that helps assure the smooth flow of power.

Electricity is transferred from the power plant to the users, through the electric grid. The grid consists of two separate infrastructures: the high-voltage transmission system and the lower-voltage distribution system. High-voltage transmission lines minimize the electrical losses and therefore are used to carry electricity hundreds of kilometers. High voltage lines, range between 69 kV to 765 kV. The voltage level is determined according to the capacity desired, distance and other technical constraints. The lower-voltage lines (distribution system) draw electricity from the transmission lines and distribute it to individual customers. Lower voltage lines range from 12 to 24 kV. The interface between different voltage transmission lines and the distribution system is the electrical substation. Substations use transformers to “step down” voltages from the higher transmission voltages to the lower distribution system voltages.

The modeling of the transmission network as defined above is the mathematical modeling of the grid so that it can mimic the real system as closely as possible for further analysis. The two models have cons and pros that are presented in the following sections.

3.7.1. Minimum cost network flow (Linear) formulation

First approach employed for the modeling of the underlying transmission network is the minimum cost network flow formulation. It has been chosen because of the simplicity of implementation and the inherent linear nature. Linearity is a desired structure since, i) the handling of linear problems is relatively easier as compared to nonlinear cases, ii) powerful and fast solvers exist and iii) analysis of the results is easier due to the simple structure. The problem can be stated as follows:

$$\min \sum_{g=0}^{I} P_g . c_g + \sum_{k}^{N} \sum_{m \neq k}^{N} P_{km} . tc_{km} \tag{3.8}$$

$s.t.$

$$\begin{aligned} & P_{Load_k} - P_{Gen_k} + P_{Netinject_k} = 0 \text{ for k=1....K} \\ & P_{Load_k} = \sum_{j \in J_k} P_{Lj} \\ & P_{Gen_k} = \sum_{i \in I_k} P_{Gi} \\ & P_{NetInject_k} = \sum_{km \text{ or } mk \in \text{BR}} P_{km} \end{aligned} \tag{3.9}$$

$$P_{Gi}^{L} \leq P_{Gi} \leq P_{Gi}^{U} \text{ for } i = 1....I \tag{3.10}$$

$$P_{km} \leq Line_{km}^{U} \text{ for } k = 1....K \;\; m = 1....K \text{ where } k \neq m \tag{3.11}$$

The list of variables and their detailed description is provided in Table 3.11 and Table 3.12. The objective function is the sum of generation and transmission costs as expressed in Equation 3.7. Generation and transmission cost functions reflects the bids received from generators and transmission lines. Equation 3.8 is the condition of the net balance at each bus such that power generated and power inflow must be equal to the power consumed. Next constraint set, Equation 3.9, is the generators capacities to produce electricity. Last set is the capacity limits of transmission lines.

In this approach the flow of power between the nodes are only subject to generators production levels and not dependent on any nonlinear AC constraint. Furthermore, there is no loss of electricity in the network during transmission. Last but not the least, voltage level fluctuations and phase differences are ignored accordingly.

Although this approach is easier to model, understand, communicate to other, solve and experiment with, it is lacking in reflecting the real network complexity. Besides, the complex interaction between load location, voltage levels, phase differences and generation activity is lost and cannot be investigated. The nonlinear model presented in the next section is far more comprehensive in capturing (and thus analyzing) all the inherited complexity of a real transmission network system.

3.7.2. Alternating Current Optimum Power Flow

Second approach employed for the modeling of the underlying transmission network is Alternating Current Optimum Power Flow (AC OPF). The problem faced by the system operator in a typical Alternating Current (AC) transmission network environment, forms the AC-OPF problem. Even if this approach for the modeling of the transmission network introduces high level of complexity, it is a far more realistic model for the investigation of the effects of the actual technical constraints over multiple and varying supply, demand node electrical power system. The problem can be stated as follows:

$$\min \sum_{g=0}^{I} P_g . c_g + \sum_{k}^{N} \sum_{m \neq k}^{N} P_{km} . tc_{km} \tag{3.12}$$

$s.t.$

$$\begin{aligned}
&P_{Load_k} - P_{Gen_k} + P_{Netinject_k} = 0 \text{ for k=1....K} \\
&P_{Load_k} = \sum_{j \in J_k} P_{Lj} \\
&P_{Gen_k} = \sum_{i \in I_k} P_{Gi} \\
&P_{NetInject_k} = \sum_{km \text{ or } mk \in \text{BR}} P_{km}
\end{aligned} \tag{3.13}$$

$$\begin{aligned}
&Q_{Load_k} - Q_{Gen_k} + Q_{Netinject_k} = 0 \text{ for k=1....K} \\
&Q_{Load_k} = \sum_{j \in J_k} Q_{Lj} \\
&Q_{Gen_k} = \sum_{i \in I_k} Q_{Gi} \\
&Q_{NetInject_k} = \sum_{km \text{ or } mk \in \text{BR}} Q_{km}
\end{aligned} \tag{3.14}$$

$$\begin{aligned}
&P_{Gi}^L \le P_{Gi} \le P_{Gi}^U \text{ for } i = 1....I \\
&Q_{Gi}^L \le Q_{Gi} \le Q_{Gi}^U \text{ for } i = 1....I
\end{aligned} \tag{3.15}$$

$$V_{Bi}^L \le V_{Bi} \le V_{Bi}^U \text{ for } i = 1....K \tag{3.16}$$

$$Line_{km} = \sqrt{P_{km}{}^2 + Q_{km}{}^2} \le Line_{km}^U \text{ for } k = 1....K \;\; m = 1....K \text{ where } k \ne m \tag{3.17}$$

$$\begin{aligned}
P_{km} &= V_k^2 g_{km} - V_k V_m \left[g_{km} \cos(\delta_k - \delta_m) + b_{km} \sin(\delta_k - \delta_m) \right] \\
Q_{km} &= -V_k^2 b_{km} - V_k V_m \left[g_{km} \sin(\delta_k - \delta_m) - b_{km} \cos(\delta_k - \delta_m) \right]
\end{aligned} \tag{3.18}$$

The list of variables and their detailed description are provided in Table 3.11. and Table 3.12. The cost functions *Cost*(Production) and *Cost*(Transmission) are still assumed to be linear cost functions (as in the literature) where the cost terms are the bids received from generators and transmission lines. Equation 3.12 is the condition of the net balance at each bus such that real power generated and real power inflow must be equal to the real power consumed. Equation 3.13 is the reactive power balance at each bus of the transmission network. Equation 3.14 is the enforcement of the technical capacity constraint of each generator. Real power production and reactive power production / consumption is limited via this equation set. The permitted voltage level range is represented via Equation 3.15. This constraint set is also related to the quality of the power in the network, since it sets the limits of deviation from the rated voltage of the network for each bus. Another important aspect is the technical capacity of each transmission line regarding the power flowing over it. Equation 3.16 constraints the power flow at each transmission line between zero and some predefined level. The fact that power flowing from each line is the square root of the sum of squares of real power flow plus reactive power flow over the line, adds non-linearity to model. The last Equation set 3.17 describe the real and reactive power flow due to the voltage and phase differences between the buses that are connected via transmission lines. As can be seen, the formulation of power flow is highly nonlinear because of the embedded sinusoidal terms. Accordingly, a model having nonlinear and nonconvex objective and constraint function is obtained. This situation arises nonlinear set of constraints and objective function, which is a non-convex nonlinear mathematical model to solve (Rosehart and Aguado, 2002).

Table 3.11.Exogenous Variables of AC OPF

Variable	Descriptions
K	Total number of transmission grid nodes(buses)
N	Total number of distinct network branches
I	Total number of generators
J	Total number consumers
I_k	Set of generators located at node k
J_k	Set of consumers located at node k
S_0	Base apparent power in three phase MVAs
V_0	Base voltage in kVs
V_k	Voltage magnitude at node k in kVs
P_{Lj}	Real power load withdrawn by consumer j
Q_{Lj}	Reactive power load withdrawn by consumer j
km	branch connecting node k and m
tc_{km}	Transmission fee of line km
g_{km}	conductance of branch km
b_{km}	susceptance of branch km
x_{km}	reactance of branch km
B_{km}	$1/x_{km}$ for branch km
$Line_{max\ km}$	Thermal limit for flow on branch km
δ_1	reference node 1 voltage angle
c_i	Bid of generator i
P_{Gi}^L	Lower real power limit for generator i
P_{Gi}^U	Upper real power limit for generator i
Q_{Gi}^L	Lower reactive power limit for generator i
Q_{Gi}^U	Upper reactive power limit for generator i
V_k^U	Upper voltage level for node k
V_k^L	Lower voltage level for node k
BR	set of all distinct branches km

This problem formulation is harder to implement in comparison to the linear case. AC OPF solution has high computational load even for a small network, while in the framework of the integrated simulation / optimization model solution process, such problems need to be iteratively solved for each simulation period (hour). In this study, Knitro non-linear optimization package is deployed for solving the AC OPF problem in the simulation runs. The average time performance of each AC OPF solution is on the order of 7 seconds.

Table 3.12.Endogenous Variables of AC OPF

Variable	Descriptions
$Line_{km}$	Total power flowing on branch km
P_{Genk}	Total real power injection at node k
Q_{Genk}	Total reactive power injection at node k
P_{Loadk}	Total real power withdrawal at node k
Q_{Loadk}	Total reactive power withdrawal at node k
$P_{NetInjectk}$	Total net real power injection at node k
$Q_{NetInjectk}$	Total net reactive power injection at node k
δ_k	denote the voltage angle at node k
V_{Bk}	Voltage value at node k
P_{km}	Total real power flowing between k and m
Q_{km}	Total reactive power flowing between k and m

4. SIMULATION SCENARIOS AND RESULTS

The simulation run results are analyzed in two section based on the minimum cost network flow (linear) and the AC OPF (non-linear) modeling approaches. The scenario analysis are carried out separately for these approaches and the outcomes are investigated independently in this framework.

4.1. The Minimum Cost Network Flow (Linear) Model Case

As discussed in section 3.7.1, this is the case where the mathematical structure governing the flow of power on the transmission network is assumed to be linear. The reference scenario in this case features only the self-learning algorithm designed for bidding strategy formation. Twelve instances of the simulation model are deployed with distinct seeds, regarding the policy function evaluation which play a crucial role in policy selection. After the runs the average, maximum and minimum values are computed for electricity sale price (as $ / MWh) and generator profits at every hour during the one-year planning horizon. For the investigation and comparison of scenarios, four time intervals are selected according to load profiles, as displayed in Table 4.1. The resulting price graphs are displayed in Figure 4.1.

Table 4.1. Selected demand time intervals.

Low demand time interval	03.00 – 04.00
Transition time interval	11:00 - 12:00
First peak time interval	17:00 - 18:00
Second peak time interval	21:00 - 22:00

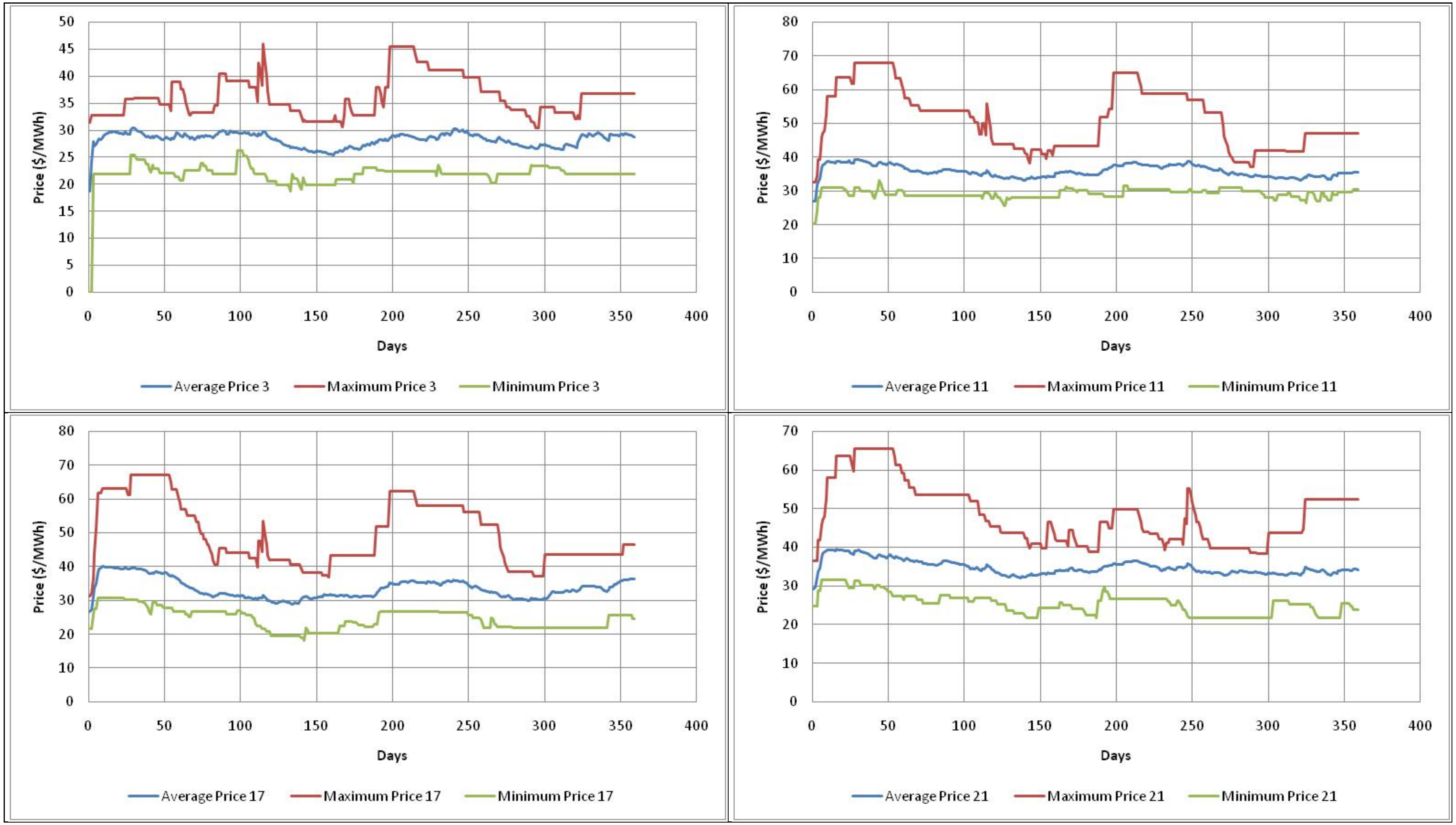

Figure 4.1.Electricity price dynamics during the planning horizon in the reference scenario at selected time intervals (linear network case).

As Figure 4.1 shows, in the low electricity demand time intervals electricity price moves in the \$25-\$30 bands on average. Minimum prices attained are not below \$20 and maximum prices attained are not above \$45. The prices movements are smooth and the maximum prices are close to average electricity sale prices, showing low levels of variations. In the transition time interval, average electricity sale prices is observed in the \$30-\$40 band. The minimum price is close to \$30, which is high relative to the other time intervals considered. Maximum price levels go up to \$70 levels with high variations. Price activity at the two peak time intervals 17-18 and 21-22 display patterns similar to the time interval 11-12, except the minimum prices attained are lower (around \$20). Another observation is that average electricity sale price for the time interval 21-22 is higher than the time interval 17-18, while in the case of maximum prices, the picture is not so as clear. In general, these four time interval price graphs reveal that low demand time intervals feature low prices and low variability, transition time intervals feature higher prices and variability, while peak time intervals feature high prices but lower variability (relative to transition time intervals).

Profit of a generator is the difference between its' income due to the electricity sold out to the network and the cost of primary energy resources used. Primary energy resource may be used for generating electricity, keeping the generator ready for the next scheduled generation time in case of no load, or starting up the generator to switch the generator to operational state if it is closed. Figures 4.2, 4.3, 4.4 and 4.5 show the profit performance of the selected generators in the reference scenario (The selected generators are described in Table 3.9.). The profit performance of generator 1 in time intervals that are described in Table 4.1 are displayed in Figure 4.2. As can be seen from the bottom line, profit can be very close zero level in time interval 3-4. In the transition time interval 11-12, average profit raises above \$2000 and maximum profit attained may go up to \$6000 at certain periods of the year. In the peak time intervals 17-18 and 21-22, average profit is above \$2000 in general with higher competition; minimum profit can go down to \$500 per hour. One point that should be emphasized is the trend of the profit curves are similar to demand curve displayed in Figure 3.11, at certain periods of the year especially at declining parts; however the maximum profit curves are more responsive (ascending much faster than the demand curve in case of demand increase) to demand levels.

The profit performance of generator 3 in time intervals that are described in Table 4.1 are displayed in Figure 4.3. As presented in Table 3.9, the technical parameters of generator 3 are more advantageous than the generator 1. Accordingly, at the time interval 3-4 average profit of generator 3 is between \$200 and \$300, while maximum levels may rise up to \$1200. Regarding minimum levels, zero level profit is observed in general. For the transition time interval 11-12 average profit is greater than \$500 and the frequency of zero profit occurrences is much lower. Additionally, maximum profit values in this case reach to \$2000 levels.

For the peak time interval 17-18 picture is similar except is the frequency of zero profit occurrences is higher, which is also true for peak time interval 21-22. The situation at the time interval 11-12 can be explained through the high flexibility of generator 3. Another point is that the frequency of zero profit occurrences of generator 3 can be explained by only network position since no other parameter is disadvantageous relative to generator 1.

The profit performance of generator 4 in time intervals that are described in Table 4.1 are displayed in Figure 4.4. For generator 4, average profit is very close to zero for each time interval. For the low demand time interval 3-4, all measures average, minimum and maximum profit is zero. At the transition time interval 11-12, maximum profit may go up to \$7000 per hour but the average is very close to zero during the year. At the peak time intervals 17-18 and 21-22 the frequency of non-zero profit is similar to the transition daytime 11-12 but peak values are lower. The general analysis indicates that generator 4 is used as peaking power plant by the SO. The primary resource of generator 4 (which is oil) supports this behavior, which has the highest purchasing price.

The profit performance of generator 7 in time intervals that are described in Table 4.1 are displayed in Figure 4.5. For generator 7, average profit is very close to zero in every time interval of the day. For the low demand time interval 3-4, it can reach maximum levels of profitability (which is around \$1000 highest during the simulation horizon). Nevertheless, for other time intervals average profit is slightly higher than zero, besides the maximum profitability can go up to \$12000. Although this generator has the cheapest primary energy resource, this behavior of the system can be explained by the network structure.

In the next section, the analysis regarding transmission network capacity and transmission fee is investigated. Scenarios based on lower levels of transmission line capacities relative to reference case are investigated. Later on, the effect of higher transmission fee levels is studied in detail. Higher levels of transmission line fee levels (compared to the reference scenario) is investigated and the results are presented.

In section 4.1.2, the hourly bidding strategy formation algorithms results are analyzed. Algorithm implementations as a standalone setup and a combined case are carried out.

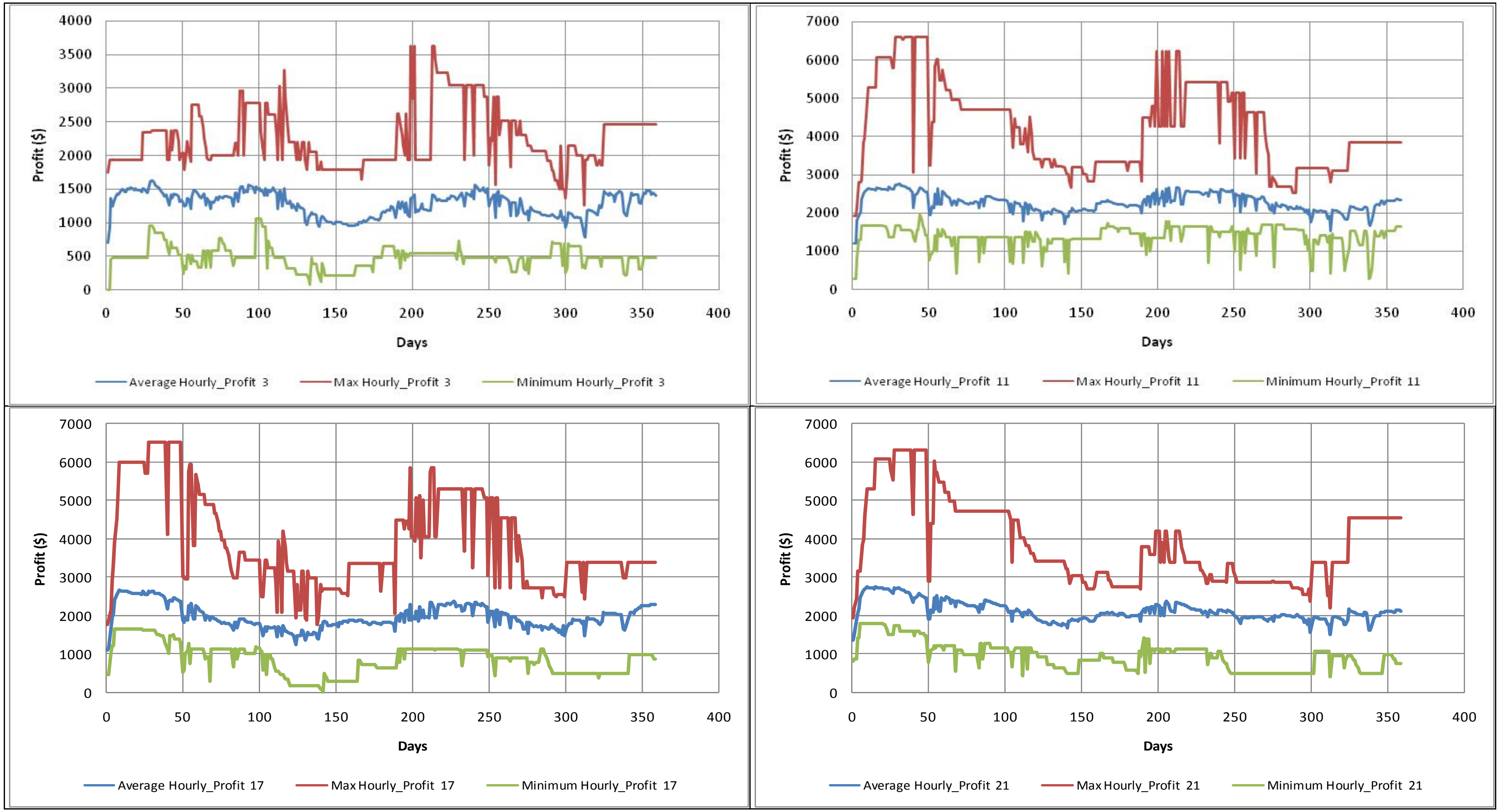

Figure 4.2.Profit performance achieved by generator 1 in the reference scenario at the selected time intervals (linear network case)

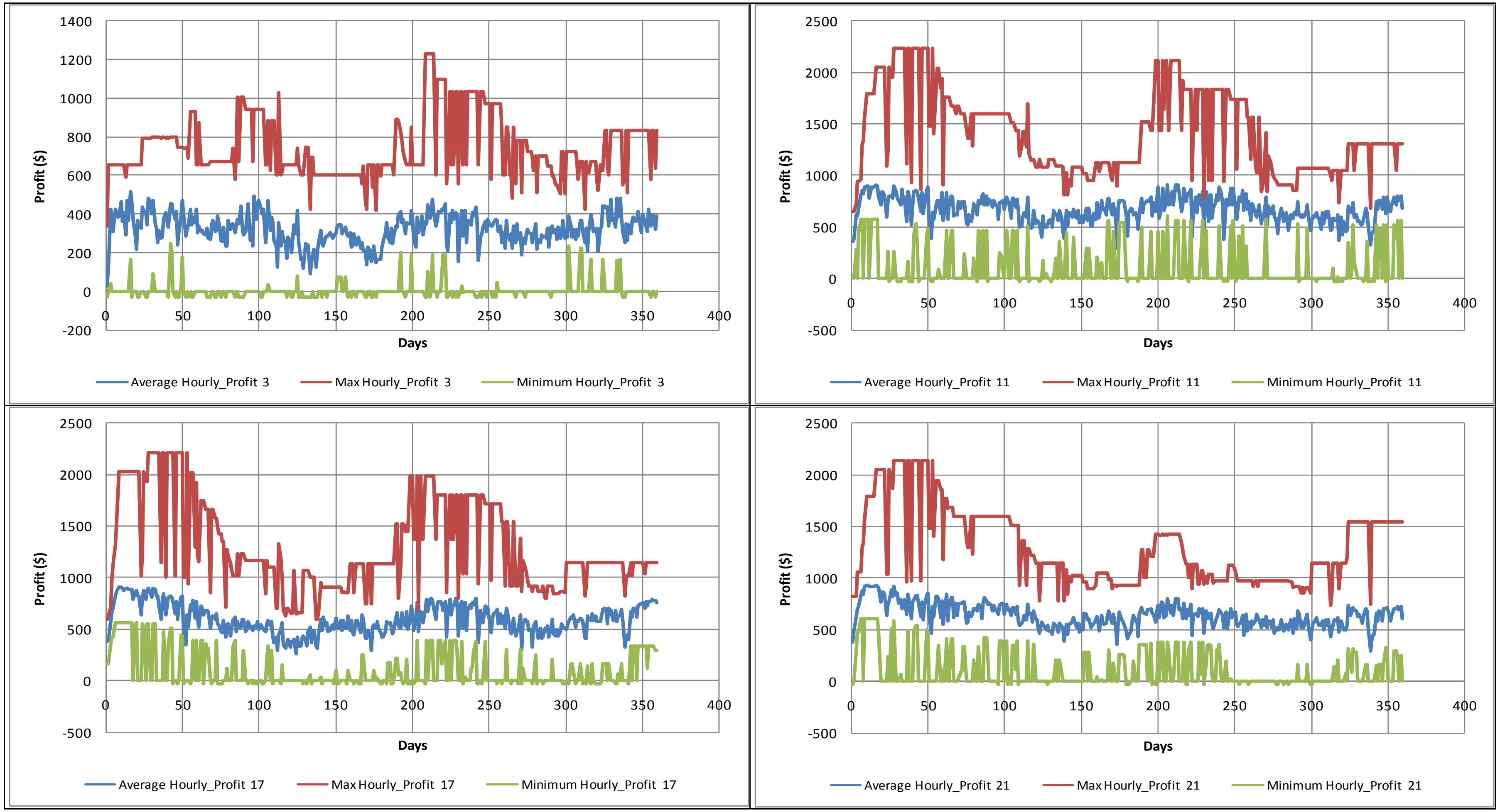

Figure 4.3.Profit performance achieved by generator 3 in the reference scenario at the selected time intervals (linear network case)

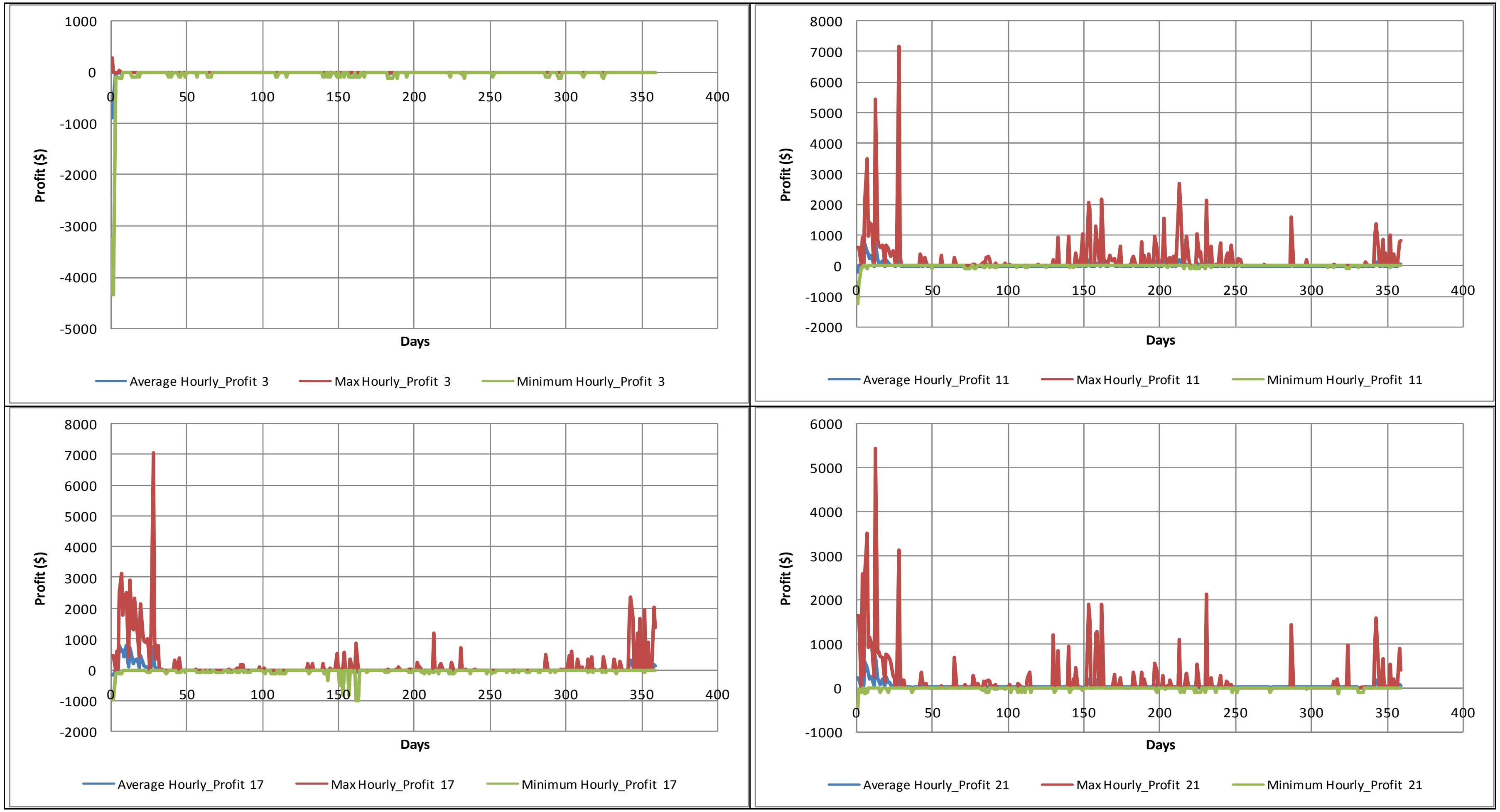

Figure 4.4.Profit performance achieved by generator 4 in the reference scenario at the selected time intervals (linear network case)

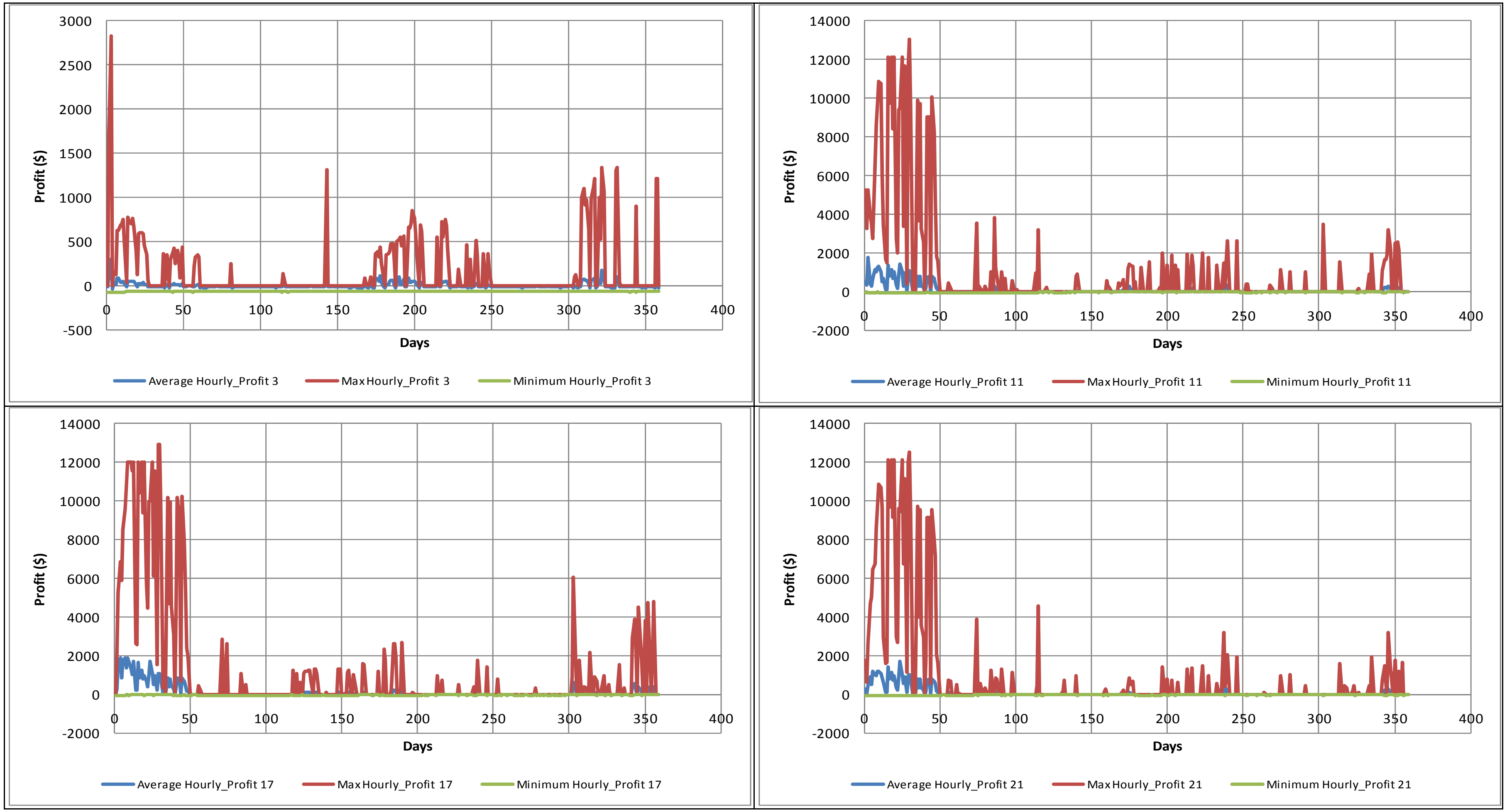

Figure 4.5.Profit performance achieved by generator 7 in the reference scenario at the selected time intervals (linear network case).

4.1.1. Parameter Change Response

In this section, the impact of changes in transmission line capacity and fee on electricity sale price is analyzed.

First, the effect of transmission capacity changes on electricity prices is investigated. Two levels of line capacities, (one half and one fourth of the levels in the reference scenario), are considered. Figure 4.6 displays the resulting electricity price behavior. It can be observed that such transmission line capacity changes do not cause significant changes in average electricity prices. However, maximum prices show significant increases and minimum prices are also higher with respect to the reference case.

Next, the effect of transmission line fee changes on electricity prices is investigated. Figure 4.7 displays the resulting electricity price behavior for two levels of transmission line fee levels (double and quadruple of the levels in the reference scenario). As can be seen, transmission line fee levels has considerable effect on electricity sale prices. Increase in transmission line fee levels show significant price increases with respect to reference case. This reveals that the physical transmission network pricing policy has significant affect over the system price. This effect may be used to promote local production of electricity.

On the other hand, further analysis of the system behavior reveals that the minimal impact of transmission capacity constraints is very much dependent on the network layout and generator characteristics: Lesser transmission capacity has induced heavier reliance on generator 6 (which does not use the transmission lines). Since that generator uses one of the cheapest primary resources, the change did not lead to any change in prices. Figure 4.8 shows how the generator 6 load levels and profit changes with decreasing line capacity levels.

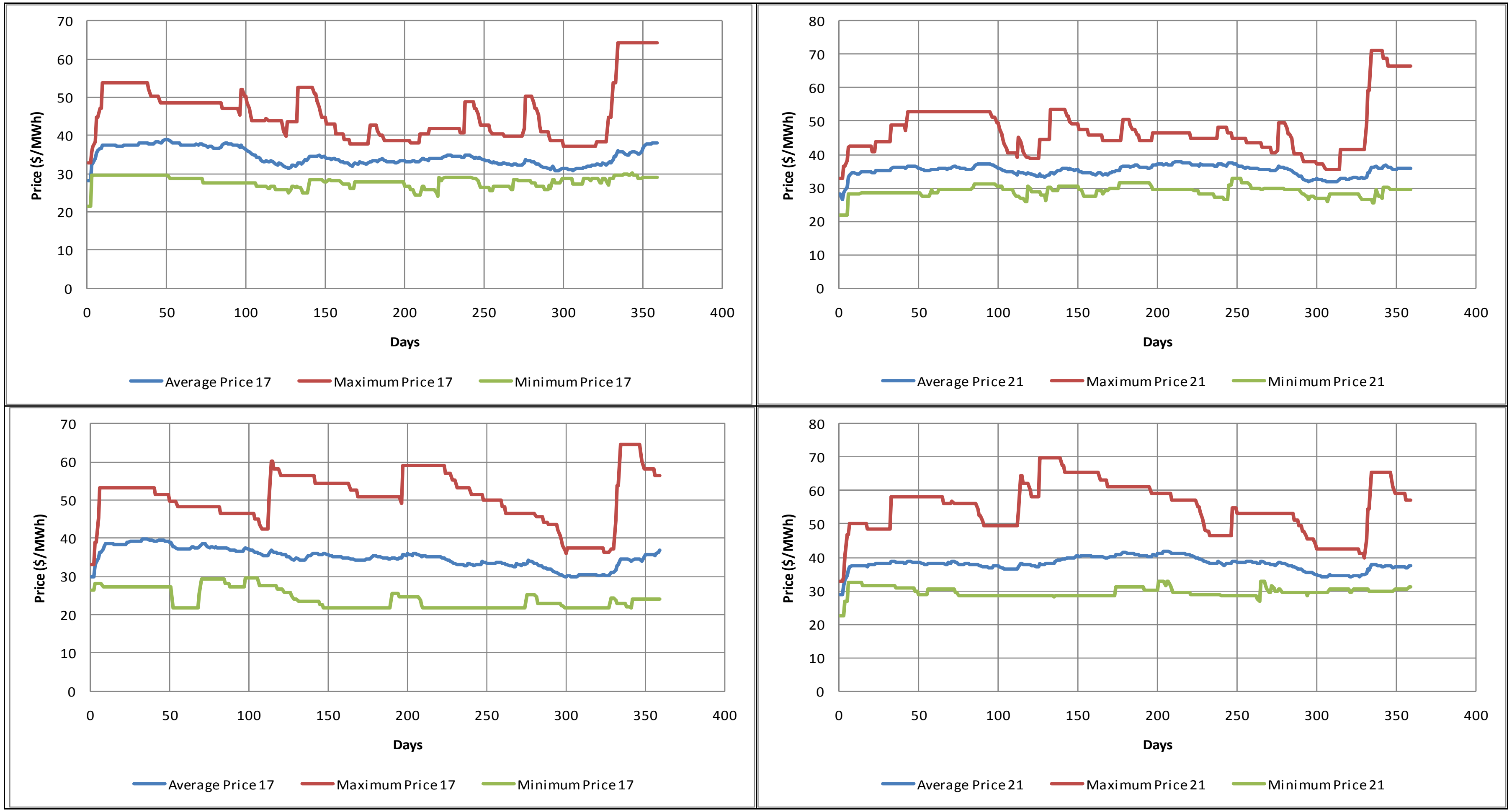

Figure 4.6.Impact of transmission line capacity (Figures on the left are associated with the one-half case, while figures on the right with the one-fourth case in comparison with reference case at the top) on electricity prices at selected time intervals (linear network case).

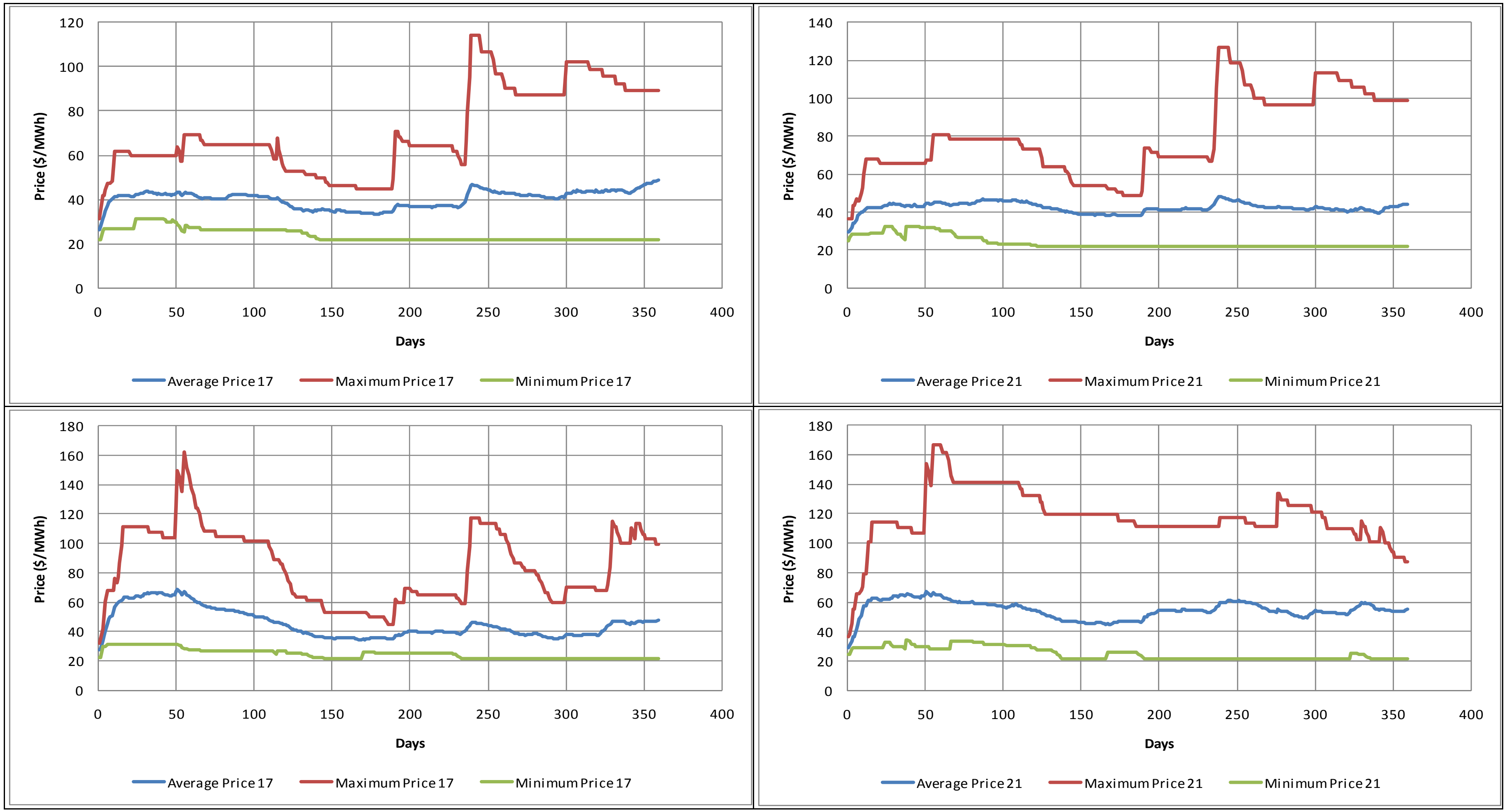

Figure 4.7. Impact of transmission line fees (Figures on the left are associated with the double initial fee case, while figures on the right with the quadruple case in comparison with reference case at the top) on electricity prices at selected time intervals (linear network case).

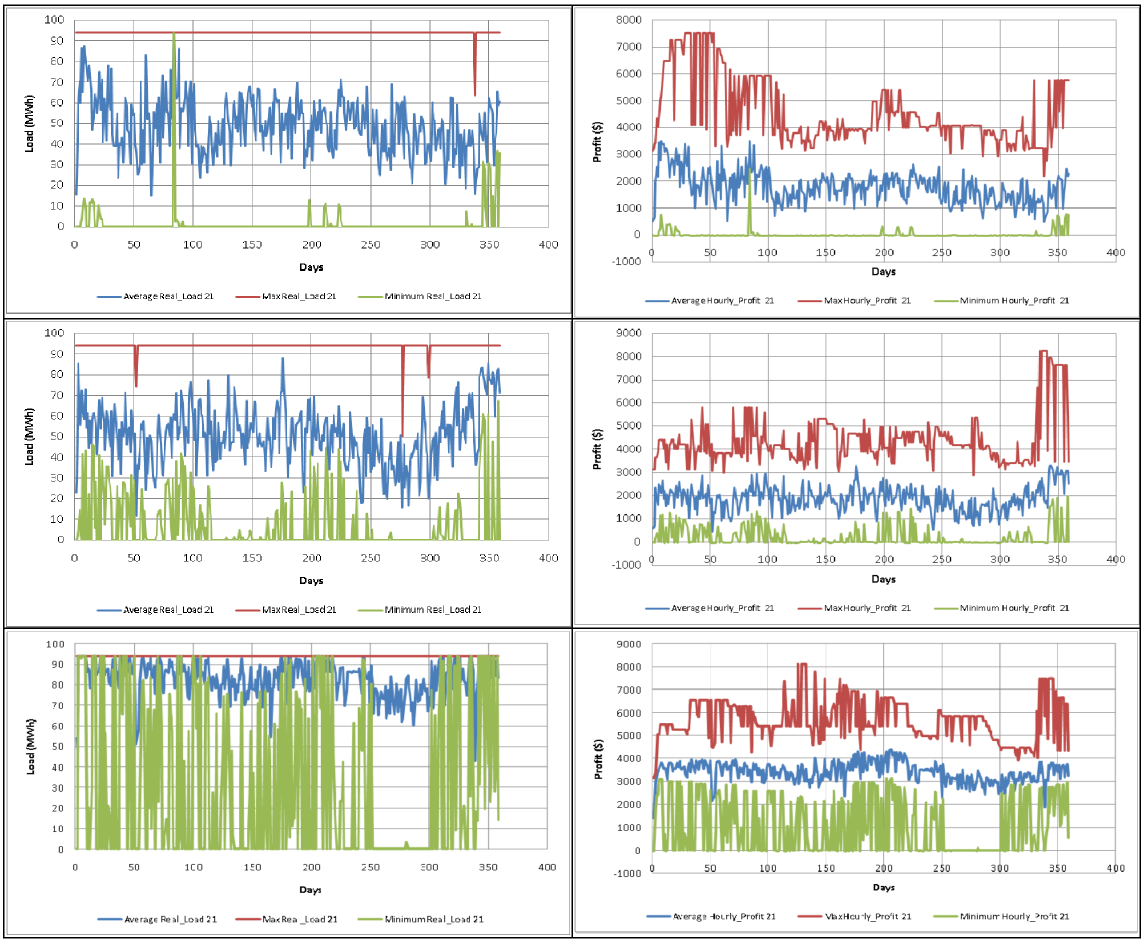

Figure 4.8. Impact of transmission line capacity (Figures in the top row for time interval 21, while figures on the mid row associated with the one half capacity and bottom row associated with one fourth capacity) on load and profit of generator 6 (linear network case).

Figure 4.8 also reveals one important sides of the linear network approach, the flexibility of the use of generators while supplying demand. Simulation with less number of constraints and lower level of complexity (compared to AC case) pushed the generator 6 out of the competition in the base case. Only the introduction of line capacity increases the market power of generator 6. In AC-OPF approach, generator 6 is one of the powerful agents effecting the price formation due to technical constraints in most of the scenarios.

4.1.2. Response Comparisons of the Bidding Algorithms

The scenarios considered in this subset are intended to facilitate a better understanding of the learning effects.

Figure 4.9. Impacts of the “Market Share” learning algorithm on electricity sales prices at the selected time intervals (linear network structure case).

Figure 4.9 displays the impacts of the “Market Share” learning algorithm with 0.1 effect factor on electricity prices. When compared with the reference scenario, it can be observed that this algorithm does not influence price formation structure significantly. Besides electricity sale prices, are impacted for peak demand time intervals 17-18, 21-22 and transition time interval 11-12. However, in the low demand time interval 3-4 the algorithm pushes the prices upward and significantly changes the supply mix.

Figure 4.10 displays the profit of generator 1 using the Market Share algorithm with factor level 0.1. As can be seen, in the time interval 3-4, profit increases significantly compared to the reference scenario. Average profitability is close to $1500; maximum profitability attained is also higher around $4500 level. For the other time intervals concerned average profit does not change much relative to reference scenario, but variability indicated by the maximum and minimum profit levels increases significantly.

Figure 4.11 displays the profitability of generator 3 using the Market Share algorithm with factor level 0.1.The results found for generator 1 is also true for generator 3. No significant difference is noted.

Figure 4.12 and Figure 4.13 displays the profitability of generator 4 and 7 using the Market Share algorithm with factor level 0.1. For all the time intervals, profitability levels attained reveals that Market Share algorithm has no significant effect over peak demand time interval power plants in terms of increasing or decreasing the load levels or profitability.

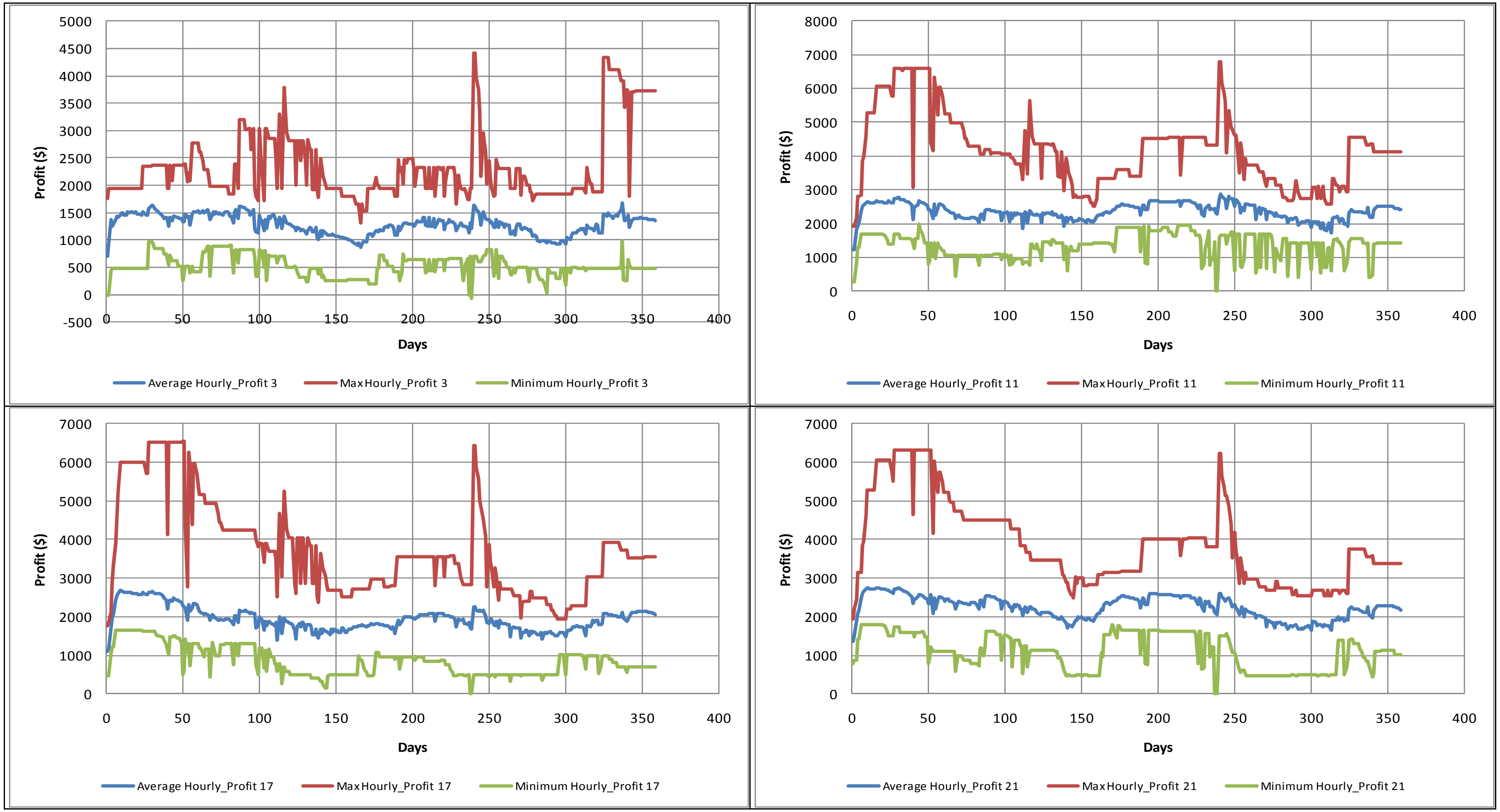

Figure 4.10. Impacts of the "Market Share" learning algorithm on profit performance of generator 1 at the selected time intervals (linear network structure case).

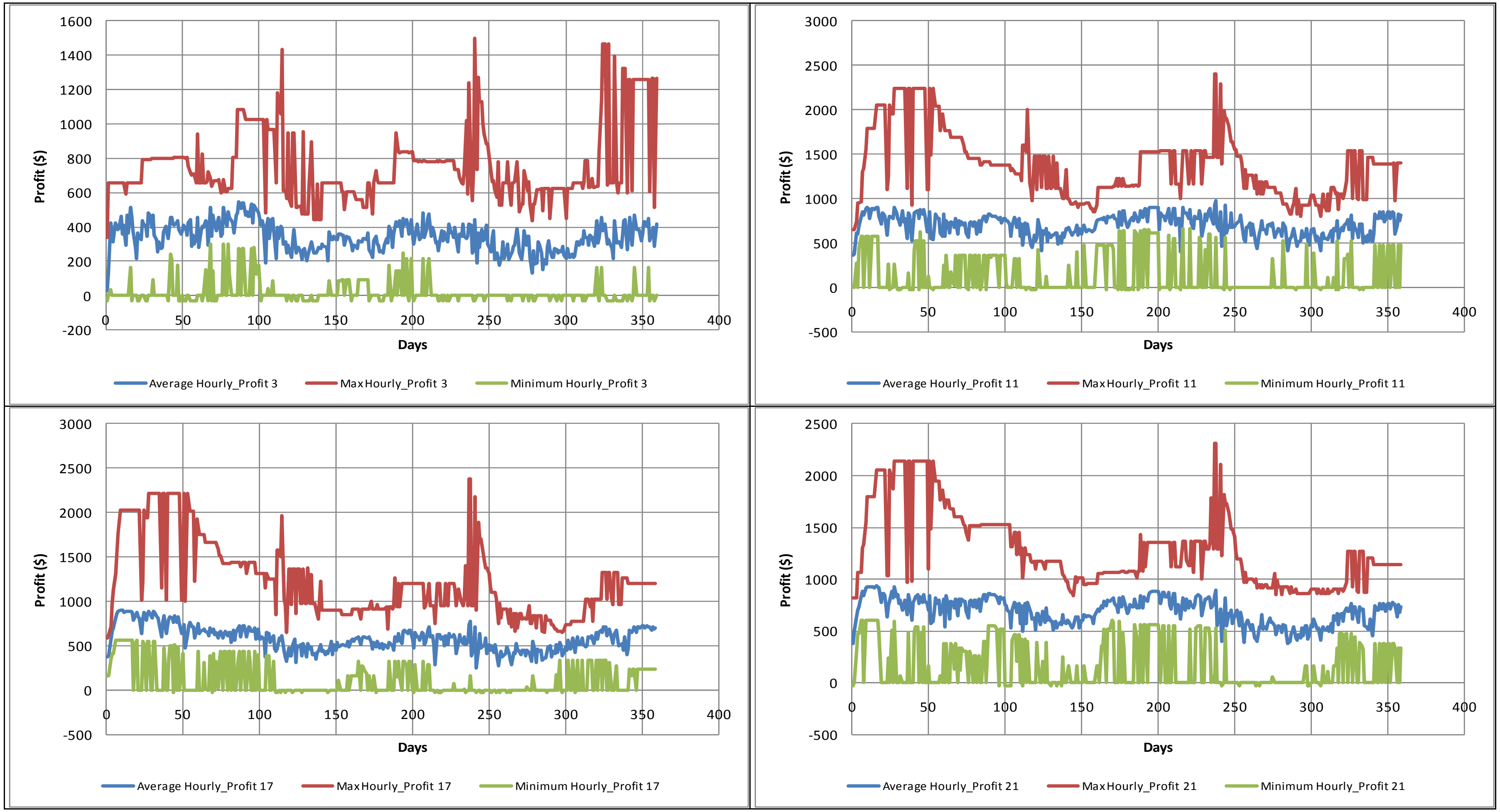

Figure 4.11. Impacts of the "Market Share" learning algorithm on profit performance of generator 3 at the selected time intervals (linear network structure case).

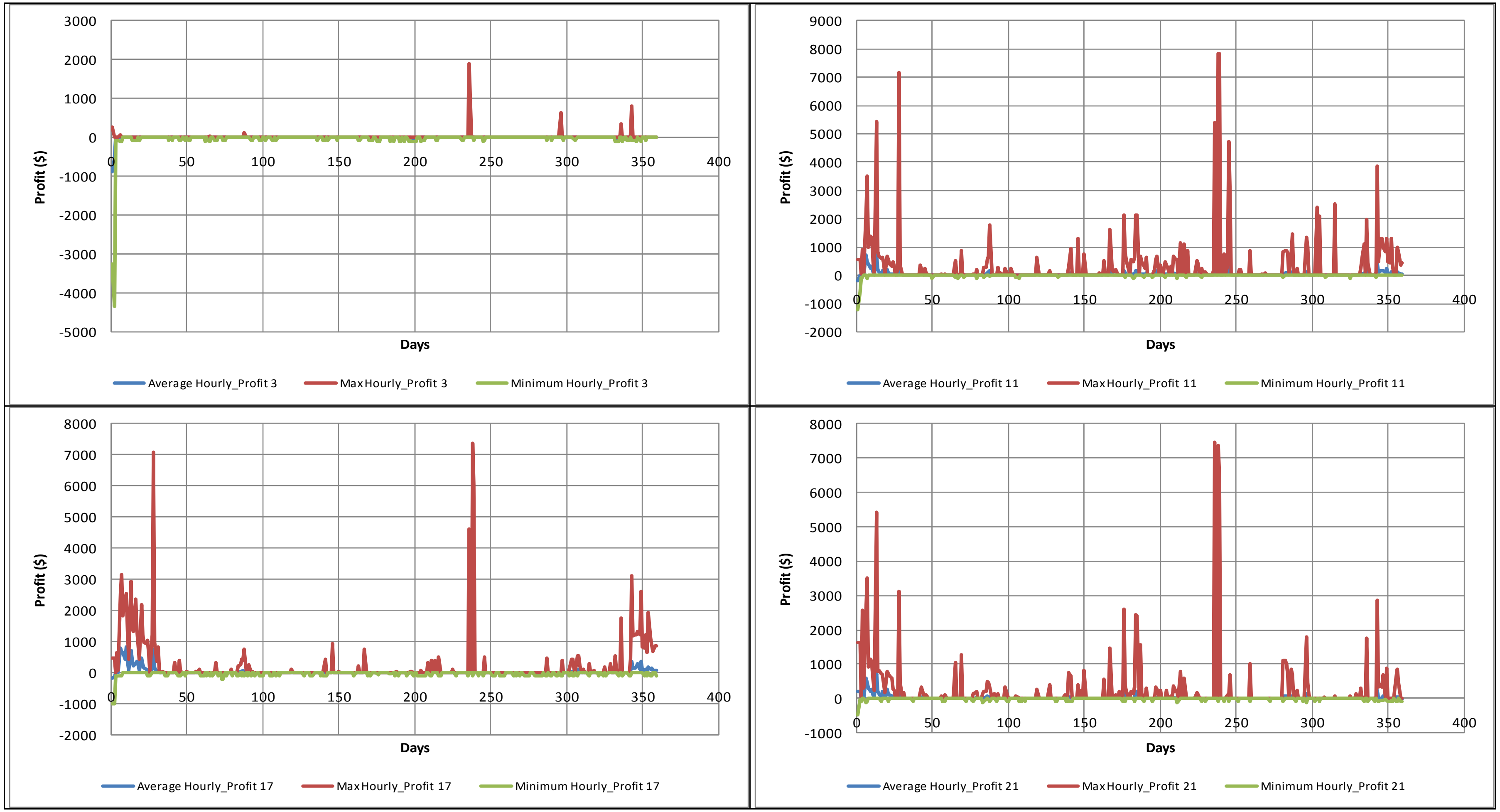

Figure 4.12. Impacts of the "Market Share" learning algorithm on profit performance of generator 4 at the selected time intervals (linear network structure case).

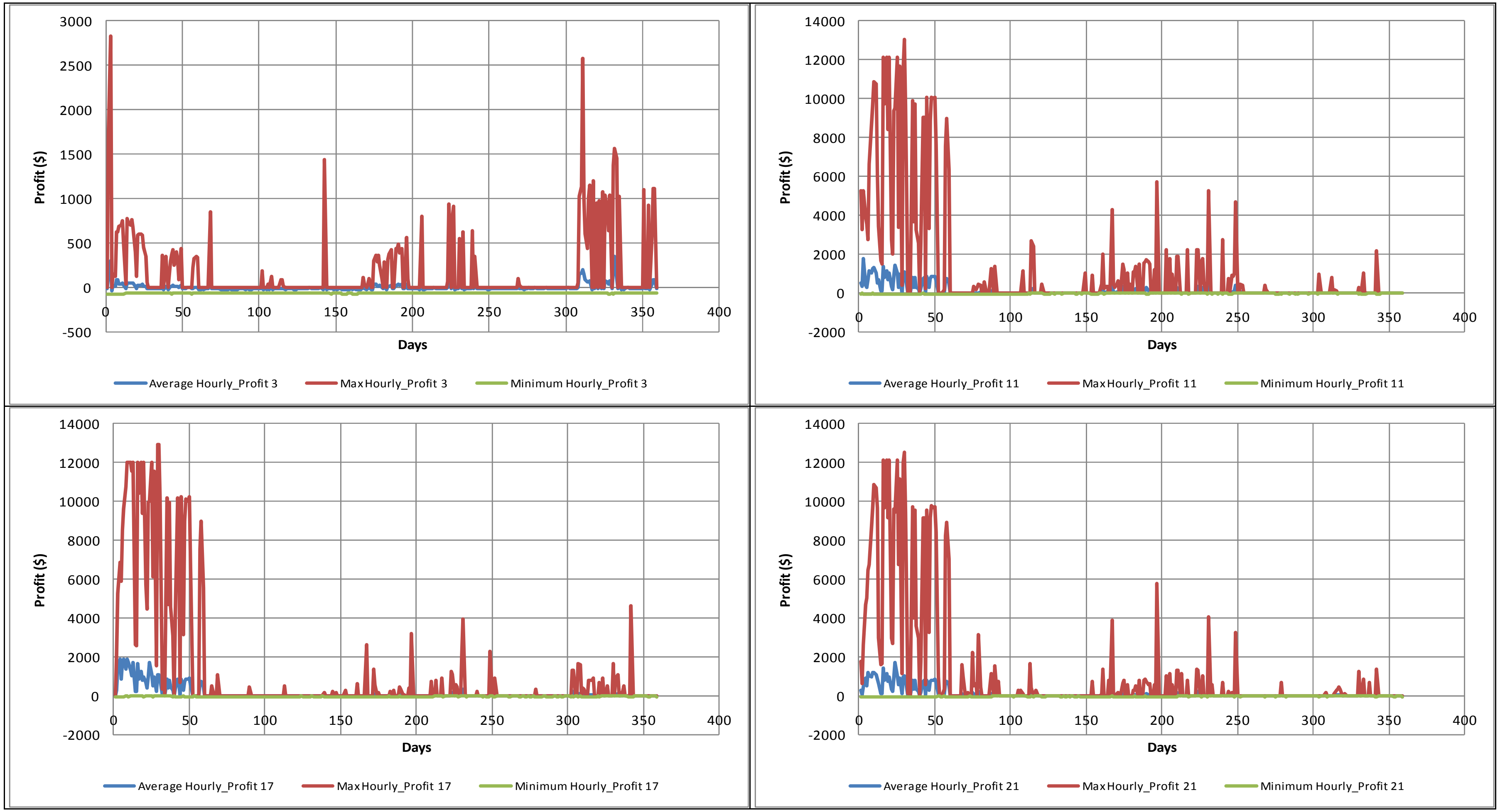

Figure 4.13. Impacts of the "Market Share" learning algorithm on profit performance of generator 7 at the selected time intervals (linear network structure case).

Figure 4.14 displays the price dynamics using the Price Tracking algorithm applied with 0.05 effect factor. As can be seen, even with such a small factor, the electricity price behavior is impacted; price levels are driven up, and settlement (formation of smooth average price level) time is delayed. The price impact is higher when the number of competitors are fewer as in the case of low demand time intervals (such as time interval 3-4), however settlement prices, through the end of planning horizon, gets closer to the reference scenario case. For the transition time interval 11-12, average electricity sale prices are pushed above \$40 and maximum price levels attained show very large deviations compared to the reference scenario. For the peak daytime intervals 17-18 and 21-22 the price impact is high as the transition time interval 11-12, but prices are more responsive to demand levels in this case. Average electricity sale prices do not converge to the reference scenario levels; instead they display an increasing trend similar to the demand levels, thereby resulting in increasing prices through the end of the year.

Figure 4.15 displays the profit of generator 1 under the Price Tracking algorithm with factor level 0.05. For the low demand time interval 3-4, this algorithm increases the profit significantly compared to reference case; average, maximum and minimum profitability attained show an increase with a very high level of variation. For the transition time interval 11-12, minimum profit attained is very similar to the reference scenario's average profit curve. Average profit is above \$2000 that go up to \$4000. Maximum profit attained go up to \$9000. For the peak time interval 17-18, all three components are impacted, minimum profit is close to zero, while maximum profit attained drops down to very low levels in the middle of the year. The average profit is around \$3000 through the end of the year, while maximum profit attained reach up to \$10000. The peak time interval 21-22 variation is less than that of the time interval 17-18. Average profit is in the \$2000-\$3000 range, while maximum profit attained drops from \$10000 to \$5000 compared to the reference case.

Figure 4.16 displays the profit of generator 3 using the Price Tracking algorithm with factor level 0.05. For the low demand time interval 3-4, this algorithm increases the profit significantly compared to reference scenario; average profit attained is above \$500 level, maximum profitability attained increases with a very high variation. Minimum profit attained is not affected from the algorithm. For the transition time interval 11-12 average profit and maximum profit show positive upward trends. However, the frequency of profit level zero is higher compared to the reference case. The peak time intervals 17-18 and 21-22 show limited impact on the electricity sale prices due to the more competitive environment the generator faces.

Figure 4.17 and Figure 4.18 display the profit of generator 4 and 7 respectively using the Price Tracking algorithm with factor level of 0.05. The Price Tracking algorithm is not significant on the price dynamics relative to reference scenario; however price levels attained show significant increases.

Figure 4.14. Impacts of the "Price Tracking" learning algorithm on electricity sales prices at the selected time intervals (linear network structure case).

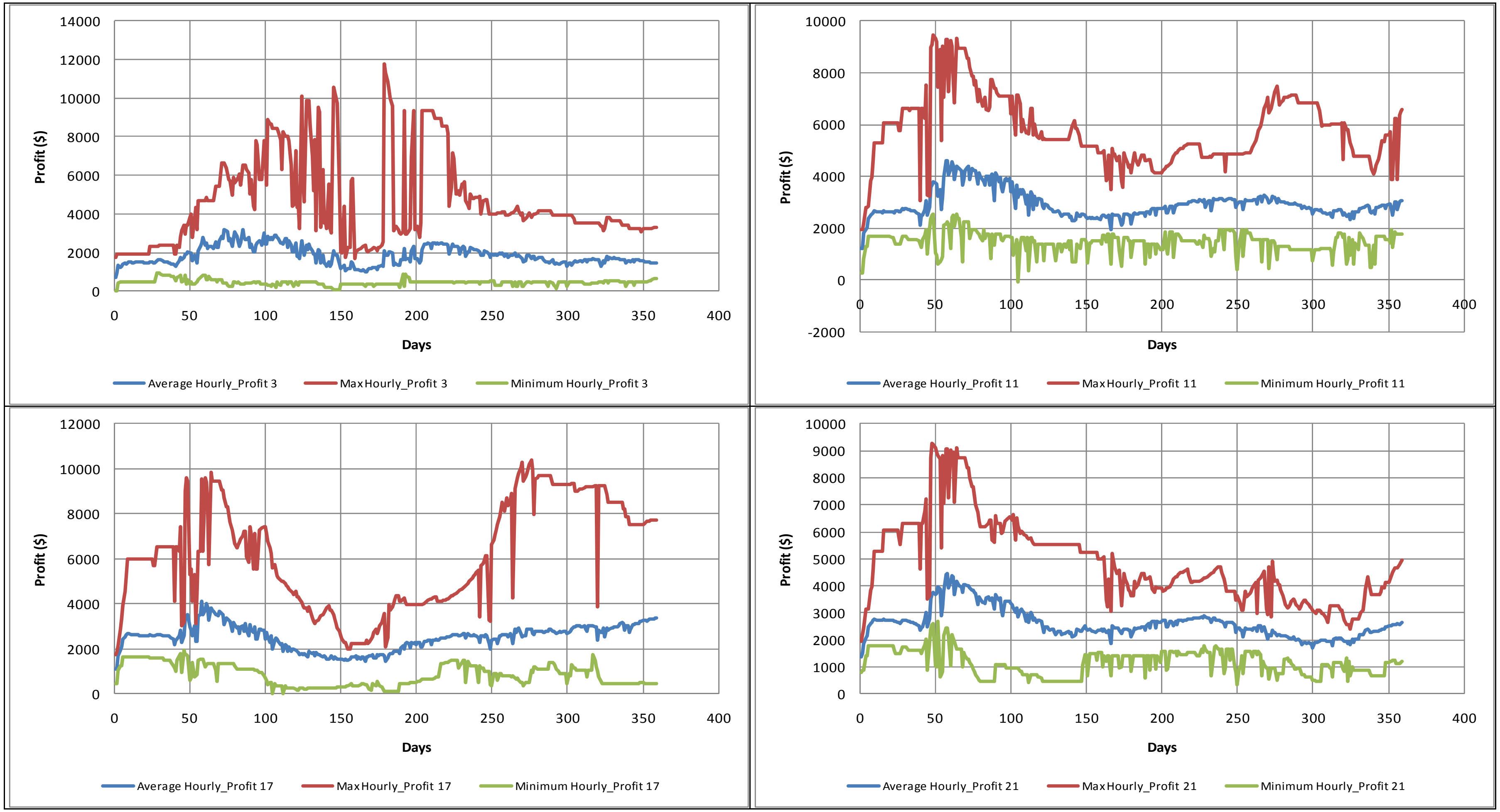

Figure 4.15. Impacts of the "Price Tracking" learning algorithm on profit performance of generator 1 at the selected time intervals (linear network structure case).

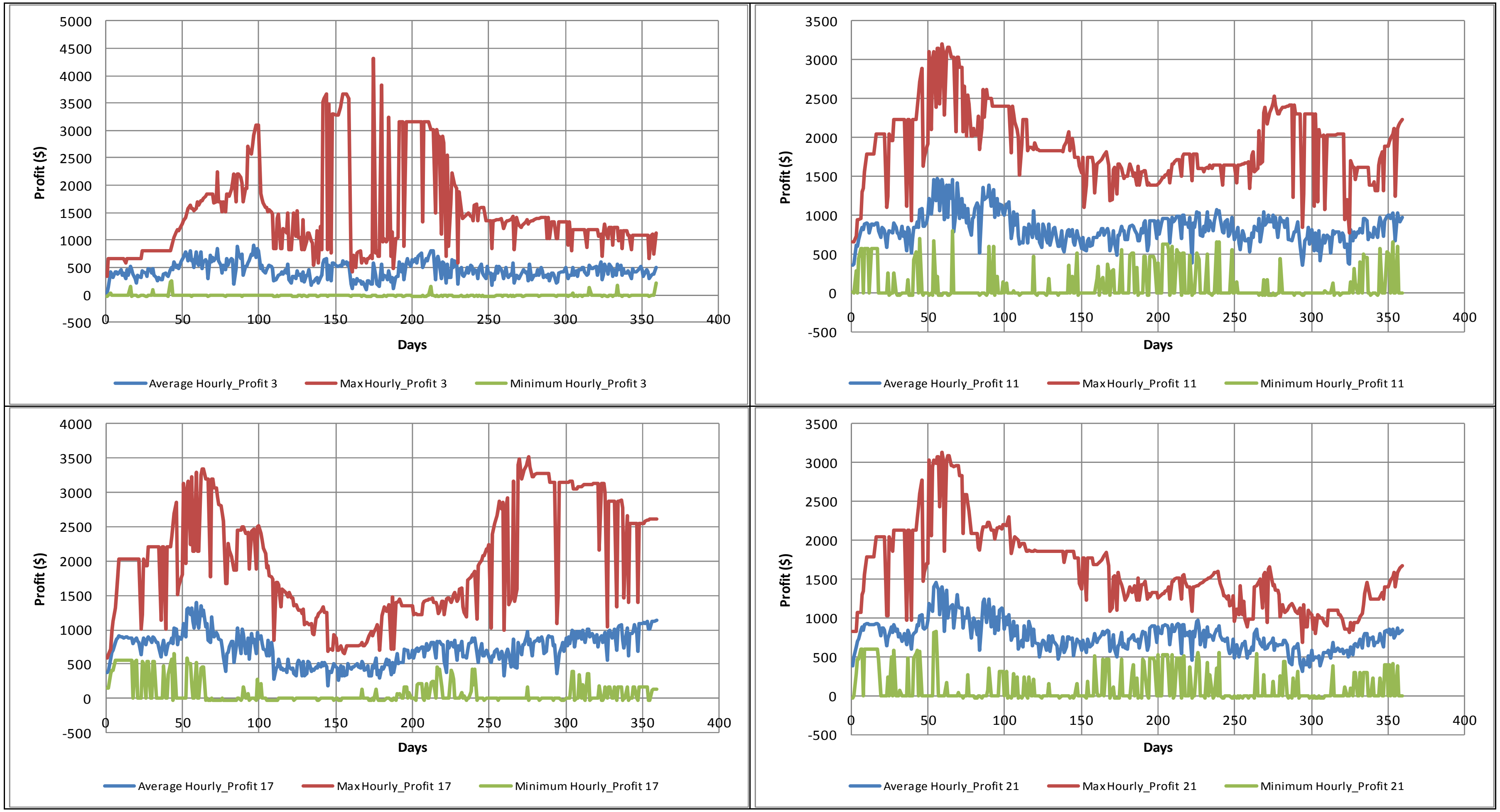

Figure 4.16. Impacts of the "Price Tracking" learning algorithm on profit performance of generator 3 at the selected time intervals (linear network structure case).

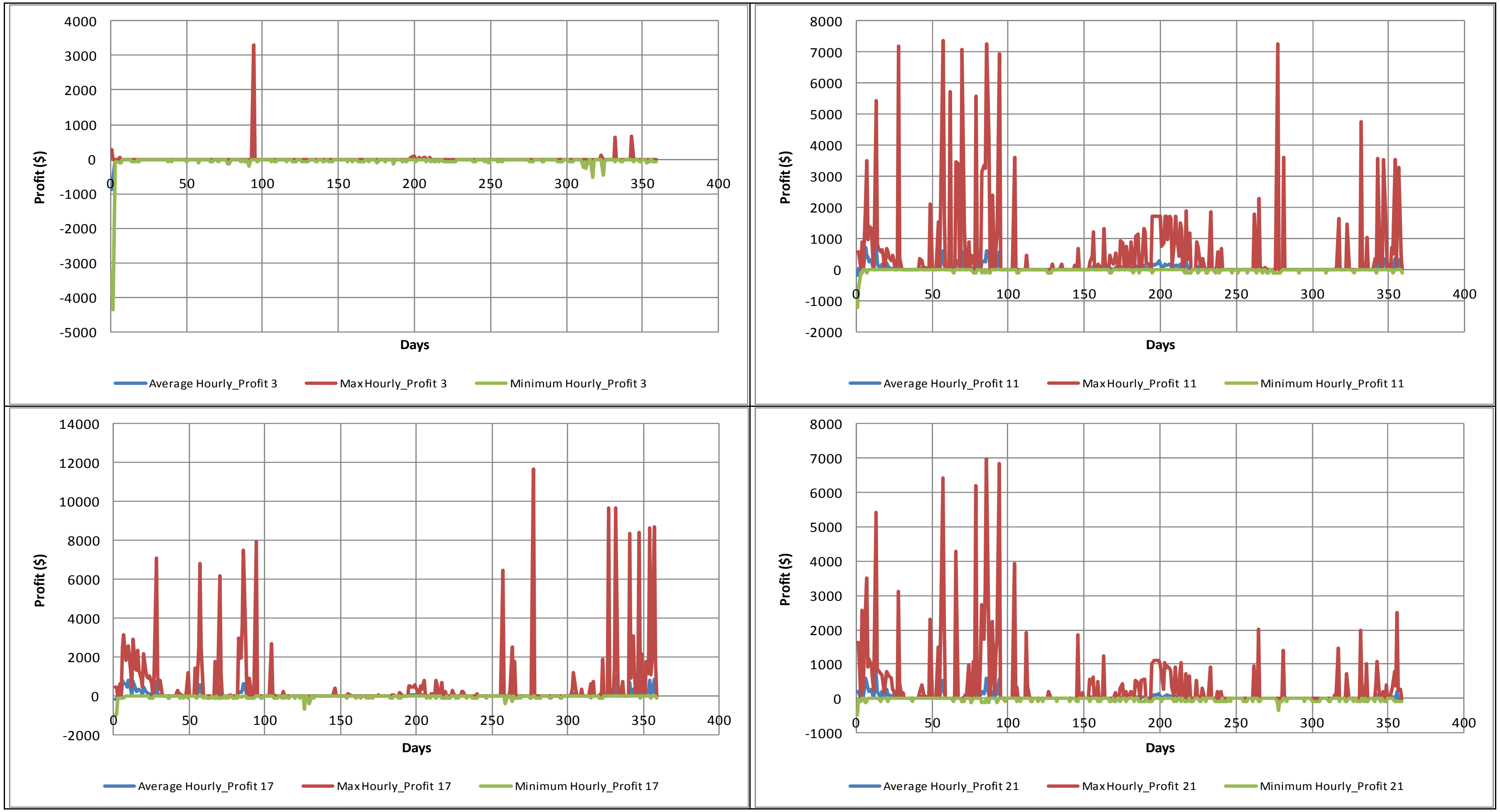

Figure 4.17. Impacts of the "Price Tracking" learning algorithm on profit performance of generator 4 at the selected time intervals (linear network structure case).

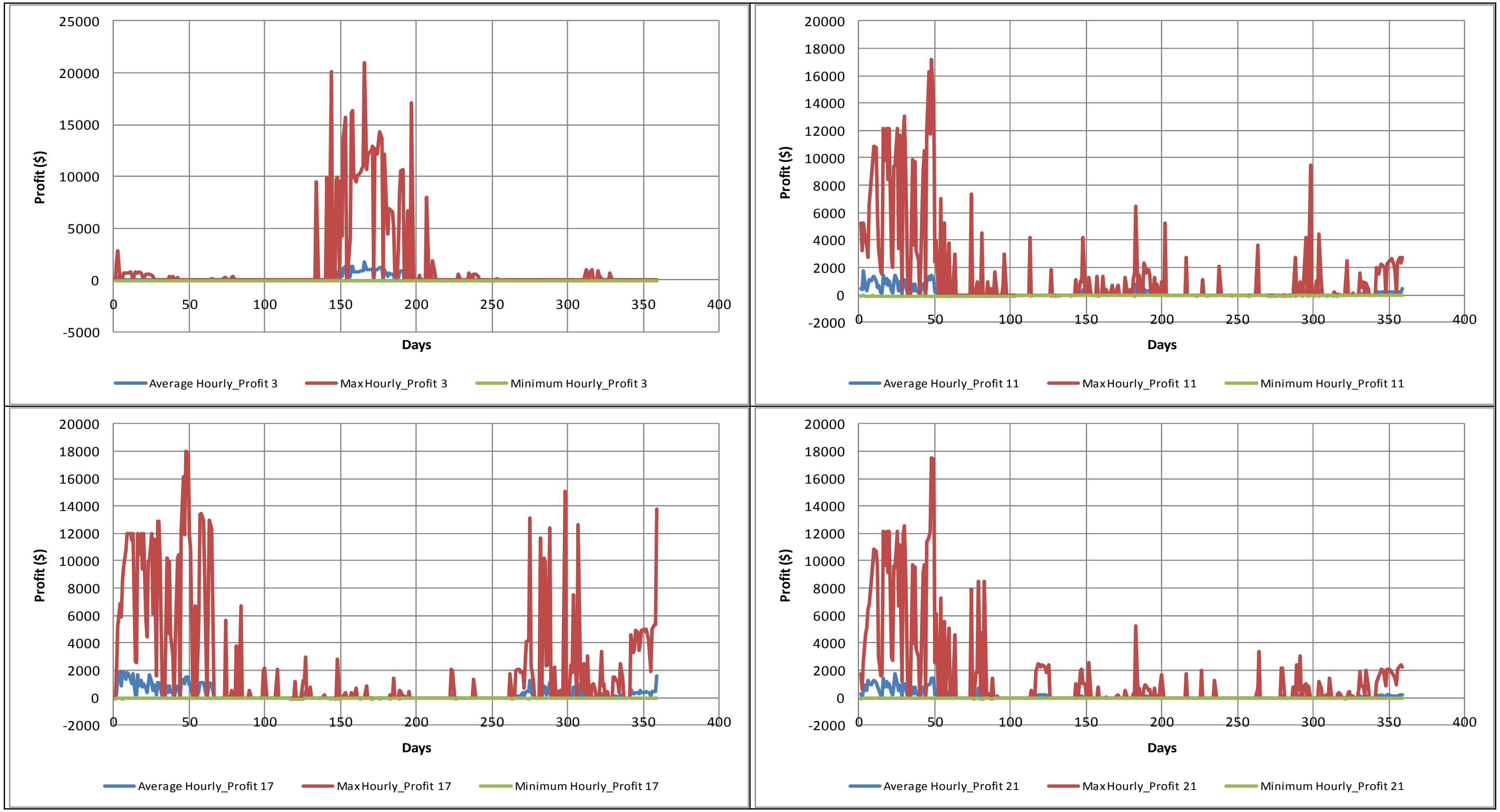

Figure 4.18. Impacts of the "Price Tracking" learning algorithm on profit performance of generator 7 at the selected time intervals (linear network structure case).

The last algorithm investigated is the *Market Power Algorithm*. Figure 4.19 displays price dynamics using the *Market Power Algorithm.* The low demand time interval 3-4 is not affected by the use of the algorithm. It is mainly influential on the prices dynamics of the other time intervals. For the transitional time interval 11-12, the peak demand time intervals 17-18 and 21-22 show an upward trend, whenever demand shows a growth trend that is much more significant than the reference case, while the impact on variability is less relative to mean trend. This indicates the high sensitivity of prices to the gap between peak level values and physical capacity. If the gap between total demand of that time interval and physical capacity increases, the price behavior converges to the reference case. The impact of the algorithm at peak demand and transition time intervals also lead to lower prices at low demand times since they have to be operational near those time intervals to produce electricity. This indicates a different area of competition lowering the prices.

Figure 4.20 displays the profit of generator 1 using the Market Power algorithm. For the low demand time interval 3, algorithm's effect over profitability of generator 1 is insignificant. The algorithm pushes the profitability to higher levels for transition and peak demand time intervals. Average profit generally follows demand dynamics closely and further increase in demand for peak time intervals increases profit levels.

Figure 4.21 displays the profit of generator 3 using the Market Power algorithm. The results are similar to generator 1 with one exception that the instances where the minimum profit attained is close to zero are rare comparatively.

Figure 4.22 displays the profitability of generator 4 using the Market Power algorithm. The algorithm's impact is insignificant in the low demand time interval 3-4. The profit dynamics has not changed much compared to other time intervals compared relative to reference case. However, maximum profits attained is higher relative to the reference case and the frequency of zero profit is also higher; (in other words variability of the profit has increased as well).

Figure 4.23 displays the profit of generator 7 with the Market Power algorithm. Although the findings for generator 4 are still valid, the impact of the algorithm on profitability and load levels is less comparatively.

Figure 4.19. Impacts of the "Market Power" learning algorithm on electricity sale prices at the selected time intervals (linear network structure case).

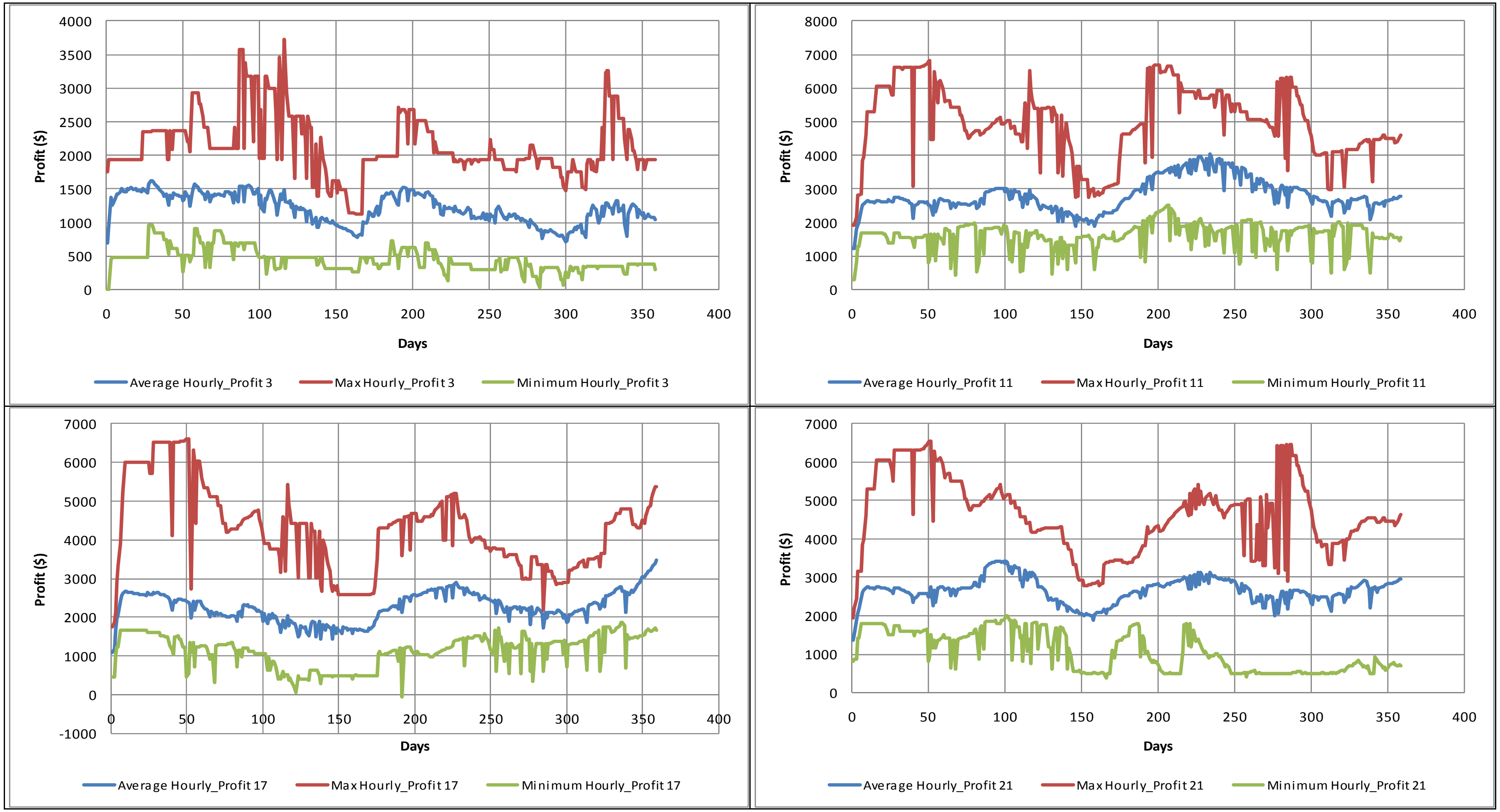

Figure 4.20. Impacts of the "Market Power" learning algorithm on profit performance of generator 1 at the selected time intervals (linear network structure case).

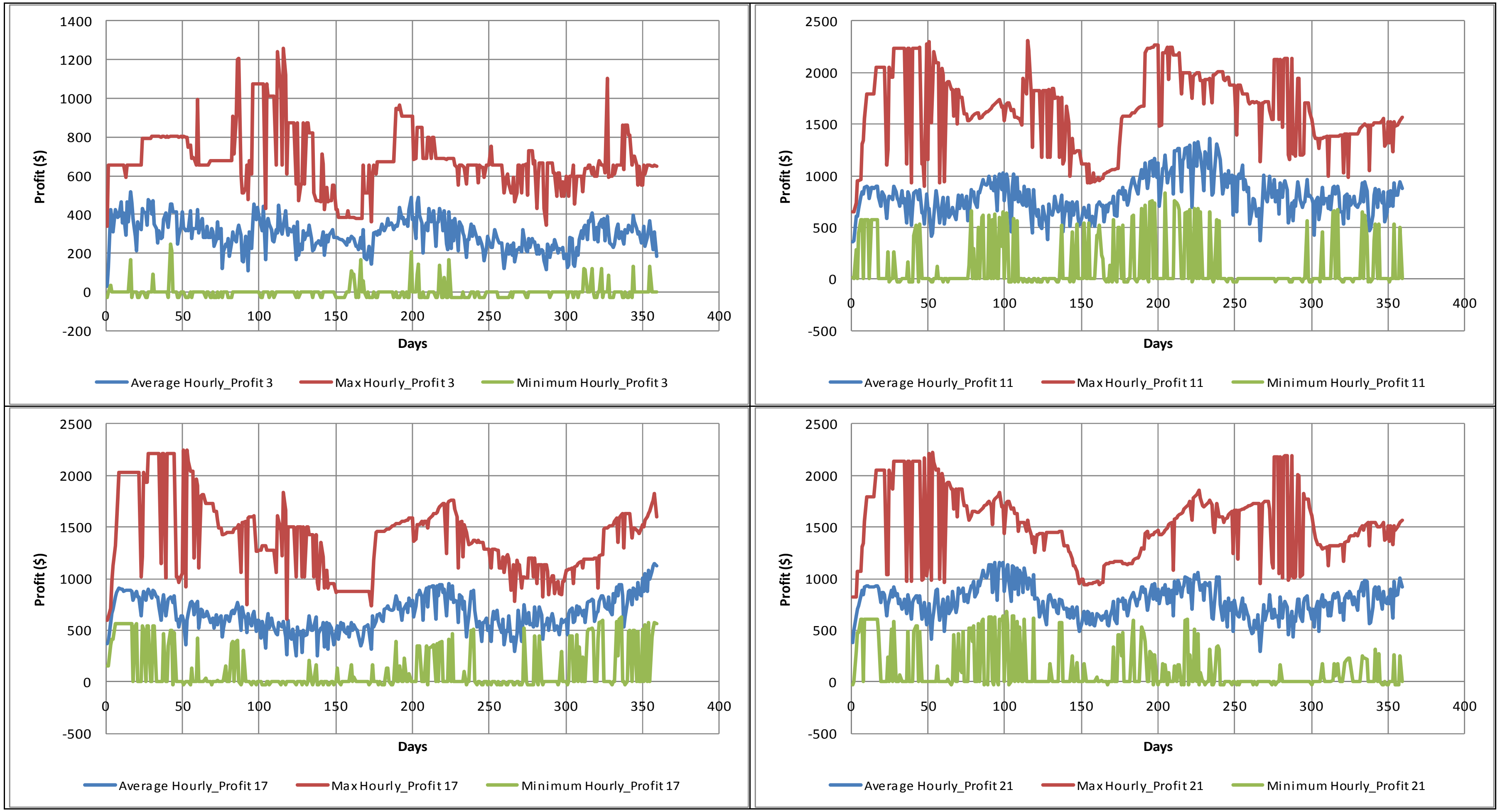

Figure 4.21. Impacts of the "Market Power" learning algorithm on profit performance of generator 3 at the selected time intervals (linear network structure case).

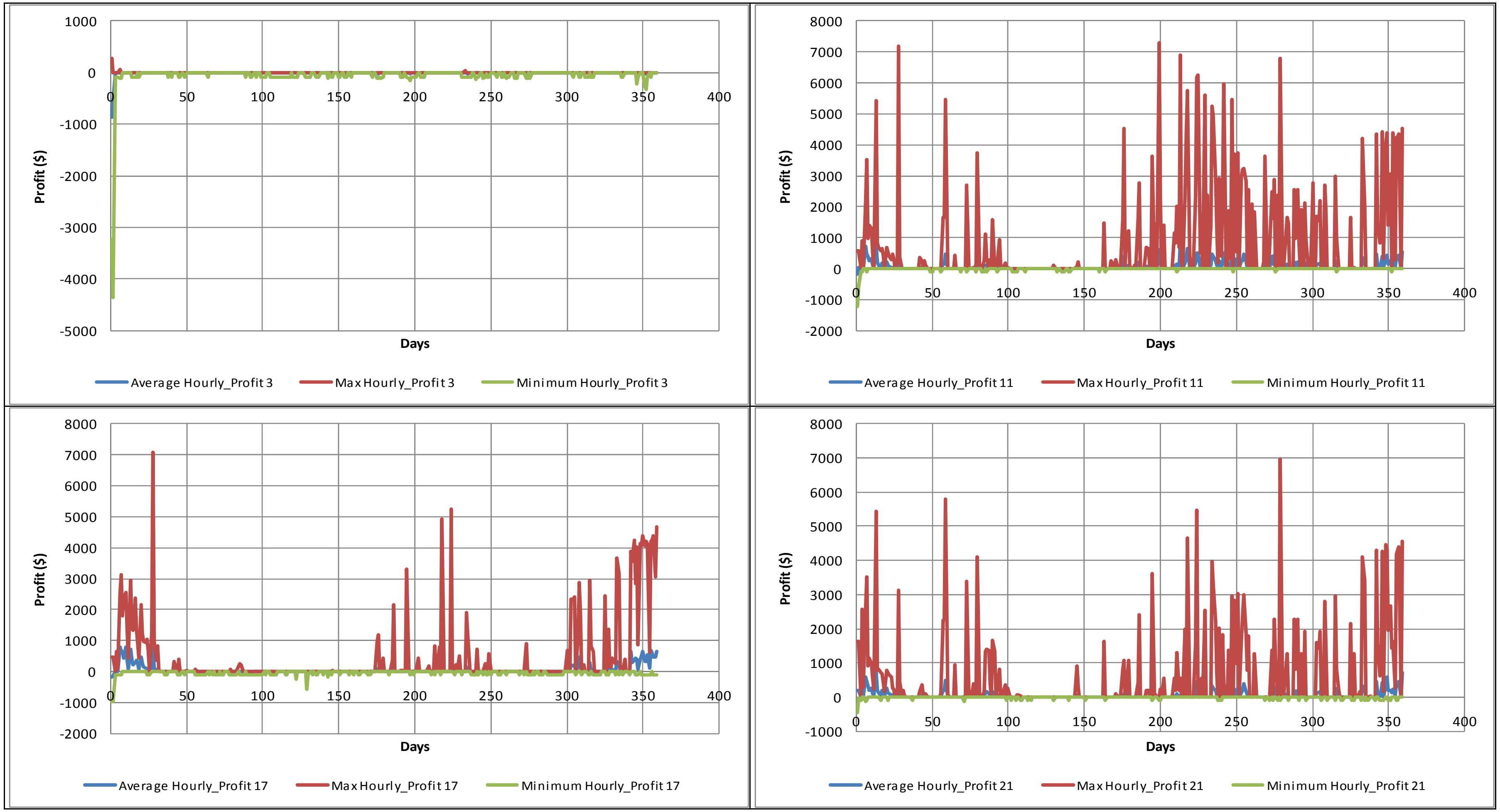

Figure 4.22. Impacts of the "Market Power" learning algorithm on profit performance of generator 4 at the selected time intervals (linear network structure case).

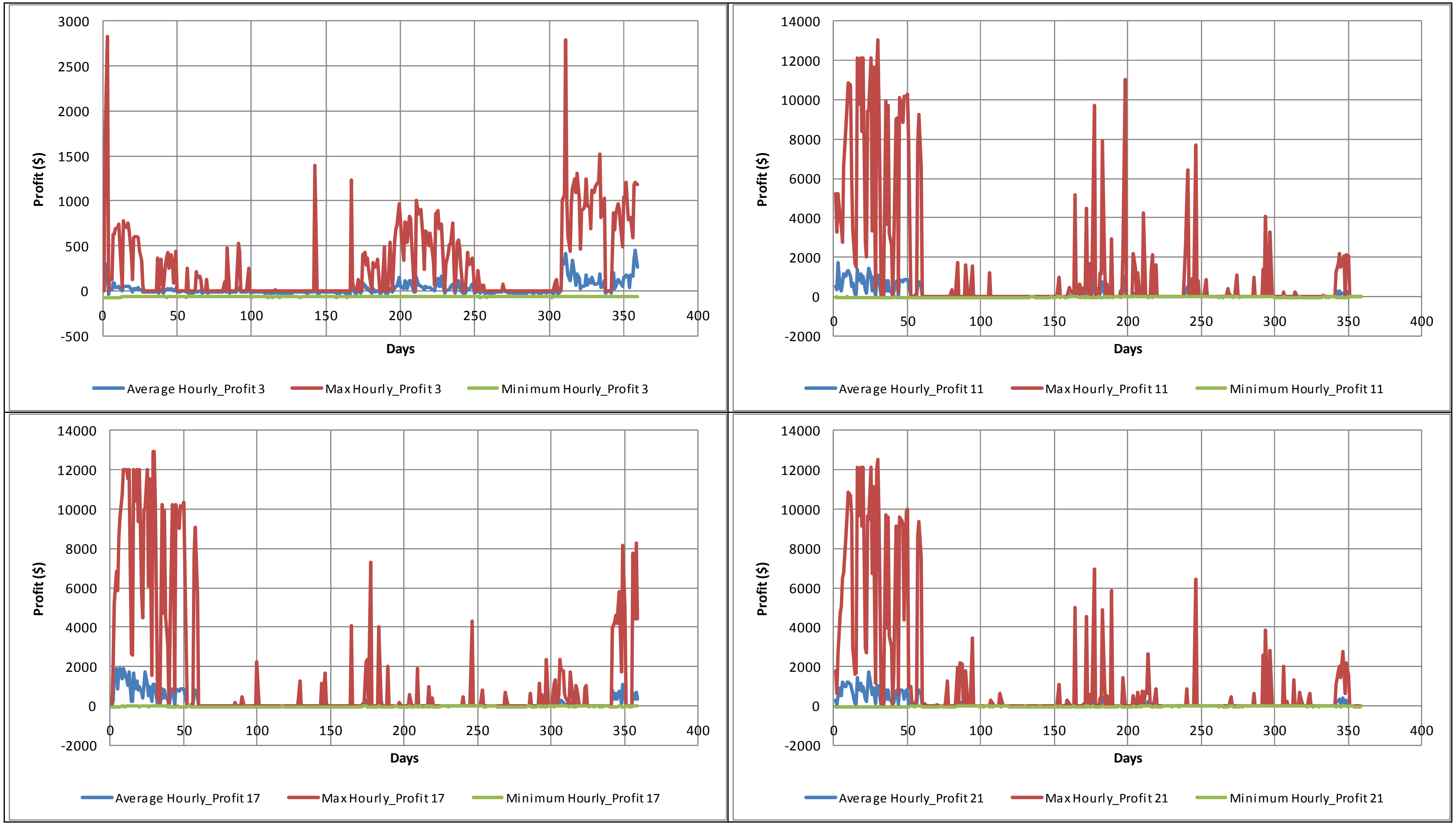

Figure 4.23. Impacts of the "Market Power" learning algorithm on profit performance of generator 7 at the selected time intervals (linear network structure case).

4.2. Alternative Current Optimum Power Flow

The second modeling approach used for power generating / transmission system modeling is the Alternative Current (AC) Optimum Power Flow (OPF). Similar to the linear case (minimum cost network flow), the reference scenario for this approach features the self-learning reinforcement algorithm embedded in bidding strategy formation. Twelve instances of the simulation model are deployed with distinct seeds, each run covering a period of 365 days. After the integrated simulation / optimization runs, the average, maximum and minimum values (over the 12 runs) for electricity price, real load, reactive load, and generator profit figures are computed for each one-hour time interval. For the reference scenario, four time intervals are selected for detailed analysis, according to the load profiles displayed in Table 4.1. The resulting average electricity sale price levels are displayed in Table 4.2.

Figure 4.24 displays electricity price behavior at the selected time intervals. It is observed that the prices formed are consistently higher than that of the linear model case. The price profile for the time interval (11- 12) is especially higher compared to the linear case. Maximum price levels increase through the end of the year, which indicates that agents learn how to increase profit and exercise market power. In addition, all time intervals displayed show that minimum prices are close to the marginal production cost of electricity. This also reveals that competition is still going on in the market for all time intervals, but some cooperation between the agents (in the sense of independently adopted similar bidding strategies) may also be present in some cases.

Table 4.2. Reference scenario electricity sale price levels for all time intervals (AC OPF approach).

Hours	The AC-OPF Reference Scenario	
	Average electricity sale Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5
1-2	151.2	53.1
2-3	138.2	50.6
3-4	122.5	25.5
4-5	170.2	52.6
5-6	172.9	48.6
6-7	151.2	34.8
7-8	167.8	38.9
8-9	181.8	76.2
9-10	345.7	205.3
10-11	164.9	45.9
11-12	280.2	161.6
12-13	238.2	103.7
13-14	153.1	48.9
14-15	170.6	66.1
15-16	193.2	106.6
16-17	163.0	45.0
17-18	203.7	55.3
18-19	178.9	48.8
19-20	172.6	53.6
20-21	194.6	63.0
21-22	186.7	69.6
22-23	240.1	94.0
23-0	160.5	48.0

Figure 4.24. Electricity price dynamics during the planning horizon in the reference scenario at the selected time intervals (AC OPF case).

Regarding generator 1, Table 4.3 displays this generator's, i) the average real load scheduled, ii) the reactive load scheduled, iii) profit performance, for all time intervals under the reference scenario. With respect to the average load level scheduled, an under loaded generator is seen recalling that the capacity of generator 1 is 133 MW. The highest load levels are achieved close to the second peak time interval (17-18). Standard deviations are relatively small compared to means. Except time interval 3-4, average load levels remain in the 20-30 MW interval, while minimum load levels go even down to zero. The indicated dynamics can be better observed in Figure 4.25.

Table 4.3. Average real, reactive load scheduled to and the profit achieved at generator 1 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	25.2	5.1	7.2	0.8	2377	1467
1-2	16.8	3.5	6.6	0.7	2201	1109
2-3	18.5	3.7	7	0.8	1720	733
3-4	16	3.2	6.5	0.8	1674	551
4-5	15.8	3.1	6.5	0.7	2351	1239
5-6	15.9	3.2	6.6	0.7	2179	841
6-7	16	3.4	6.7	0.8	1954	668
7-8	16.8	3.5	6.7	0.8	2370	833
8-9	19.6	4	7.4	1	3176	1895
9-10	25.7	4.8	8.1	1.1	7051	5851
10-11	22.1	4	8.8	1.1	3132	1306
11-12	22.4	4.2	8.1	1.1	5897	4798
12-13	21.5	3.9	8	0.9	4567	2745
13-14	21.7	3.9	7.8	0.9	2931	1444
14-15	25.6	4.8	8.1	1	3145	1625
15-16	24.6	5.1	7.8	1	3943	3274
16-17	22.6	5.4	8.2	1.2	3141	1444
17-18	25.9	5.4	8.6	1.1	3827	1518
18-19	26.1	4.8	8.3	1.1	3246	959
19-20	22.4	4.1	8.3	1	3444	1465
20-21	24.3	5	8.3	0.8	3901	1605
21-22	22.6	3.7	8.3	0.9	3450	1495
22-23	22.1	3.6	7.8	0.9	4410	2066
23-0	20.9	4.1	7.7	0.9	2841	1197

With respect to the reactive load scheduled to generator 3, by analyzing the standard deviation levels, it can be concluded that variation of load is very low on an hourly basis. In addition, reactive load levels are very low when compared to generator capacity. It is clear that variation throughout the year is low and average value follows the general demand pattern which can be observed in Figure 4.26.

Regarding the average profit of generator 1 and its’ standard deviation levels, minimum profit is seen at the low demand time interval 3-4 with standard deviation one third of the average profit. Highest average profits are observed in transition time intervals, especially 9-10 and 11-12 with $6000 and $7000 profit levels, respectively. However, standard deviations are very close to average profit, which makes the profit levels highly uncertain. Figure 4.27 also supports these observations. Furthermore, it shows the effect of seasonality over profit performance.

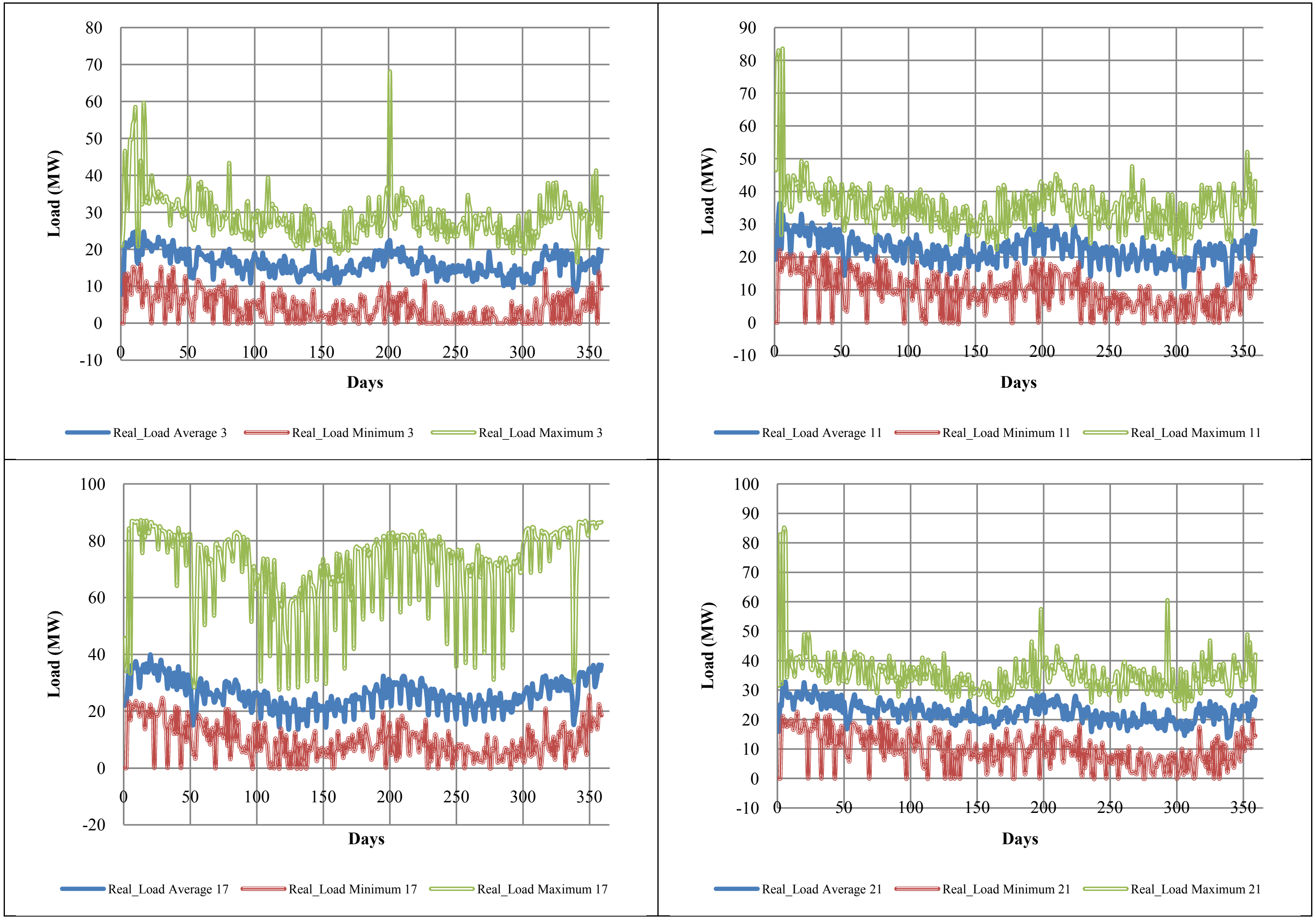

Figure 4.25. Average real load graphs of generator 1 in the reference scenario for selected time intervals (AC OPF case).

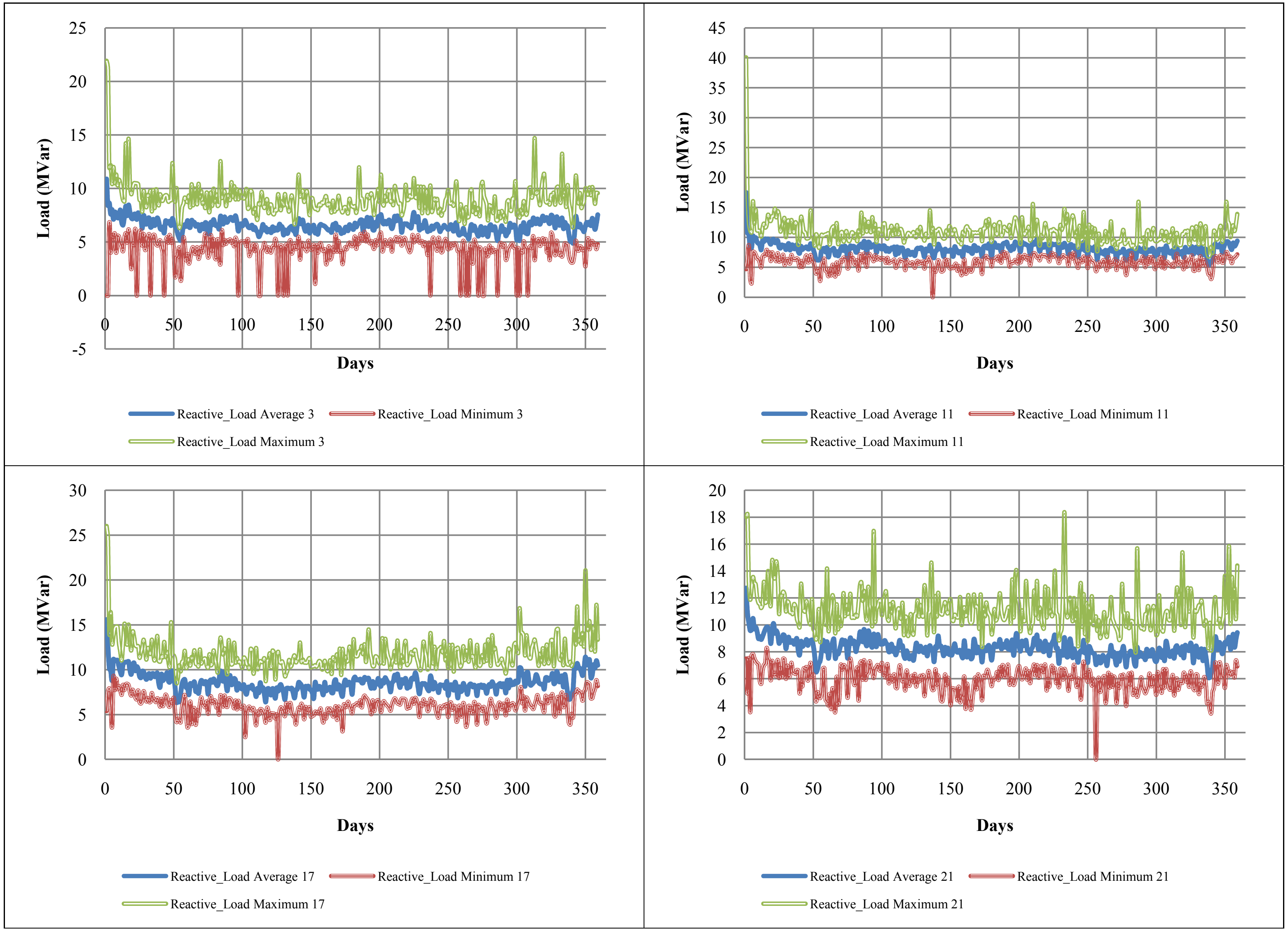

Figure 4.26. Average reactive load graphs of generator 1 in the reference scenario for the selected time intervals (AC OPF case).

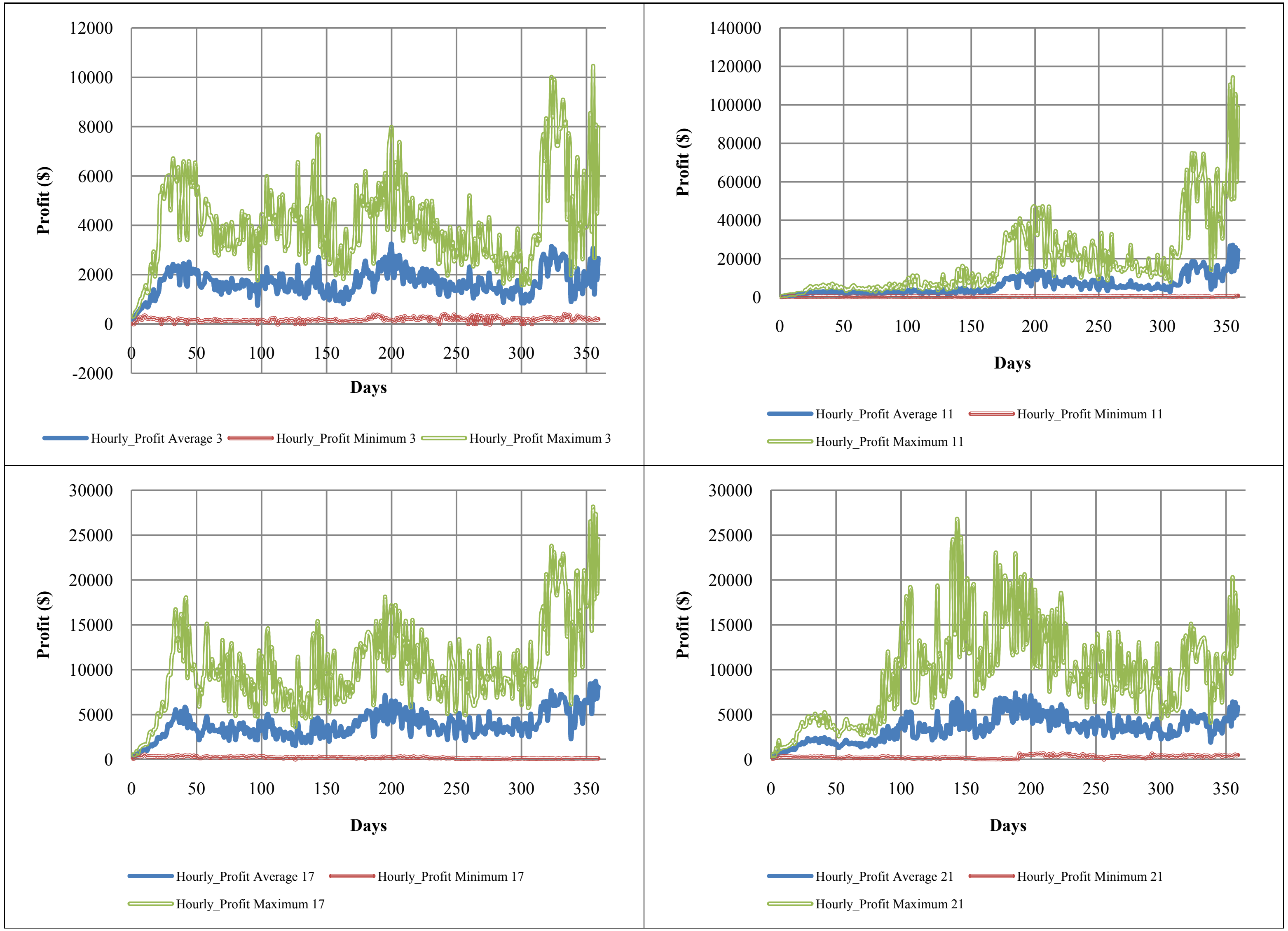

Figure 4.27. Profit performance achieved by generator 1 in the reference scenario for the selected time intervals (AC OPF case).

Regarding generator 2, Table 4.4. displays this generator's, i)the average real load scheduled, ii) the reactive load scheduled, iii) profit performance, for all time intervals under the reference scenario. Since the capacity of this generator is 45 MW, the average load levels show that its' activity levels are between one half and two thirds of the capacity. Generator 2 is one of the most flexible generators in the supply mix. Transition time interval loads are comparable to the peak time loads. Standard deviation levels are between one quarter and one fifth of the real load levels in general.

Table 4.4. Average real, reactive load scheduled to and the profit achieved at generator 2 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	26.2	5.2	10.2	1.8	3234	1738
1-2	24.8	5	8.6	1.7	3390	1577
2-3	26.3	5.4	8.6	1.7	3671	2057
3-4	23.7	5.6	8.2	1.9	2733	892
4-5	22.4	6.2	8.4	2	3318	1401
5-6	23.2	5.6	8.3	1.8	3831	1617
6-7	24.5	5.6	8.1	2	3363	1178
7-8	24.3	5.7	9.4	2.2	4517	1390
8-9	26.2	5.8	11.9	2.5	4408	2204
9-10	29	5.3	12.4	2.3	9617	6648
10-11	32.7	4.6	10.9	2.2	5578	1911
11-12	28.6	5.1	14	2.5	8148	5553
12-13	28	5.7	13.2	2.6	6782	3342
13-14	26.3	5.6	14.3	2.7	4125	1680
14-15	29.3	4.9	12.8	2.5	4987	2323
15-16	27.4	5.3	13.1	2.7	5117	3638
16-17	31	4.7	10.8	2.7	4805	1675
17-18	31.4	5.3	11.9	3	6011	2101
18-19	30.6	5.5	13.1	2.3	5522	1982
19-20	29.9	6.1	13.3	2.4	5867	2243
20-21	29.2	5.9	14.5	2.2	5786	2191
21-22	30.1	5.8	13.6	2.1	6331	2927
22-23	26.6	5.7	14.7	2.1	7456	3702
23-0	27.6	5.6	12.4	2	4379	1576

With respect to the reactive load scheduled, the general loading profile of generator 2 for reactive load is very similar to the general load curve of the system. Variation is low when compared to real load variations. Regarding the average profit achieved, it is higher than generator 1 in all time intervals. Lowest variation of profit is seen in the time interval 3-4, while highest variances are seen in time intervals 9-10 and 11-12. Highest profit levels are also seen at these time intervals.

Regarding generator 3, Table 4.5. displays this generator's, i)the average real load scheduled, ii) the reactive load scheduled, iii) profit levels, for all time intervals under the reference scenario. With respect to the average load real load scheduled, generator 3 is the smallest and the most flexible generator in the system. The effect of location is observed when the performance of generator 2 and 3 are compared. Average real loads scheduled for generator 3 are always higher than those scheduled for generator 2. Since all other technical conditions and constraints are similar, this indicates the impact of physical location on market power potential. Figure 4.28 displays load scheduled to generator 3. As can be observed, average load levels are very close to the generator capacity, which is an indication of the market power of the generator. The standard deviations of average load levels for generator 2 and generator 3 are very close, which supports the importance of physical location on market power potential.

With respect to the reactive load scheduled to generator 3, load levels are less than that of generator 2. However, the importance of generator 3 for system balance should be highlighted. The maximum levels of reactive power for the selected time intervals in Figure 4.29 indicate the use of generator for system balance up to two thirds of the capacity for reactive power.

Regarding profit levels, it can be observed that, profit levels are more sensitive to prices than load scheduled (since the generator is nearly at maximum capacity during most of the simulation period). The standard deviation is mainly due to price fluctuations. This situation can be better understood by analyzing Figure 4.30.

Table 4.5. Average real, reactive load scheduled to and the profit achieved at generator 3 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	30.5	5.4	4.7	2.6	3814	2473
1-2	29.3	5.2	3.9	2.5	3826	2053
2-3	30.7	5.7	3.6	2.4	3539	2234
3-4	29.2	5.8	3.7	2.3	3010	1082
4-5	28.3	6.6	3.5	2.8	4477	2290
5-6	28.8	5.9	3.6	2.3	4351	2009
6-7	29.8	6.5	3.4	2.8	3732	1568
7-8	29.7	6.1	4.1	2.8	4838	1601
8-9	32.1	6.2	4.9	2.6	5252	3120
9-10	34.3	5.7	5.5	2.5	10885	8210
10-11	37.5	5.3	5.5	2.8	5512	2037
11-12	33.2	6	6.5	3	8811	6578
12-13	33.4	6	5.8	2.7	7087	4024
13-14	32	6.3	6.1	2.8	4514	1989
14-15	34.2	5.8	6	2.9	4826	2439
15-16	32.7	6.1	6.4	3	5945	4536
16-17	35	5.5	5.8	2.7	5335	1996
17-18	35.1	6.2	5.5	2.7	5900	2359
18-19	34.2	6.4	6.1	2.5	5148	2233
19-20	34.6	6	6.3	2.7	5794	2376
20-21	33.9	5.8	6.4	2.5	5781	2462
21-22	34.4	6	6.4	2.6	5778	2938
22-23	32.3	6.3	6.4	2.6	6929	3887
23-0	32.4	5.9	5.7	3.2	4599	1918

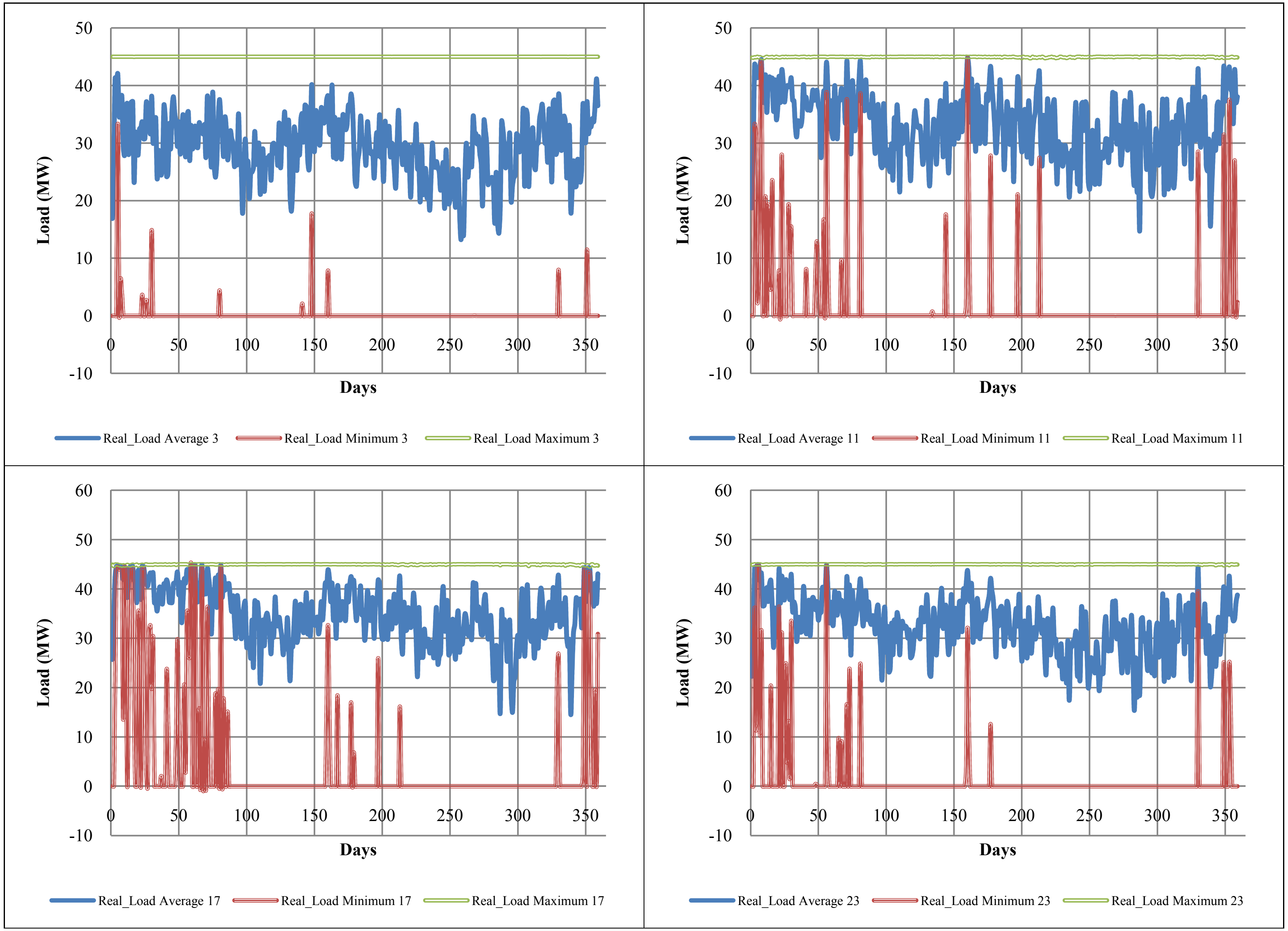

Figure 4.28. Average real load graphs of generator 3 in the reference scenario for the selected time intervals (AC OPF case).

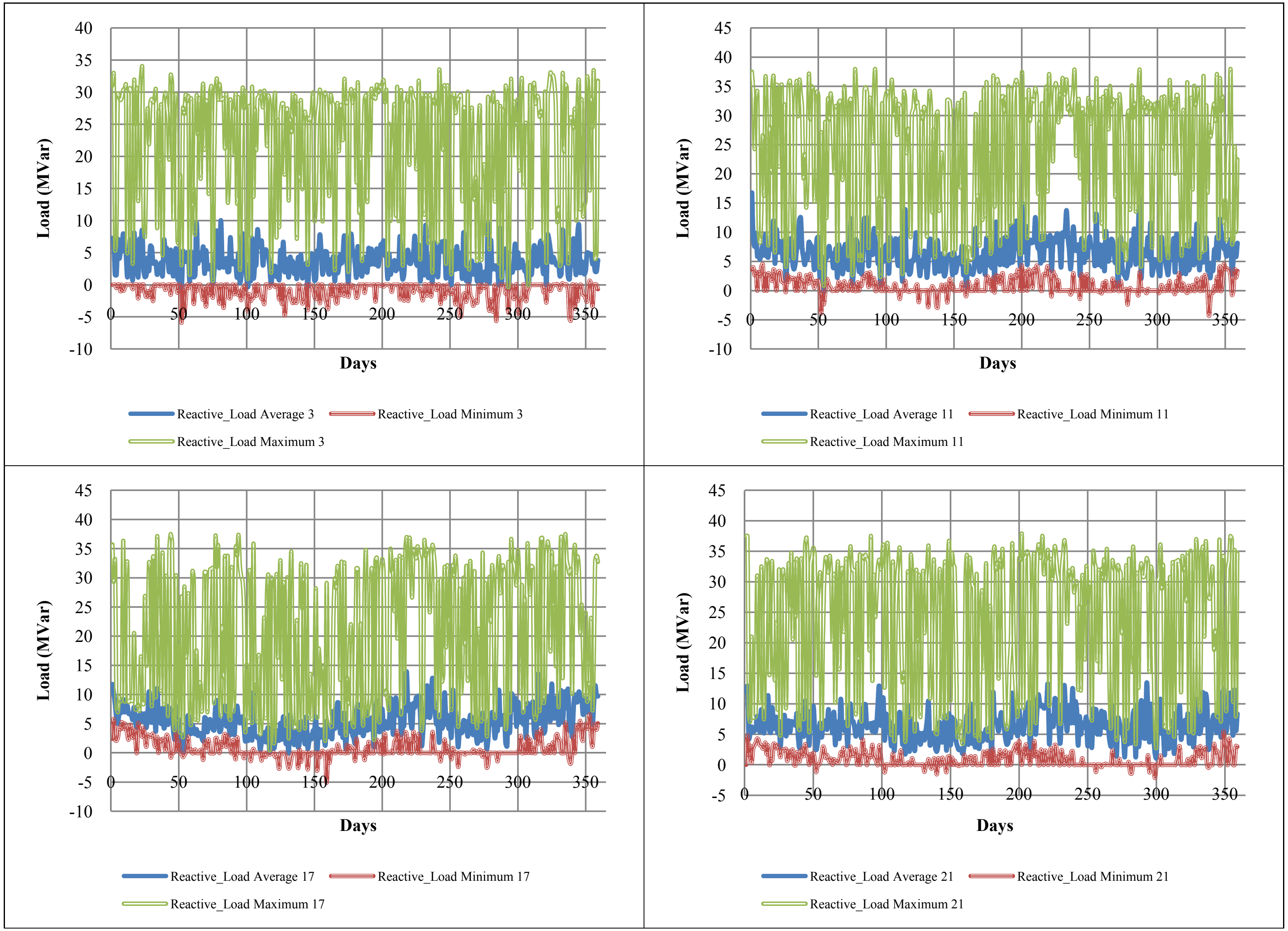

Figure 4.29. Average reactive load graphs of generator 3 in the reference scenario for the selected time intervals (AC OPF case).

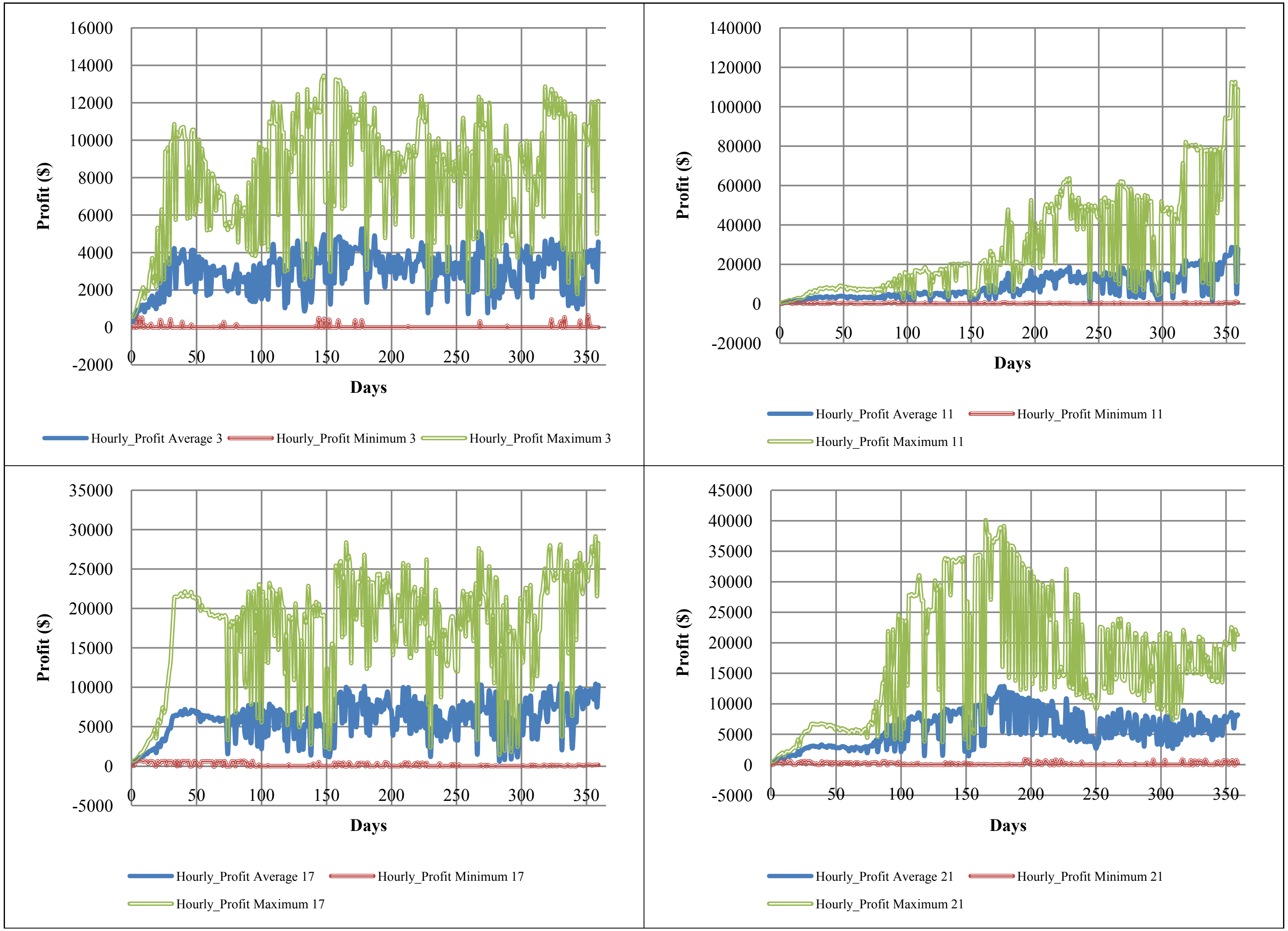

Figure 4.30. Profit performance achieved by generator 3 in the reference scenario at the selected time intervals (AC OPF case).

Regarding generator 4, Table 4.6 displays this generator's, i) average real load scheduled, ii) the reactive load scheduled iii) profit performance, for all time intervals in the reference scenario. The first observation is the variation of load between different time intervals, which is more dominant than observed for any other previously considered generator. Peak loads can be observed on two different portions of the load curve. First during transition time intervals (10-13) and secondly, during peaking time intervals (19-23).

Table 4.6. Average real, reactive load scheduled to and the profit achieved at generator 4 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	46.3	13.9	42.9	11.8	11258	8928
1-2	48.2	13.6	41.8	11.2	11262	7876
2-3	45.3	13.5	43.5	12.9	9722	7046
3-4	47.1	14.2	41.5	12.1	7840	4120
4-5	46.5	15.8	40.3	11.4	11624	8282
5-6	47.4	15.7	42	13.1	11590	7532
6-7	47.4	15	42	12.4	9582	5675
7-8	51	16.4	43.6	12.3	11487	6384
8-9	62.6	18.8	41.8	12.2	14641	11609
9-10	68	19.7	42.4	12.3	33767	30560
10-11	75.1	20.7	43.6	11.2	12419	7813
11-12	74	19.9	41.6	11.3	26352	23680
12-13	71	19.8	42.7	12.7	21302	16174
13-14	70.9	20.1	43	11.7	12220	7818
14-15	65.4	21	43.2	11.6	14205	9675
15-16	64.6	21.7	41.8	11.9	16746	16155
16-17	66.7	23.4	42.8	11.8	12925	8073
17-18	69.6	23	42.9	10.9	15961	9828
18-19	70.6	23.2	43.8	12.1	13463	8647
19-20	75.7	21.5	41.4	11.9	14206	8595
20-21	75.3	19.9	41.2	12.3	16517	10228
21-22	75.1	19.1	40.9	11	16261	10801
22-23	72.5	19.2	41.3	11.5	22065	15081
23-0	65.6	18.1	41.5	12.1	12051	7663

With respect to the reactive load scheduled to generator 4, average reactive load levels are high relative to its capacity and when compared with the previously analyzed generators. This situation indicates the critical role of this generator for system balance.

Load levels and their standard deviations are nearly smooth and do not change much between time intervals.

Regarding the profit performance of generator 4, unlike previous generators, changes in the load scheduled (and changes in price) over the time intervals of a day are both significant for this generator. As these two drivers of profit change, the profit performance over time intervals varies considerably. The same effect also increases the standard deviations. For the time intervals 9-10 and 11-12, standard deviations are higher than average profits, indicating high uncertainty levels at those time intervals.

Regarding generator 5, Table 4.7 displays this generator's, i) the average real load scheduled, ii) the average reactive load scheduled, iii) profit performance, for all time intervals, under the reference scenario. Even if the generator's capacity is lower than that of generator 4, average real load levels are similar. However, standard deviation levels are lower in every time interval, indicating less variance than that of generator 4.

With respect to the average reactive loads scheduled to generator 5, in low demand time intervals, negative values are observed, which shows that the generator had to consume some reactive power in order to stabilize network balances.

Regarding the profit performance of generator 5, general characteristics of its profit are similar to that of generator 4. However, all values are lowered by 10% to 30 %.

Regarding generator 6, Table 4.8 displays this generator's, i) the average real load scheduled, ii) the average reactive load scheduled, iii) profit levels, for all time intervals under the reference scenario. As the generator's capacity is 133 MW, the load levels displayed imply that the generator is working almost at full capacity in all time intervals. Standard deviation gets lower close to peak demand time intervals indicating that the SO wants to get as much as the generator can provide This is due to the low marginal cost of the generator and its physical location in the network (being only one branch away from a high demand node). Figure 4.28 displays the real load scheduled to generator 6, which supports the given explanation

Table 4.7. Average real, reactive load scheduled to and the profit achieved at generator 5 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	67.6	11.5	5.8	6.9	9024	6650
1-2	48	10.3	3.9	7.1	9147	6317
2-3	52.7	10.4	-1	7.6	8602	6272
3-4	46.2	9.8	-0.5	7.6	6191	3119
4-5	47.6	10.1	-1	7.5	9516	6397
5-6	46.7	9.8	-0.9	7.5	10193	6096
6-7	47.4	10	-0.4	7.9	8637	4517
7-8	50.9	11.3	1.7	7.5	9210	4696
8-9	60.5	13.1	7.8	8.4	12195	8926
9-10	73.3	14	11.1	8.1	26266	20895
10-11	66	13.5	13.4	8.4	12041	5999
11-12	70.7	14	12.5	8.5	21682	16194
12-13	66.4	13.1	11.4	8.4	18263	12053
13-14	68.2	13.6	11	8.2	10847	5819
14-15	74.2	13.9	10.3	8	13128	7707
15-16	71.4	13.9	11.5	8.8	13988	10521
16-17	67.8	13.8	11.8	8.6	11728	5912
17-18	72.9	13.1	11.1	8.2	15873	7352
18-19	74.6	13.2	11.8	8.4	14100	5730
19-20	69.9	12.9	13.1	8	12628	5997
20-21	73	12.2	14.3	7.3	15638	7496
21-22	70	11.5	14.1	7.5	15255	8912
22-23	69.4	12	13	8.3	20201	12148
23-0	63.5	11.4	10.1	8	10929	5450

With respect to the reactive load scheduled to generator 6, it can be concluded that load levels are small compared to capacity of the generator and standard deviations are nearly the same as the average reactive load levels. Hence, high uncertainty in load levels can be conjectured. The reactive load levels' development for the selected time intervals, which are displayed in Figure 4.32, supports this explanation. The hypothesis also reveals the importance of the generator for system stability.

Table 4.8. Average real, reactive load scheduled to and the profit achieved at generator 6 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	123.9	12	4.6	5.6	14820	6852
1-2	118.7	11.8	6.9	7.7	14972	6220
2-3	116.9	12	8.3	8.1	13112	5709
3-4	113.6	12.8	10.2	8.3	11980	3167
4-5	113.3	12.3	10.9	8.8	16574	6027
5-6	113.7	12.4	10	8.3	16509	5528
6-7	114.1	12.5	10	9.3	14864	4071
7-8	115.9	12.9	8.8	7.9	17051	4650
8-9	123.4	11.5	6	5.9	19813	9012
9-10	125.9	10.5	6.7	5.4	39308	24938
10-11	127.2	9.5	6.9	5.9	18933	5786
11-12	126.8	9.9	7.5	6.2	32402	19902
12-13	126.4	10	6.2	5.9	27116	12677
13-14	126.2	10.2	6.6	5.8	17568	6100
14-15	126.5	10.2	6.4	5.7	19360	8255
15-16	126.7	10.1	6.2	5.6	22106	13189
16-17	126.1	9.8	6.7	6.1	18414	5725
17-18	126.1	9.5	8.3	7.3	23329	7044
18-19	127	9	8.3	6.7	20513	5638
19-20	126.7	9.4	7.8	6.5	19790	6712
20-21	127.7	8.8	7.5	5.6	22723	7734
21-22	127.9	9	6.4	5.1	21586	8736
22-23	127	9.4	6	5.3	27410	11481
23-0	125.1	10.1	5.8	5.7	17977	5791

Regarding the profit performance of generator 6, it's average profit level is the highest of all generators and standard deviations are small compared to other generator agents. Nevertheless, this does not change the fact that highest standard deviation occurs in transient time intervals (9-11) and lowest standard deviation is attained in low demand time intervals. Figure 4.33 also supports these findings.

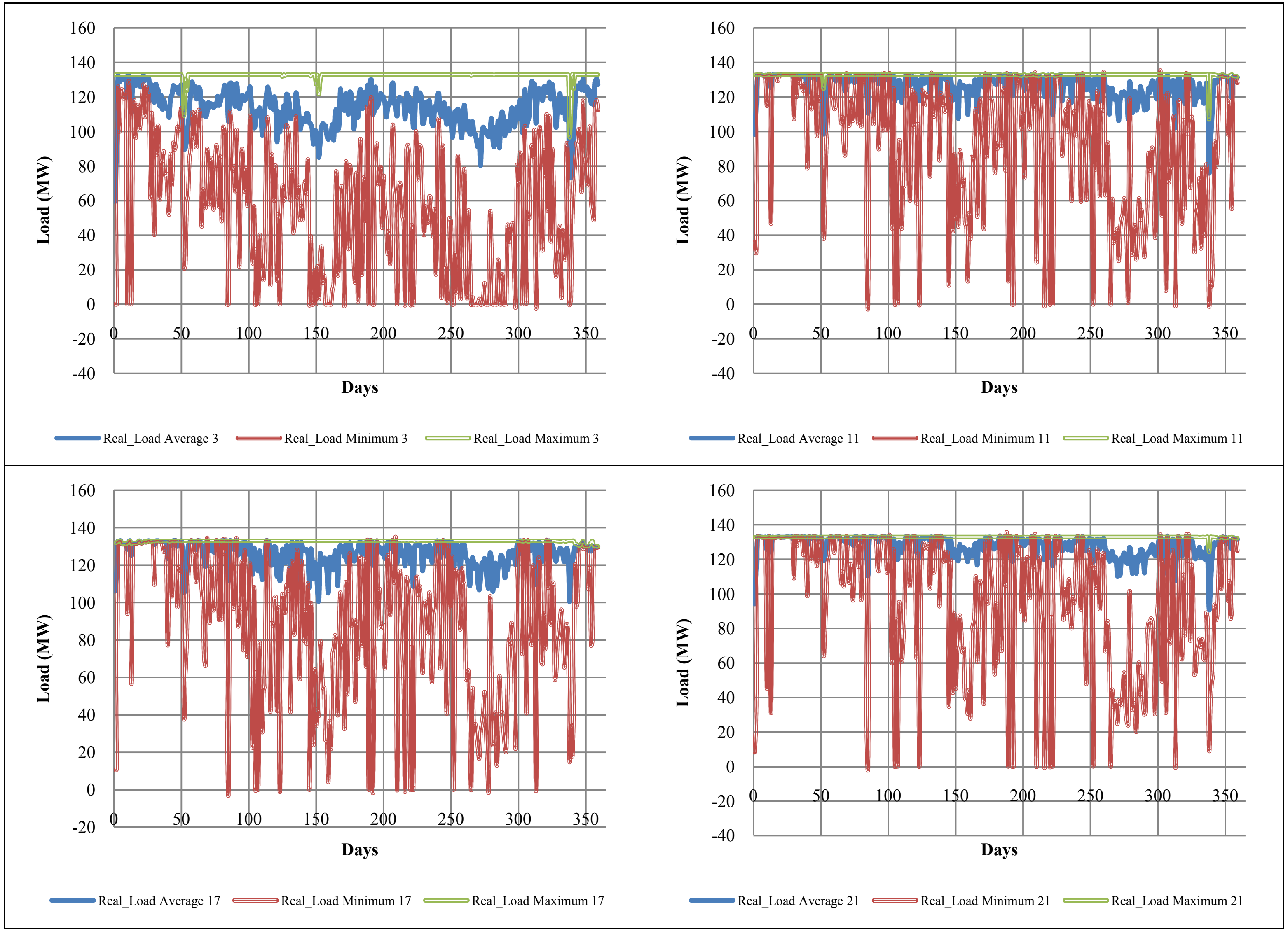

Figure 4.31. Average real load graphs of generator 6 in the reference scenario at the selected time intervals (AC OPF case).

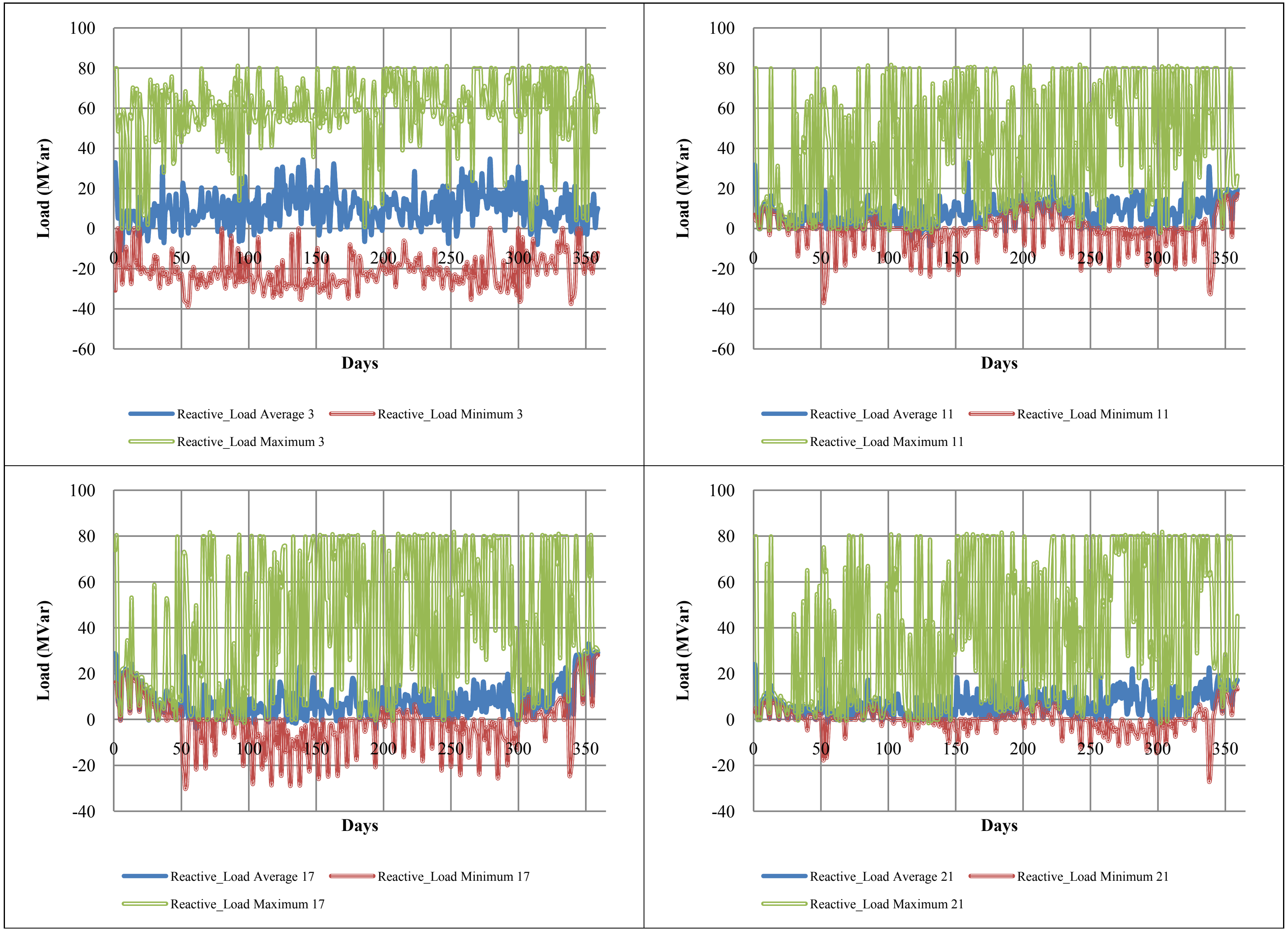

Figure 4.32. Average reactive load graphs of generator 6 in the reference scenario at the selected time intervals (AC OPF case).

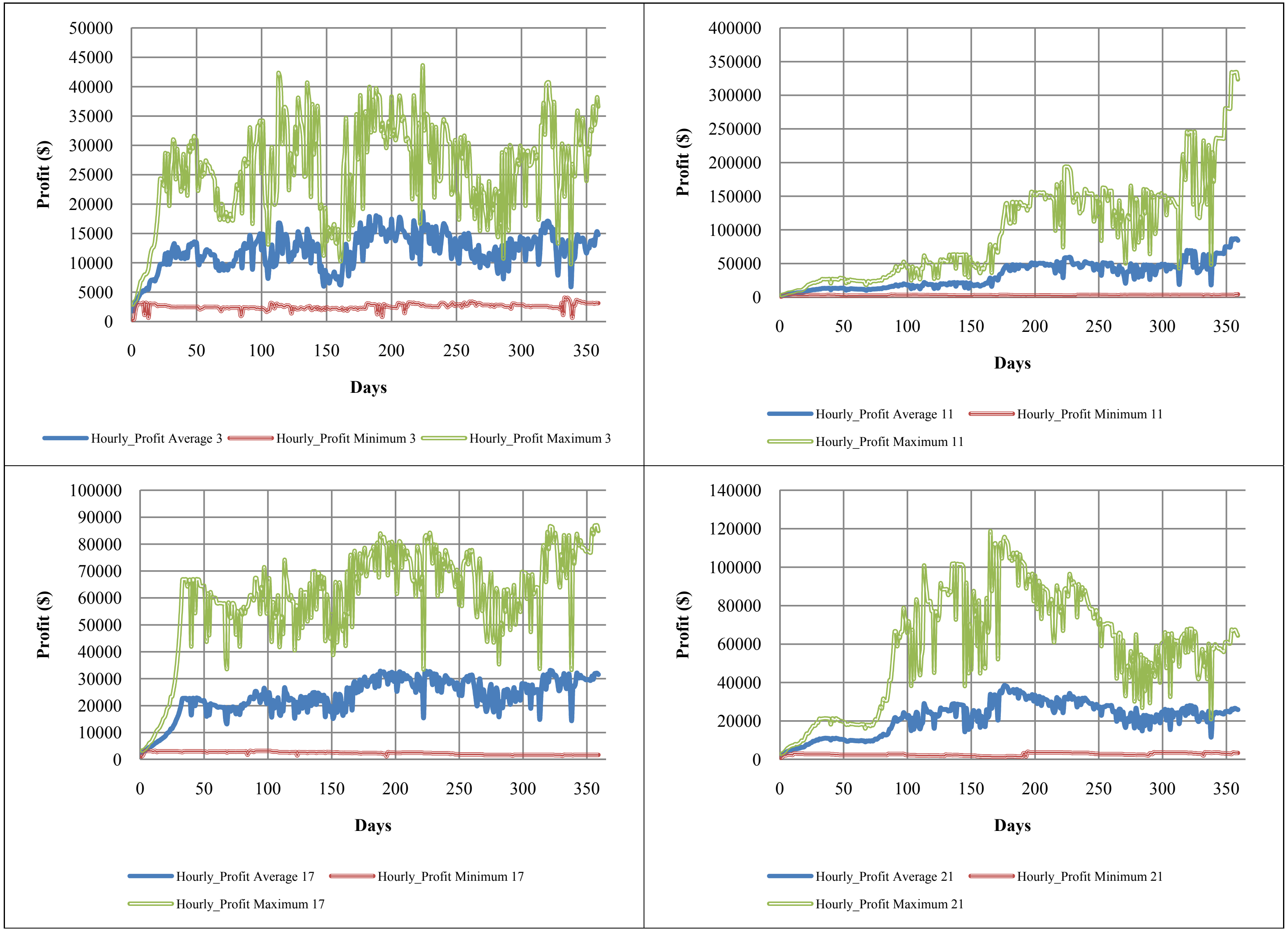

Figure 4.33. Profit performance achieved by generator 6 in the reference scenario at the selected time intervals (AC OPF case).

Regarding generator 7, Table 4.9 displays this generator's, i) the average real load dispatched, ii) the reactive load scheduled, iii) profit levels, under the reference scenario. Although it is the biggest generator in the system with 222 MW capacity, the load levels dispatched by the SO remain low and standard deviation levels are high compared to average levels. This indicates that generator 7 has not been very successful in the auction processes which may be due to the inflexibility caused by its high minimum up and down times, and due to its less favorable location. It is noted that maximum load assigned is for time interval 15-16, which is on the smooth part of the daily load curve.

Table 4.9. Average real, reactive load scheduled to and the profit achieved at generator 7 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	36.7	13.6	4.6	2.4	4966	5500
1-2	37.1	13.1	3.7	2.4	5067	4895
2-3	18.5	12.6	3.3	2	3862	4318
3-4	22.4	13.5	3.2	1.9	3591	2283
4-5	23.8	13.8	3.5	1.9	6478	5075
5-6	22.2	10.6	3.5	2	6792	4803
6-7	22.1	13.6	3.5	2	5749	3829
7-8	26.3	14.4	3.5	2	6877	4557
8-9	29.2	15.2	4.4	2.4	7406	7194
9-10	34.7	16.3	5.1	2.6	16686	22106
10-11	30.3	15.7	4.9	2.4	8997	6165
11-12	36.8	16.7	5	2.3	14649	18742
12-13	31.9	15.9	4.9	2.2	11552	10792
13-14	33.5	16	4.6	2.3	7070	5452
14-15	36.3	18.8	4.8	2.5	8248	6945
15-16	40.5	16.5	5.2	2.5	9735	11211
16-17	38.6	16.7	5.1	2.6	7751	5767
17-18	33	15.6	5.2	2.4	11626	7536
18-19	34.6	15.5	5	2.7	9840	5922
19-20	33.6	15.5	4.9	2.7	7563	5931
20-21	38.4	16.1	5.4	2.5	10345	7072
21-22	34.7	15.8	5.2	2.7	8419	7346
22-23	36.1	15.9	4.9	2.6	11006	10180
23-0	32.5	15.5	4.6	2.2	7530	4783

With respect to the reactive load scheduled to generator 7, load levels and their standard deviations are very low compared to the capacity of the generator.

Regarding the profit performance of generator 7, it is clear that this generator is not performing well compared to its capacity. In addition, standard deviations of average profit levels are very high, even for low demand time intervals, which makes the generator unreliable in terms of profit. This serves an example on how a low marginal cost generator may be eased out of the competition by its highly flexible, better located rivals.

Regarding generator 8, Table 4.10 displays this generator's, i) the average real load dispatched, ii) the reactive load scheduled, iii) profit levels, for all time intervals under the reference scenario. Average load levels are between 40-60 MW, while standard deviation is between 12-18 MW. In comparison to its capacity, those load levels are sensed to be low, when compared with other generators. Figure 4.34 displays the load levels throughout the simulation period for the selected time intervals. The generator's load profile shows seasonal fluctuations at average level, while maximum load curve shows that there are cases where the full capacity is used during the simulation runs.

With respect to the reactive load scheduled to generator 8, it is clear that reactive load levels are high compared to other generators and capacity. This indicates that the SO mainly deploys generator 8 for system stability. This situation is depicted in Figure 4.35. It should also be noted that the reactive supply limit of this generator (which is 124 MW) is reached numerous times during the simulation duration. Analysis reveals that generator is mainly used for balancing the system in the planning horizon.

Regarding profit levels of generator 8, it can be concluded that average profit increases when demand increases (with the exception of transition time intervals). Standard deviation also follows a similar pattern with one exception: the time interval 15. The Profit performance in selected time intervals can be seen in Figure 4.36.

Table 4.10. Average real, reactive load scheduled to and the profit achieved at generator 8 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	35.9	11.7	39	13.9	9103	7317
1-2	40.7	12.1	39	15.5	8798	6251
2-3	40.1	12	34.9	13.5	7046	5501
3-4	42	12.7	36.1	14.8	6050	3163
4-5	40.5	13.3	34.3	15.3	8516	6602
5-6	41	13	35.4	14.6	8759	5962
6-7	41.2	13.2	34.6	14.6	7078	4303
7-8	44.8	13.7	39.8	14.5	9086	5180
8-9	49.9	14.7	47.5	15.9	12102	9442
9-10	48	14.3	48.5	16.4	26162	24571
10-11	54.9	16.5	50.3	15.6	10311	6371
11-12	56.3	17	51.3	14.8	22094	19771
12-13	54.5	16.2	51.6	14.7	17830	13478
13-14	55.2	16.2	50.5	15.6	10157	6616
14-15	49.7	16.3	49.1	15.6	11968	8627
15-16	48.7	18	48.8	16.2	13827	13632
16-17	49.5	18.2	48.7	16.1	10739	6635
17-18	51.3	18.1	49.9	15.7	14153	8565
18-19	52.9	17.4	48.4	15	11908	6439
19-20	57.1	17.1	51	15.2	12128	6615
20-21	57.3	16.8	51.3	15.7	13717	8450
21-22	57.3	15.9	51.5	14	13288	8910
22-23	56.3	16	53.6	15.1	18095	12488
23-0	52.3	15.1	50.4	16.1	10389	6137

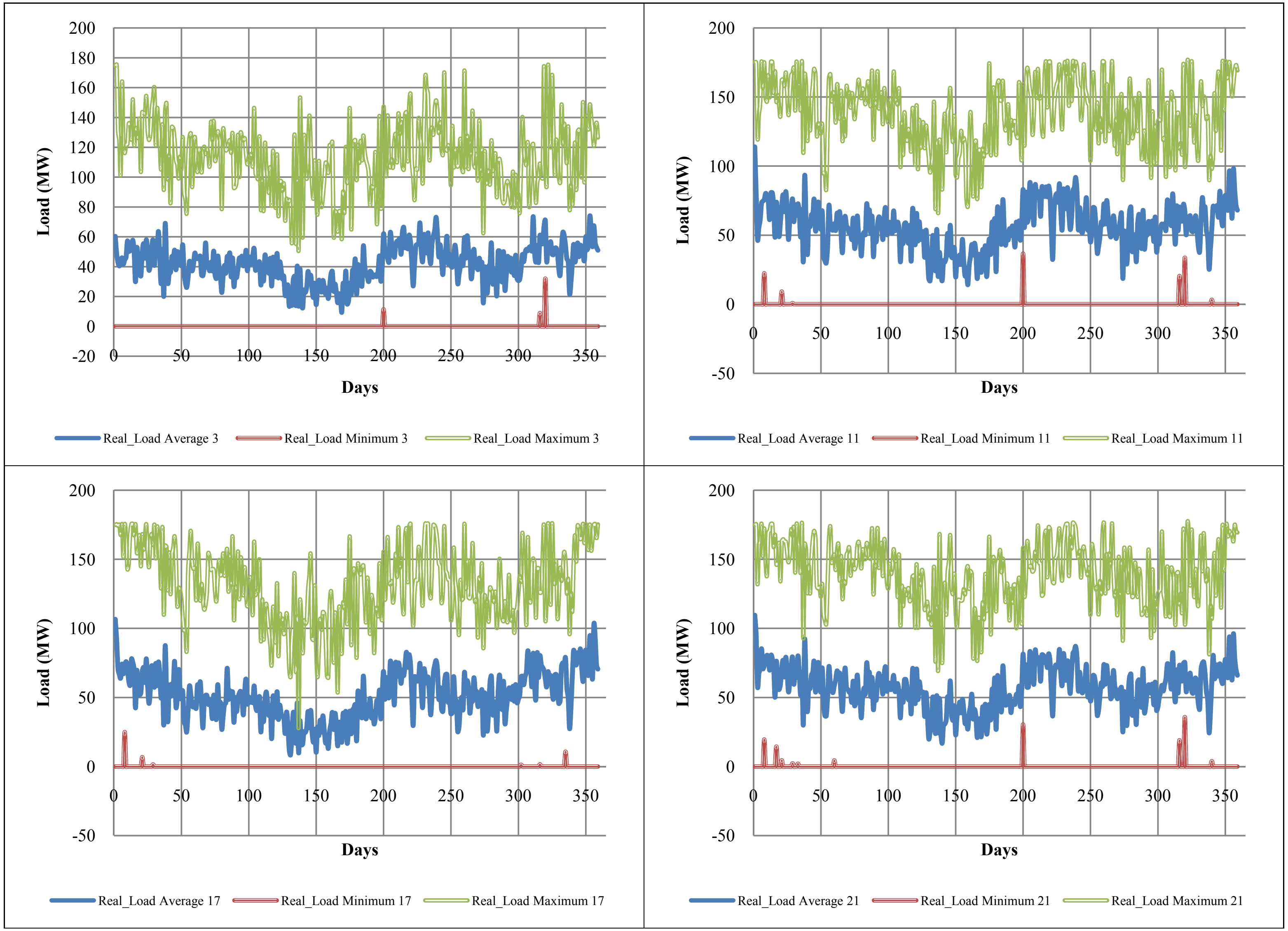

Figure 4.34. Average real load graphs of generator 8 in the reference scenario at the selected time intervals (AC OPF case).

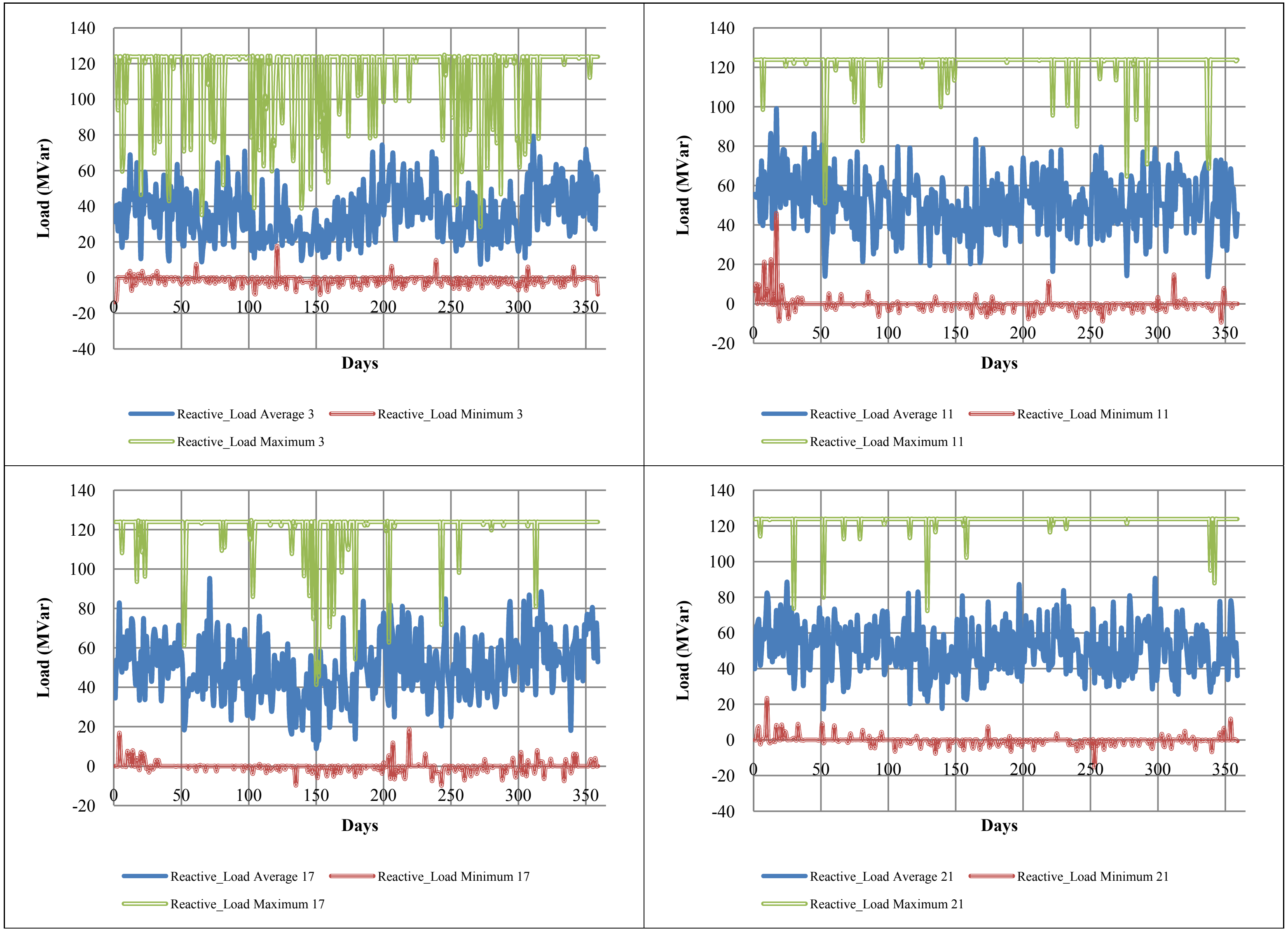

Figure 4.35. Average reactive load graphs of generator 8 in the reference scenario for the selected time intervals (AC OPF case).

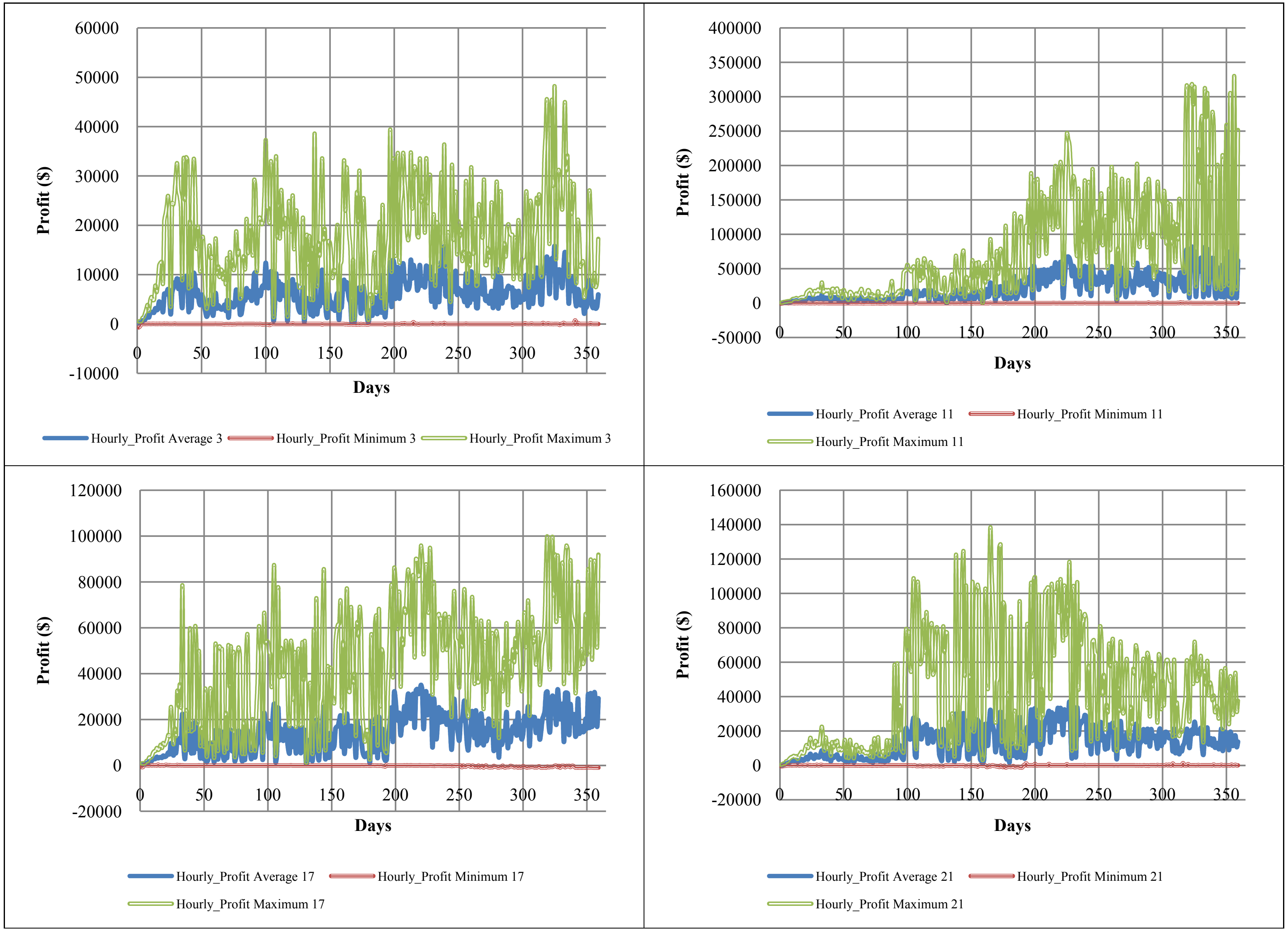

Figure 4.36. Profit performance achieved by generator 8 in the reference scenario at the selected time intervals (AC OPF case).

Regarding generator 9, Table 4.11 displays this generator's, i) the average load scheduled, ii) the reactive load scheduled, iii) profit performance, for all time intervals in the reference scenario. Average load levels for time intervals 19-20, 20-21, 21-22 and 22-23 are similar and standard deviations are very close. This generator seems to be deployed in response to changing load level between portions of the day. Besides, changes in load levels are not similar to the system demand curve on hourly time interval basis. In addition, the load levels are small compared to capacity. Nevertheless, real load levels are generally less than those of generator 8, which is similar in terms of technical parameters.

Table 4.11. Average real, reactive load scheduled to and the profit achieved at generator 9 in the reference scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario					
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Reactive Load (MVAR)	Standard Deviation of Reactive Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	29.3	9.1	9.9	3.1	4263	3978
1-2	32.9	9.6	8.9	3	4090	3183
2-3	32.3	10	7.6	2.8	2734	1835
3-4	34.6	10.4	7.4	2.8	3084	1598
4-5	34.8	10.4	7.1	2.9	4616	3394
5-6	34.5	9.8	6.9	2.8	4239	2567
6-7	34.5	9.7	7.2	2.8	3687	2003
7-8	36.2	10.1	9.1	3	4555	2443
8-9	40.6	11.1	11.9	3.7	6303	5059
9-10	40.1	11.1	15	4.5	14436	15171
10-11	44.7	12.4	16.8	5	6154	3692
11-12	45.7	12.7	15.5	4.4	12218	12627
12-13	44.5	12.4	14	3.9	9096	7477
13-14	44.7	12.2	13.9	4.1	5833	3900
14-15	39.7	11.3	14.6	4.6	6053	4345
15-16	40.1	12.2	13.7	4.6	7961	8260
16-17	41.1	13.3	15.6	5	6067	3925
17-18	41.1	12.1	16	5.4	7599	4409
18-19	41.9	11	15.9	5.1	5959	2704
19-20	45.4	11.4	16.1	4.3	6732	4228
20-21	45.2	11.7	15.8	3.7	7596	4677
21-22	45.8	11.6	16	3.5	6360	3845
22-23	45.2	11.6	14.4	3.1	8212	5511
23-0	41.9	11.3	13.2	3.4	5493	3276

With respect to the reactive load levels of generator 9, it differs from the real load case. Reactive load levels of generator 9 rise with increasing demand. In addition, the standard deviation levels are nearly insensitive to those load changes. Compared to generator 8, which is technically similar to generator 9, reactive load levels are very low.

Regarding the profit performance of generator 9, it is worse than that of generator 8. This is may be due to the location of this generator (as all other technical parameters are the same). Besides, a high variability in transition time intervals is present, indicating uncertainty.

4.2.1. Parameter Change Responses

In this part of the study, it is tried to better understand the effects of the key parameters of the transmission network, without changing the basic infrastructure. First, the effect of transmission lines capacities is investigated, through a capacitated transmission line scenario, where line capacities are taken as displayed in Table 4.12 (In general the lines with higher rated voltage levels are assumed to have higher capacities). Then the effect of transmission line fee is analyzed by considering two extreme end-pricing policies.

The analysis includes the investigation of electricity prices and loads / profitability of generators under the altered conditions.

Table 4.12. Transmission line capacities in the capacitated lines scenario.

Branch No	From-to	Capacity (MW)
1	1-2	150
2	1-3	150
3	2-4	150
4	3-4	150
5	2-5	150
6	2-6	150
7	4-6	150
8	5-7	150
9	6-7	150
10	6-8	150
11	6-9	100
12	6-10	100
13	9-11	100
14	9-10	100
15	4-12	100
16	12-13	100
17	12-14	100
18	12-15	100
19	12-16	100
20	14-15	100
21	16-17	100
22	15-18	100
23	18-19	100
24	19-20	100
25	10-20	100
26	10-17	100
27	10-21	100
28	10-22	100
29	21-22	100
30	15-23	100
31	22-24	100
32	23-24	100
33	24-25	100
34	25-26	100
35	25-27	100
36	28-27	100
37	27-29	100
38	27-30	100
39	29-30	100
40	8-28	150
41	6-28	150

In Table 4.13, the electricity prices of the capacitated lines scenario and the reference scenario are compared by the means of average values and standard deviations. The comparison of the prices reveals that the peaking and transient time interval electricity prices feature significant increases, while low demand time intervals prices are lower compared to the reference scenario. In addition, the standard deviations levels are lower in low demand time intervals, supporting the argument that line capacity have minimal effect in low demand time intervals. An interesting effect of line capacities is that since very profitable high prices are being realized at peaking time intervals, generator agents do not hesitate to lower their bids at low demand time intervals in order to keep the plant operational at the beginning of peaking demand portion of the day.

In the transient time intervals such as 9-10 and 11-12, even though the prices have increased the standard deviations are lowered. This indicates how transmission line capacity would significantly drive the prices up, while reducing volatility. In the peaking time intervals, high electricity prices are still realized, but the standard deviation levels are also comparatively higher, indicating more uncertainty in price formation.

Figure 4.37 displays the electricity price behavior in time intervals 3-4, 11-12, 17-18 and 21-22. The distance between maximum and minimum price levels are lowest in the time interval 3-4. Close to the last quarter of the year, the gap between the minimum and maximum prices attained closes there by almost converging to the average price (this behavior is not observed in other time intervals considered). In the transient time interval, 11-12, and the peaking time intervals, 17-18 and 21-22, the price behavior shows diverging maximum and minimum price levels, indicating increasing uncertainty. This also shows how the agents' self learning reinforcing algorithm learns the nature of peak inelastic demands and manipulates the prices accordingly for profit maximization.

Table 4.13. Average electricity sales prices in the reference scenario and capacitated lines scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Capacitated Lines Scenario	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5	171.9	41.5
1-2	151.2	53.1	169.7	40.4
2-3	138.2	50.6	135.3	34.1
3-4	122.5	25.5	108.5	23.8
4-5	170.2	52.6	119.6	23.0
5-6	172.9	48.6	108.7	24.2
6-7	151.2	34.8	126.1	24.2
7-8	167.8	38.9	160.9	35.7
8-9	181.8	76.2	187.0	49.0
9-10	345.7	205.3	255.7	94.3
10-11	164.9	45.9	287.2	110.3
11-12	280.2	161.6	319.9	124.9
12-13	238.2	103.7	314.0	143.9
13-14	153.1	48.9	257.8	93.4
14-15	170.6	66.1	281.1	133.5
15-16	193.2	106.6	242.1	110.5
16-17	163.0	45.0	225.1	69.5
17-18	203.7	55.3	265.5	90.2
18-19	178.9	48.8	252.5	83.7
19-20	172.6	53.6	346.8	186.0
20-21	194.6	63.0	263.8	87.2
21-22	186.7	69.6	328.5	153.6
22-23	240.1	94.0	293.9	145.6
23-0	160.5	48.0	253.3	103.3

Figure 4.37. Impacts of transmission line capacities on electricity sales prices at the selected time intervals (AC OPF case).

Regarding generator 6, Table 4.14 displays this generator's, i) the average real load scheduled, ii) profit levels, for all time intervals under the reference and the capacitated line scenarios. In all time intervals the effect of capacitated transmission lines over the agent for is minor generation reductions which are minimal on the order of 1 to 4 MW. The utilization levels are near full capacity (which is 133 MW).

Table 4.14. Average real load scheduled to and the profit achieved at generator 6 in the reference scenario and in the capacitated line scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Capacitated Lines Scenario		The AC-OPF Reference Scenario		The Capacitated Lines Scenario	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	123.9	12	119.9	12.7	14820	6852	18654	5021
1-2	118.7	11.8	115.7	12.5	14972	6220	17450	4929
2-3	116.9	12	112.5	13.1	13112	5709	13706	3700
3-4	113.6	12.8	113	12.6	11980	3167	10973	2766
4-5	113.3	12.3	113.3	13	16574	6027	12144	2569
5-6	113.7	12.4	112.8	13.2	16509	5528	11038	2825
6-7	114.1	12.5	112.1	13.4	14864	4071	12629	2876
7-8	115.9	12.9	115.3	13.3	17051	4650	16663	4219
8-9	123.4	11.5	121.3	12	19813	9012	21085	6065
9-10	125.9	10.5	123.5	11.4	39308	24938	29981	11497
10-11	127.2	9.5	124	11	18933	5786	34192	13623
11-12	126.8	9.9	124.3	10.8	32402	19902	38193	15328
12-13	126.4	10	123.5	10.8	27116	12677	36842	17384
13-14	126.2	10.2	123.6	11	17568	6100	30327	11396
14-15	126.5	10.2	124.3	10.8	19360	8255	33042	16155
15-16	126.7	10.1	125.3	10.1	22106	13189	28337	13471
16-17	126.1	9.8	124.3	10.6	18414	5725	26062	8662
17-18	126.1	9.5	123.1	11.1	23329	7044	31335	11339
18-19	127	9	123.2	11.2	20513	5638	29862	10771
19-20	126.7	9.4	125.3	9.9	19790	6712	41839	23390
20-21	127.7	8.8	126.5	9.1	22723	7734	32022	11216
21-22	127.9	9	125.8	9.4	21586	8736	39723	18903
22-23	127	9.4	125.4	9.5	27410	11481	34982	17808
23-0	125.1	10.1	123.2	10.3	17977	5791	29135	12081

Regarding profit levels, it is observed that, profit performance is mainly dependent on price changes. Another important observation is lower standard deviation of profitability in low demand time intervals, compared to the reference scenario. In other words, the generator realizes almost the same profit levels but with higher certainty. In peaking time intervals, even though higher profit levels are observed, there is also higher uncertainty, indicating coupling of risk and opportunity.

Regarding generator 8, Table 4.15 displays this generator's, i) the average real load dispatched, ii) profit levels, for all time intervals under the reference and the capacitated line scenarios. In the capacitated lines scenario, this generator is one of the losers in the system, based on average load scheduled. Primarily due to its location, transmission line capacities introduce barriers to it in peaking time intervals. Accordingly, especially in the peaking time intervals, general production levels of this generator falls, compared to the reference scenario.

However, in terms of profit, generator 8 is quite a winner. Even in low demand time intervals, profit levels are higher than the reference scenario. On the other hand, except for low demand time intervals, standard deviation levels are very high compared to average profit levels. This indicates capacitated lines bringing about higher uncertainty in profitability for this agent. This uncertainty shows the risks inherent in higher profits, due to possible similar behavior of agents driving the prices to higher and / or lower levels.

In the capacitated lines scenario, generator 7 is observed as the most successful agent regarding production level increases (compared to reference scenario). Especially significant are the increases in the transient and peaking time intervals, as displayed in Table 4.16. This generators' case shows how a disadvantageous position in the network may become favorable due to capacity limitations that may be present in the network.

As a result of the success in average real load taking, the average hourly profit values of generator 7 in the capacitated lines scenario are also significantly better than the reference scenario, as displayed in Table 4.16. In low demand time intervals, standard deviations are also lower due to prices formed in the scenario. However, the peaking and transient time intervals feature standard deviations as high as average levels, indicating high uncertainty even for a successful agent.

Table 4.15. Average real load scheduled to and the profit achieved at generator 8 in the reference scenario and in the capacitated line scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Capacitated Lines Scenario		The AC-OPF Reference Scenario		The Capacitated Lines Scenario	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	35.9	11.7	38.4	12.1	9103	7317	11073	4660
1-2	40.7	12.1	37.4	12	8798	6251	11504	5226
2-3	40.1	12	34.5	11.8	7046	5501	7345	3159
3-4	42	12.7	38.3	12.7	6050	3163	6068	2376
4-5	40.5	13.3	36.4	12.1	8516	6602	6585	2663
5-6	41	13	38.4	12.7	8759	5962	5794	2361
6-7	41.2	13.2	37.6	12.7	7078	4303	7143	2882
7-8	44.8	13.7	40	12.1	9086	5180	10485	4700
8-9	49.9	14.7	39.1	11.5	12102	9442	12521	5738
9-10	48	14.3	44.4	12.2	26162	24571	18295	10971
10-11	54.9	16.5	45.1	12.5	10311	6371	19471	11759
11-12	56.3	17	45.3	12.3	22094	19771	23261	13787
12-13	54.5	16.2	40.4	12	17830	13478	21425	14382
13-14	55.2	16.2	44.7	12.5	10157	6616	17003	9519
14-15	49.7	16.3	41.1	12	11968	8627	19664	13599
15-16	48.7	18	41.2	12.3	13827	13632	16831	11538
16-17	49.5	18.2	44.4	13	10739	6635	16209	8725
17-18	51.3	18.1	45.5	13.2	14153	8565	18718	10086
18-19	52.9	17.4	45.6	13.3	11908	6439	17756	9547
19-20	57.1	17.1	46.4	12.8	12128	6615	25594	19136
20-21	57.3	16.8	45.5	12.1	13717	8450	19017	10060
21-22	57.3	15.9	45.9	12.2	13288	8910	22619	15408
22-23	56.3	16	45.6	12.6	18095	12488	19609	14364
23-0	52.3	15.1	44.2	12.6	10389	6137	17968	11322

The general situation in the capacitated transmission lines scenario can be briefly explained by examining Figure 3.9. In the reference scenario, the use of transmission lines 1, 2 and 4, that are the ones connecting buses 1, 3, 4 and 2, is not preferred, since lines 8 and 9 able to supply all the electricity of bus 5,which is the bus with highest demand. However, with the introduction of limited transmission capacity, this path become inadequate, forcing the use line 5, which connects bus 2 and 5 (but at an additional cost). Accordingly, generator 7 becomes very much competitive since other nearby generators use higher marginal cost primary fuel.

Table 4.16. Average real load scheduled to and the profit achieved at generator 7 in the reference scenario and in the capacitated line scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Capacitated Lines Scenario		The AC-OPF Reference Scenario		The Capacitated Lines Scenario	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	36.7	13.6	49.1	14	4966	5500	7976	3839
1-2	37.1	13.1	47.6	13.6	5067	4895	7162	3533
2-3	18.5	12.6	28.3	12.4	3862	4318	4795	2265
3-4	22.4	13.5	26.9	13.3	3591	2283	3535	1881
4-5	23.8	13.8	25.5	12.8	6478	5075	3854	1921
5-6	22.2	10.6	26.4	10.3	6792	4803	3713	2045
6-7	22.1	13.6	26.1	12.6	5749	3829	3810	1890
7-8	26.3	14.4	29.9	11.9	6877	4557	5843	2952
8-9	29.2	15.2	37.1	14.1	7406	7194	8763	5115
9-10	34.7	16.3	43.2	16	16686	22106	12500	9384
10-11	30.3	15.7	47.2	18.3	8997	6165	15816	11172
11-12	36.8	16.7	49	18.3	14649	18742	18624	12604
12-13	31.9	15.9	43	18.2	11552	10792	16282	13173
13-14	33.5	16	42.2	17.7	7070	5452	13108	8315
14-15	36.3	18.8	43.5	18.5	8248	6945	14077	11547
15-16	40.5	16.5	37.4	16.9	9735	11211	11887	10458
16-17	38.6	16.7	41.8	16.5	7751	5767	11781	7733
17-18	33	15.6	45.7	18.3	11626	7536	13901	9816
18-19	34.6	15.5	46.5	18.4	9840	5922	13153	8765
19-20	33.6	15.5	45.2	17.6	7563	5931	17094	17059
20-21	38.4	16.1	46.6	17	10345	7072	15500	11047
21-22	34.7	15.8	46.8	17.4	8419	7346	17319	14445
22-23	36.1	15.9	41.8	16.7	11006	10180	13842	12673
23-0	32.5	15.5	40.2	16.4	7530	4783	11811	8764

Next parameter considered is the transmission fee. Two scenarios are formed by setting the transmission fee to lower and higher levels respectively. The main aim for the construction of the scenarios is to better understand the effect of transmission cost over the electricity price formation in the system. In the low transmission fee scenario, the cost of transmitting power over a branch is taken as one third of the reference scenario (which is 0.67 $ / MW). Table 4.17 displays the low transmission fee scenario, high transmission fee scenario and the reference scenario results, regarding electricity prices and standard deviations. It can be observed that, price levels have increased significantly in all except five time intervals; (1-2, 4-5, 5-6, 8-9 and 9-10). Other time intervals show upward price level changes. Especially, the price levels for the peaking time intervals close to 21-22, feature significant price increases. This behavior indicates that the low transmission fee levels open a way of collusion behavior in the sense of independently adopted similar bidding strategies.

Figure 4.38 displays the electricity price behavior over the planning horizon for the low transmission fee scenario. The sharp price changes start by the end of first quarter, for each time interval displayed. Nevertheless, the low demand levels in time intervals 3-4, 11-12 and 17-18, force competition and avoid similar bidding behavior by the agents, thereby driving the maximum and average prices closer to reference scenario levels. Breakdown of such similar decision making trend drive the maximum and average electricity sale prices close to reference scenario levels, while time interval 21-22 demand levels support formation of similar strategies regarding profit maximization.

The next setting of considered is the high transmission fee scenario. In this scenario, the cost of transmitting power over a branch is taken as three times of the reference scenario (that is 6 \$ / MW). It can be observed that increased transmission fees help lower generation prices substantially. The pressure of the transmission prices lead to lower bidding values of generators (compared to the reference scenario) that leads to lowering of overall prices. The uncertainty in average electricity sale prices decreases in such lower price conditions, (since generator have less room for manipulation and hence the competition is not as fierce).

Figure 4.39 displays the price behavior in the time intervals 3-4, 11-12, 17-18 and 21-22. Compared to reference case, price dynamics show increasing trends until the mid year. Besides, the difference between the minimum and the maximum electricity sale prices attained, which is an indicator of the variability of the prices, is larger compared to the reference scenario.

Table 4.17. Average electricity sales prices in the reference scenario, the low transmission fee scenario and the high transmission fee scenarios for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Low Transmission Fee Scenario		The High Transmission Fee Scenario	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5	242.2	103.7	95.6	24.8
1-2	151.2	53.1	146.9	55.8	116.1	23.0
2-3	138.2	50.6	173.8	63.8	141.6	38.8
3-4	122.5	25.5	142.0	47.3	127.5	29.6
4-5	170.2	52.6	136.1	45.0	111.8	23.7
5-6	172.9	48.6	150.0	61.1	147.0	31.3
6-7	151.2	34.8	158.3	60.5	134.3	35.6
7-8	167.8	38.9	282.9	126.1	136.8	34.6
8-9	181.8	76.2	153.6	56.1	134.1	45.1
9-10	345.7	205.3	152.4	59.7	122.9	32.2
10-11	164.9	45.9	285.7	125.7	166.2	49.0
11-12	280.2	161.6	310.9	140.5	152.3	41.0
12-13	238.2	103.7	318.7	142.2	147.0	47.1
13-14	153.1	48.9	229.8	89.7	152.6	44.1
14-15	170.6	66.1	250.0	108.8	134.9	33.6
15-16	193.2	106.6	218.8	90.0	129.1	33.5
16-17	163.0	45.0	188.2	69.2	120.7	34.9
17-18	203.7	55.3	204.5	81.5	163.2	45.0
18-19	178.9	48.8	237.5	97.6	165.7	45.9
19-20	172.6	53.6	338.3	155.5	160.9	44.1
20-21	194.6	63.0	265.0	109.0	137.2	41.1
21-22	186.7	69.6	462.6	220.3	127.4	37.4
22-23	240.1	94.0	237.4	115.5	126.4	36.5
23-0	160.5	48.0	204.5	90.5	103.0	27.1

In summary, these scenarios indicate that raising or lowering transmission fee is an effective parameter in electricity price formation. Higher fees led to pressure over the generators, which lowers price levels and variability simultaneously. This effect is mainly due to the generators at the buses which are far away from the high demand points. On the other hand, lower fees open the door for price manipulations, which elevate the price levels and increase the variability considerably.

Figure 4.38. Impacts of low transmission fee scenario on electricity sales prices at the selected time intervals (AC OPF case)

Figure 4.39. Impacts of high transmission fee scenario on electricity sales prices at the selected time intervals (AC OPF case).

As displayed in Table 4.18, lower transmission fees have a negative effect on generator 9, regarding the average load taken. This case highlights how lower transmission fees can reduce the local market power of a generator: Since transmission of power between buses is now cheaper (compared to the reference scenario), the high marginal cost generator 9 suffers from this parameter change.

Table 4.18. Average real load scheduled to and the profit achieved at generator 9 in the reference scenario and in the low transmission fee scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Low Transmission Fee Scenario		The AC-OPF Reference Scenario		The Low Transmission Fee Scenario	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	29.3	9.1	26	10.8	4263	3978	8377	6270
1-2	32.9	9.6	25.3	10.8	4090	3183	4175	2801
2-3	32.3	10	24.6	10.7	2734	1835	4968	3378
3-4	34.6	10.4	25.2	10.7	3084	1598	3679	2401
4-5	34.8	10.4	24.7	11.2	4616	3394	3401	2182
5-6	34.5	9.8	25.1	11.2	4239	2567	4123	3034
6-7	34.5	9.7	24.9	11.7	3687	2003	4224	2847
7-8	36.2	10.1	26.8	11.1	4555	2443	8227	5692
8-9	40.6	11.1	30.7	12.3	6303	5059	5009	3211
9-10	40.1	11.1	35.1	13	14436	15171	5545	3504
10-11	44.7	12.4	36.7	13.2	6154	3692	12150	8221
11-12	45.7	12.7	35.2	13	12218	12627	13248	10065
12-13	44.5	12.4	35.2	13.1	9096	7477	13363	9786
13-14	44.7	12.2	34.5	12.9	5833	3900	9232	5634
14-15	39.7	11.3	35.2	13	6053	4345	10083	7097
15-16	40.1	12.2	34.3	12.9	7961	8260	8478	5584
16-17	41.1	13.3	34	13.3	6067	3925	7108	4738
17-18	41.1	12.1	35.9	14	7599	4409	8046	5312
18-19	41.9	11	36.3	14.4	5959	2704	9680	6243
19-20	45.4	11.4	36.9	14.2	6732	4228	14638	10327
20-21	45.2	11.7	37.9	13.4	7596	4677	11442	7128
21-22	45.8	11.6	35.3	12.7	6360	3845	21048	15831
22-23	45.2	11.6	35.3	12.8	8212	5511	9785	6853
23-0	41.9	11.3	32.3	12.7	5493	3276	7654	5562

However, the negative effect of lower transmission fees cannot be seen in profit levels, due to the increase in prices (except in time intervals 4-5 and 9-10). This is mainly due to the price decreases in those time intervals. The effect of higher prices counters lesser average load taken and the profit performance is better than the reference scenario. However, standard deviations and thus uncertainty are higher, due higher price and load uncertainties.

Lower transmission fees have a positive effect on the performance of generator 7. As displayed in Table 4.41, the average load levels scheduled to this generator increases. The case of generator 7 serves as a good example how a generator may become competitive by changes in transmission fees. Since this generator is far away from the high demand buses, the reference scenario transmission fee pushed the generator to a disadvantageous state, while lower fees allow generator 7 bid for and carry more active load in the system.

Profit levels of generator 7, supported by the increased average real load taken, show increase in every time interval (except intervals 4-5 and 9-10 where price behavior shows significant decreases). The higher standard deviations, (comparable and higher than the average profit levels), indicate higher uncertainty in profit realization due to the competitive behavior of the opponents in the market.

In the high transmission fee scenario, generator 7 is the loser due to its disadvantageous location in the network. Loss of load is at substantial levels in every time interval considered. Nearly 50% of the load is lost compared to the reference scenario (the loss is lesser only in the peaking time interval 21-23.). This indicates how a generator may be pushed out of the production mix if transmission fee is increased to further levels as compared to the reference case.

As displayed in Table 4.20, profit levels of generator 7 have also decreased dramatically. This however is expected, since both load assigned to generator 7 and generation prices in general have decreased in this scenario. Highest profitability is attained in the transient time interval 10-11. It may be conjectured that due to changing demand levels of the transition periods, less flexible competitors are less able in price / bid manipulation.

Table 4.19. Average real load scheduled to generator 7 in the reference scenario, the low transmission fee scenario and high transmission fee scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The Low Transmission Fee Scenario		The High Transmission Fee Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0	36.7	13.6	62.7	16.6	13.1	10.8
1	37.1	13.1	46.0	15.7	12.9	8.8
2	18.5	12.6	39.7	16.7	11.5	8.8
3	22.4	13.5	41.4	16.1	10.6	8.3
4	23.8	13.8	41.3	16.1	9.4	7.6
5	22.2	10.6	40.3	15.8	11.6	8.3
6	22.1	13.6	41.4	16.0	11.8	8.8
7	26.3	14.4	45.7	16.6	11.9	8.6
8	29.2	15.2	51.8	17.9	14.4	10.5
9	34.7	16.3	55.5	19.1	14.7	11.2
10	30.3	15.7	57.7	19.3	17.6	12.7
11	36.8	16.7	58.4	19.4	18.1	12.7
12	31.9	15.9	55.6	18.4	17.0	12.7
13	33.5	16.0	56.9	19.0	17.6	13.0
14	36.3	18.8	57.2	20.4	16.3	12.2
15	40.5	16.5	57.0	19.1	15.4	12.1
16	38.6	16.7	55.2	19.1	14.8	13.1
17	33.0	15.6	56.3	19.6	19.3	15.4
18	34.6	15.5	59.1	20.7	20.3	15.7
19	33.6	15.5	59.6	20.1	18.2	14.8
20	38.4	16.1	59.5	19.7	17.4	14.3
21	34.7	15.8	57.0	18.8	31.3	13.7
22	36.1	15.9	56.1	18.2	30.0	12.9
23	32.5	15.5	55.7	17.3	28.1	12.1

Just like the case of generator 7, generator 5 also suffers from high transmission fees. As displayed in Table 4.21, the resulting outcome is similar, but the load loss is less compared generator 7 (10%-20% load loss is observed in general). As expected, the loss is higher in low demand time intervals, and less in peaking time intervals. As displayed in Table 4.21, profitability of generator 5, also shows significant decreases due to general price drops and loss of average load for this generator.

Table 4.20. Average profit of generator 7 in the reference scenario, the low transmission fee scenario and high transmission fee scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The Low Transmission Fee Scenario		The High Transmission Fee Scenario	
Hours	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0	4966	5500	12304	10336	1670	1043
1	5067	4895	6966	4129	2292	1452
2	3862	4318	8249	6292	2745	1949
3	3591	2283	6958	5160	1942	1056
4	6478	5075	5902	3968	1516	746
5	6792	4803	6713	5401	2568	1448
6	5749	3829	7299	4799	2193	1328
7	6877	4557	14337	13373	2299	1300
8	7406	7194	7953	4790	2779	2140
9	16686	22106	9297	5332	3061	2264
10	8997	6165	17289	12908	5039	3785
11	14649	18742	16788	14806	3944	2773
12	11552	10792	18347	14525	3949	2940
13	7070	5452	13621	9501	3753	2453
14	8248	6945	14688	10984	3374	2220
15	9735	11211	12993	8110	2775	1837
16	7751	5767	10341	8049	2543	1868
17	11626	7536	11592	7859	4156	2802
18	9840	5922	14002	9307	4602	3094
19	7563	5931	19717	15999	4567	3313
20	10345	7072	17296	12072	3353	2619
21	8419	7346	26630	25083	3345	2298
22	11006	10180	14147	9580	3155	1926
23	7530	4783	11008	8063	2127	1104

In the high transmission fee scenario, generator 6 is the most successful generator in terms of load scheduled. As displayed in Table 4.22, the average load taken is higher than the reference scenario and standard deviation levels are smaller, for each time interval. Average load has increased; hitting the capacity limit (which is 133 MW). Besides, as can be observed in Figure 4.40, variability decreases as time intervals approach peaking time intervals.

Table 4.21. Average real load scheduled to and the profit achieved at generator 5 in the reference scenario and in the high transmission fee scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The High Transmission Fee Scenario		The AC-OPF Reference Scenario		The High Transmission Fee Scenario	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	67.6	11.5	52.2	9.2	9024	6650	4001	1395
1-2	48	10.3	38.1	7.3	9147	6317	4451	1789
2-3	52.7	10.4	42.4	7.6	8602	6272	5831	2704
3-4	46.2	9.8	37.3	7.1	6191	3119	4851	1752
4-5	47.6	10.1	37.1	7	9516	6397	4113	1326
5-6	46.7	9.8	37.2	8	10193	6096	5717	2200
6-7	47.4	10	38.2	7.9	8637	4517	5184	1896
7-8	50.9	11.3	39.9	8.2	9210	4696	5534	2019
8-9	60.5	13.1	53.2	10.5	12195	8926	6386	2739
9-10	73.3	14	54.7	11.4	26266	20895	6567	2749
10-11	66	13.5	57.4	11.2	12041	5999	9948	4481
11-12	70.7	14	58.8	11.5	21682	16194	9047	3359
12-13	66.4	13.1	55.4	10.6	18263	12053	8506	4012
13-14	68.2	13.6	56.2	11	10847	5819	8845	3420
14-15	74.2	13.9	55.9	11.3	13128	7707	7512	2934
15-16	71.4	13.9	54.7	11	13988	10521	7020	2724
16-17	67.8	13.8	55.7	11.2	11728	5912	6578	2851
17-18	72.9	13.1	58	12.2	15873	7352	9699	3640
18-19	74.6	13.2	58.5	12.1	14100	5730	9712	3594
19-20	69.9	12.9	58.5	10.9	12628	5997	9641	4063
20-21	73	12.2	64.9	9.6	15638	7496	8209	3221
21-22	70	11.5	59.6	8.7	15255	8912	7503	2854
22-23	69.4	12	57.1	9.1	20201	12148	6989	2703
23-0	63.5	11.4	55.5	8	10929	5450	5016	1847

The profitability of generator 6, under the high transmission fee scenario is displayed in Table 4.22. Compared to the reference scenario, profitability of even this most successful generator is lesser (due to the lowering of generation prices, even though the scheduled loads are larger). However, the standard deviations are lower compared to the reference scenario's and other generators' standard deviations. This decreases in uncertainty (in profitability) may be due to the increased market power as generator 6 in the high transmission fee scenario (it's biddings are more successful leading to higher loads and less variability).

Table 4.22. Average real load scheduled to and the profit achieved at generator 6 in the reference scenario and in the high transmission fee scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The High Transmission Fee Scenario		The AC-OPF Reference Scenario		The High Transmission Fee Scenario	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	123.9	12	128.5	11.3	14820	6852	11024	3037
1-2	118.7	11.8	125.3	10.4	14972	6220	13199	2840
2-3	116.9	12	122	11.4	13112	5709	15809	4513
3-4	113.6	12.8	120.6	11.9	11980	3167	14334	3473
4-5	113.3	12.3	121.5	11.3	16574	6027	12623	2876
5-6	113.7	12.4	119.4	12	16509	5528	16414	3756
6-7	114.1	12.5	120.4	11.9	14864	4071	15142	4132
7-8	115.9	12.9	123.2	11.4	17051	4650	15647	4093
8-9	123.4	11.5	128	9.9	19813	9012	15926	5646
9-10	125.9	10.5	130.3	8.8	39308	24938	14796	4183
10-11	127.2	9.5	129.8	8.6	18933	5786	20170	6223
11-12	126.8	9.9	130.1	8.4	32402	19902	18580	5238
12-13	126.4	10	130	8.7	27116	12677	17846	6057
13-14	126.2	10.2	129.8	8.8	17568	6100	18610	5628
14-15	126.5	10.2	129.8	8.9	19360	8255	16296	4333
15-16	126.7	10.1	129.9	8.9	22106	13189	15621	4324
16-17	126.1	9.8	130.2	8.3	18414	5725	14566	4526
17-18	126.1	9.5	129.2	8.3	23329	7044	19958	5760
18-19	127	9	129.3	8.1	20513	5638	20221	5887
19-20	126.7	9.4	130.1	7.9	19790	6712	19687	5707
20-21	127.7	8.8	131	7.8	22723	7734	16817	5348
21-22	127.9	9	131	7.8	21586	8736	15476	4805
22-23	127	9.4	131	7.9	27410	11481	15412	4779
23-0	125.1	10.1	130.7	8.3	17977	5791	12279	3475

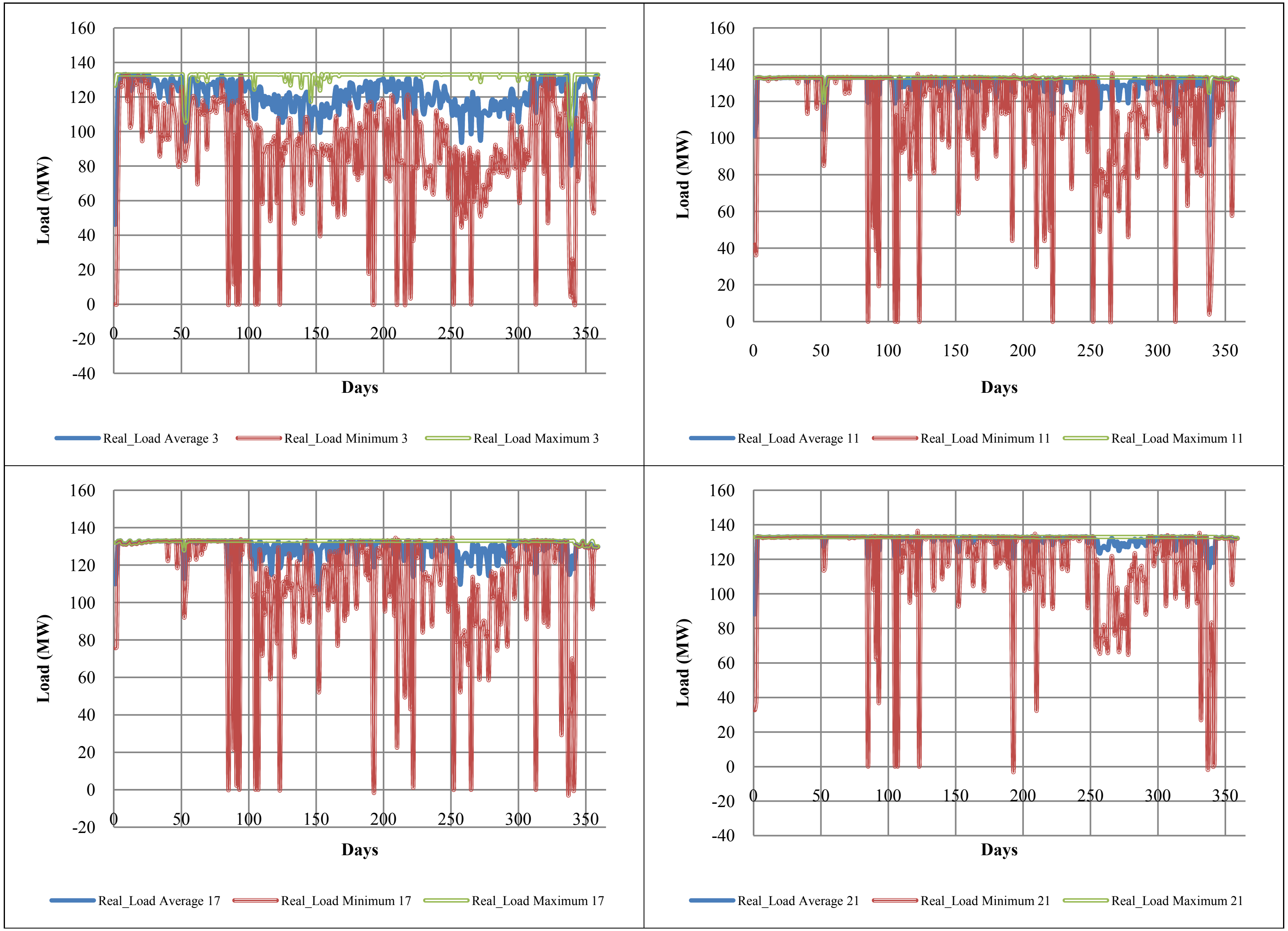

Figure 4.40. Impacts of high transmission fee scenario on real load behavior of generator 6 at the selected time intervals (AC OPF case).

4.2.2. Response Comparisons of the Bidding Algorithms

The scenarios considered in this section are intended to facilitate a better understanding of the learning effects deployed in the bidding strategies, under the AC OPF model.

The impacts of various learning effects are analyzed by first investigating the electricity prices behavior at selected time intervals. Next, the generators responses under the new settings are investigated to see the effects of the learning algorithms. Table 4.23 displays the electricity prices under the “Market Share learning effects based” bidding strategy, “Market Power learning based” bidding strategy and the “Learning by Price Tracking based” bidding strategy.

First, the Market Share algorithm is analyzed. As can be observed from this table, average electricity prices in all time intervals have declined substantially, compared to the reference scenario. Additionally, the decline in the standard deviations are significant in every time interval (especially for the transient demand time intervals). It is conjectured that this reduction in electricity price variations is caused by the introduced component of competition, market share maximization. Accordingly, the algorithm is regarded as successful both in terms of lowering the electricity price and its standard deviation.

Figure 4.41 displays the price behavior in time intervals 3-4, 11-12, 17-18 and 21-22. Compared to the reference scenario, maximum prices are at substantially lower levels. Additionally, just like the case in the reference scenario time interval 11-12, there is no continuously increasing price trend. This learning algorithm seems to negate the formation of similar strategies regarding profit maximization that drives the prices to higher levels. It can be said that; competition for market share leads to lower prices and lower price variation simultaneously.

As the next step, the electricity prices during the planning horizon, under the “Market Power learning based” bidding strategy is investigated. As can be observed from the table, each time interval shows different price responses, compared to the reference scenario. Generally, a decrease in price levels is observed in low and transient demand time intervals. Price drops are not substantial, but significant compared to the reference scenario. For peaking time intervals, decreases in prices are not significant, while some price increase is seen for the time interval 18-19.

Figure 4.42 displays the price behavior of the time intervals 3-4, 11-12, 17-18 and 21-22. The upward trend in price behavior (compared to the reference scenario) that was visible in the previous bidding strategy can no longer be observed. In addition, the average electricity sale prices are smooth, relative to the reference scenario, while maximum prices have a tooth saw pattern in general.

On the overall, the purposed strategy smoothes down the prices in non-peak time intervals. Higher prices in peaking time intervals lead to lesser prices at non-peak time intervals (to be operational close to peak times), which is in line with the objective of the strategy; maximizing profit while minimizing uncertainty.

Finally, “Learning by Price Tracking based” bidding strategy is investigated. The standard deviations are higher by ten fold compared to the reference scenario and any other learning based pricing strategy, which leads to standard deviations larger than average electricity prices in certain time intervals. The standard deviations indicate very high level of uncertainty in price levels, which makes it harder to form an expectation for future price levels based on previous data. Since the self reinforcing learning algorithm, which forms the basis for the bidding process, rely on expectations, this situation effects the decision-making processes of the generators significantly.

The effect of the Price Tracking strategy over electricity price behavior is displayed in Figure 4.43. The abrupt price changes in the figure, shows how a real world situation under inelastic demand may go out of control if there is no control of the authority over price abuse in bidding.

Table 4.23. Average electricity sales prices in the reference scenario, under the Market Share bidding strategy, the Price Tracking based bidding strategy, the Market Power bidding strategy for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Price Tracking Bidding Strategy		The Market Share Bidding Strategy		The Market Power Bidding Strategy	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5	250.6	147.5	97.9	19.2	128.6	30.3
1-2	151.2	53.1	293.9	220.3	118.0	27.0	148.8	31.7
2-3	138.2	50.6	295.5	326.6	99.2	17.6	131.6	26.3
3-4	122.5	25.5	214.5	199.5	79.6	14.3	133.7	26.6
4-5	170.2	52.6	176.9	136.5	72.1	13.6	118.4	22.1
5-6	172.9	48.6	249.5	181.3	91.1	18.3	141.0	29.2
6-7	151.2	34.8	252.6	174.5	83.1	13.9	135.2	27.8
7-8	167.8	38.9	297.5	328.4	95.2	19.2	116.6	25.0
8-9	181.8	76.2	206.1	120.2	81.2	17.5	187.8	58.6
9-10	345.7	205.3	310.1	318.0	90.7	16.8	113.4	22.9
10-11	164.9	45.9	374.7	334.7	88.3	18.2	135.2	37.4
11-12	280.2	161.6	374.5	279.9	111.5	30.4	229.3	78.3
12-13	238.2	103.7	483.8	524.0	117.5	32.2	236.0	76.5
13-14	153.1	48.9	332.8	280.0	136.9	36.4	265.5	100.7
14-15	170.6	66.1	415.3	343.4	102.0	23.9	234.9	76.6
15-16	193.2	106.6	340.0	299.7	106.7	17.6	122.5	27.0
16-17	163.0	45.0	414.7	436.7	103.3	23.0	128.4	35.8
17-18	203.7	55.3	368.5	309.1	120.2	25.2	200.4	46.9
18-19	178.9	48.8	364.3	313.8	106.5	25.0	246.0	85.9
19-20	172.6	53.6	302.5	237.7	136.2	38.5	162.5	36.1
20-21	194.6	63.0	337.8	265.6	125.2	30.6	165.5	52.4
21-22	186.7	69.6	261.9	167.0	103.7	31.3	188.8	63.8
22-23	240.1	94.0	250.1	196.5	104.2	27.0	126.3	25.0
23-0	160.5	48.0	252.0	196.6	66.1	11.4	141.6	32.3

Figure 4.41. Impact of the Market Share based bidding strategy on electricity prices at the selected time intervals (AC OPF case).

Figure 4.42. Impact of the Market Power based bidding strategy on electricity prices at the selected time intervals (AC OPF case).

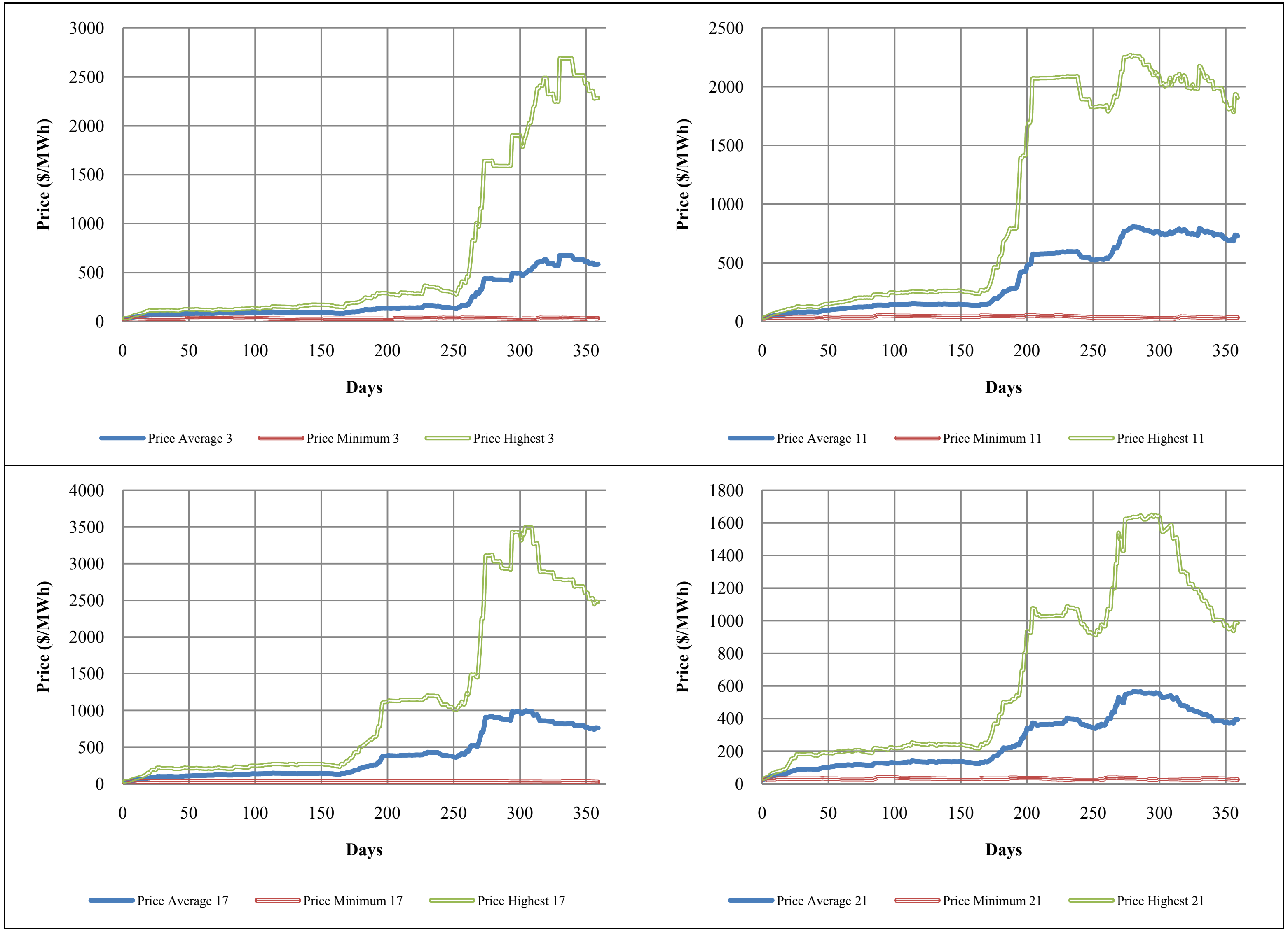

Figure 4.43. Impact of the Price Tracking based bidding strategy on electricity prices at the selected time intervals (AC OPF case).

As displayed in Table 4.24, under the Market Share based bidding strategy, generator 1 loses some of its scheduled load, especially in time intervals 14-18. For other time intervals, the average load taken is close to the reference scenario load levels. In this case, generator 1 is neither the winner nor the loser in terms average load levels.

Table 4.24 The average real load scheduled to and the profit achieved at generator 1 in the reference scenario and in the Market Share based bidding scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Market Share Bidding Strategy		The AC-OPF Reference Scenario		The Market Share Bidding Strategy	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	25.2	5.1	21.7	4.2	2377	1467	1595	423
1-2	16.8	3.5	16.7	3.3	2201	1109	1696	457
2-3	18.5	3.7	18.1	3.9	1720	733	1416	358
3-4	16	3.2	15.9	3.2	1674	551	1050	264
4-5	15.8	3.1	18.6	3.6	2351	1239	940	214
5-6	15.9	3.2	17.4	3.6	2179	841	1212	306
6-7	16	3.4	16.2	3.7	1954	668	1070	254
7-8	16.8	3.5	16.8	3.6	2370	833	1299	330
8-9	19.6	4	20	3.9	3176	1895	1256	324
9-10	25.7	4.8	21.6	4.1	7051	5851	1610	365
10-11	22.1	4	26.4	4.8	3132	1306	1636	433
11-12	22.4	4.2	22.7	4.6	5897	4798	2111	639
12-13	21.5	3.9	21.4	3.8	4567	2745	2101	649
13-14	21.7	3.9	21.4	3.9	2931	1444	2559	736
14-15	25.6	4.8	21.6	3.9	3145	1625	1799	498
15-16	24.6	5.1	21.3	4	3943	3274	1995	512
16-17	22.6	5.4	21.5	4.3	3141	1444	1866	513
17-18	25.9	5.4	22.1	4.9	3827	1518	2284	571
18-19	26.1	4.8	23.1	6	3246	959	1912	503
19-20	22.4	4.1	26.2	4.5	3444	1465	2783	901
20-21	24.3	5	23.3	4.3	3901	1605	2498	609
21-22	22.6	3.7	24.5	5.3	3450	1495	1900	578
22-23	22.1	3.6	26.4	3.8	4410	2066	1969	501
23-0	20.9	4.1	30.9	5.9	2841	1197	1169	228

Even though load levels has not changed much (except in time interval 14-18), average profit of generator 1 falls substantially, mainly due to price level changes, as displayed in Table 4.24. Additionally, standard deviations are significantly lower compared to the reference scenario. Furthermore, ratio of the standard deviation to the average profit (of generator 1) is relatively low compared to other generator agents under the same bidding strategy and in the reference scenario. Both findings indicate higher certainty for profit levels.

Table 4.25. The average real load scheduled to and the profit achieved at generator 4 in the reference scenario and in the Market Share based bidding scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Market Share Bidding Strategy		The AC-OPF Reference Scenario		The Market Share Bidding Strategy	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	46.3	13.9	58.5	16	11258	8928	6443	3020
1-2	48.2	13.6	55	15.9	11262	7876	8408	4790
2-3	45.3	13.5	48.4	15.1	9722	7046	6163	3033
3-4	47.1	14.2	49.4	15.7	7840	4120	4333	2185
4-5	46.5	15.8	47.1	15	11624	8282	3741	2007
5-6	47.4	15.7	50.1	14.1	11590	7532	5419	3042
6-7	47.4	15	53.4	14.3	9582	5675	4748	2233
7-8	51	16.4	56.5	15.8	11487	6384	6074	2919
8-9	62.6	18.8	67.9	17.7	14641	11609	5171	2686
9-10	68	19.7	77.4	20.1	33767	30560	6547	2714
10-11	75.1	20.7	76.8	20.6	12419	7813	6293	2864
11-12	74	19.9	81.1	20.8	26352	23680	9122	4848
12-13	71	19.8	77.2	20.3	21302	16174	9506	5144
13-14	70.9	20.1	77.9	21.3	12220	7818	11520	5991
14-15	65.4	21	78.1	21.5	14205	9675	7920	3991
15-16	64.6	21.7	76.2	21.8	16746	16155	7714	3202
16-17	66.7	23.4	76.4	21.7	12925	8073	7529	3654
17-18	69.6	23	79.5	22.3	15961	9828	9551	4186
18-19	70.6	23.2	81.3	22.2	13463	8647	8472	4144
19-20	75.7	21.5	79.2	20.3	14206	8595	11859	6541
20-21	75.3	19.9	85.6	19.1	16517	10228	10672	5471
21-22	75.1	19.1	83.6	18.8	16261	10801	8830	5085
22-23	72.5	19.2	77.1	18	22065	15081	8314	4195
23-0	65.6	18.1	61.2	16.6	12051	7663	3756	1653

As displayed in Table 4.25, generator 4 is the successful generator in terms of average load increase, nearly for all time intervals, as displayed in Table 4.25. The level of load increase is highest at the peaking time intervals 17-18, and 21-22, with the transient time intervals following the peaking time intervals. The increase in load levels does not significantly affect the standard deviations, while a decreasing trend is observed close to peaking time intervals.

Even though generator 4 is regarded as successful with respect to the increases in real load levels, profit levels show substantial decreases compared to the reference scenario (as displayed in Table 4.25). The success of real load increase prevents further profit decrease.

As displayed in Table 4.26, generator 7 loses substantial amount of real load in most time intervals, under the Market Share bidding strategy. This situation can be explained with the long minimum up and down times of this generator resulting in long time intervals without load that leads to unprofitability. In addition, price levels are not sufficiently high to compensate startup costs; thus the generator prefers to bid higher prices and take fewer load assignments, while maintaining profitability.

The profit of generator 7 shows substantial decreases compared to the reference scenario, as displayed in Table 4.26. Two main underlying dynamics causes this outcome; i) prices shifting to lower levels, ii) loss of load (to other agents) because of the high competition during the planning horizon.

Table 4.26. The average real load scheduled to and the profit achieved at generator 7 in the reference scenario and in the Market Share based bidding scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Market Share Bidding Strategy		The AC-OPF Reference Scenario		The Market Share Bidding Strategy	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	36.7	13.6	23.5	13.9	4966	5500	2609	1485
1-2	37.1	13.1	23	13.3	5067	4895	3288	2143
2-3	18.5	12.6	21.2	12	3862	4318	2581	1493
3-4	22.4	13.5	29	14.2	3591	2283	1886	974
4-5	23.8	13.8	16.5	12.8	6478	5075	1430	838
5-6	22.2	10.6	18.4	9.2	6792	4803	2044	1202
6-7	22.1	13.6	18.2	12.8	5749	3829	1765	1076
7-8	26.3	14.4	23.1	13.2	6877	4557	2369	1436
8-9	29.2	15.2	24.9	14.1	7406	7194	2206	1478
9-10	34.7	16.3	29.7	14.9	16686	22106	2577	1337
10-11	30.3	15.7	30	15.4	8997	6165	2991	1784
11-12	36.8	16.7	33.6	16	14649	18742	3999	2453
12-13	31.9	15.9	31.4	15.3	11552	10792	4089	2792
13-14	33.5	16	35.2	15.9	7070	5452	5098	3047
14-15	36.3	18.8	32.4	15.2	8248	6945	3581	2016
15-16	40.5	16.5	31.8	15.4	9735	11211	3646	1845
16-17	38.6	16.7	33.2	15.4	7751	5767	3886	2165
17-18	33	15.6	34.5	16.5	11626	7536	4390	2458
18-19	34.6	15.5	29.6	15	9840	5922	3518	2221
19-20	33.6	15.5	33.4	16.5	7563	5931	5228	4101
20-21	38.4	16.1	32.7	16.1	10345	7072	4798	3016
21-22	34.7	15.8	28.2	14.7	8419	7346	3125	2618
22-23	36.1	15.9	32.3	15.3	11006	10180	3508	2171
23-0	32.5	15.5	26.3	14.2	7530	4783	1889	923

The Market Power strategy does not change the generators' load assignments significantly. The main profit change is driven by price behavior. Table 4.27 displays the profit of generator 5. The profit change with respect to reference scenario is very similar for every generator agent (higher profit at peak demand times, lower profits at non peak time intervals). Table 4.27 also summarizes the profit situation for all generators.

Table 4.27. The average real load scheduled to and the profit achieved at generator 5 in the reference scenario and in the Market Power based bidding scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The Market Power Bidding Strategy	
Hours	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	9024	6650	8214	3647
1-2	9147	6317	9121	3863
2-3	8602	6272	8080	3383
3-4	6191	3119	8180	3434
4-5	9516	6397	6979	2867
5-6	10193	6096	8918	3657
6-7	8637	4517	8005	3245
7-8	9210	4696	7535	3292
8-9	12195	8926	16078	8143
9-10	26266	20895	7636	2967
10-11	12041	5999	10013	4373
11-12	21682	16194	20408	9816
12-13	18263	12053	20841	10278
13-14	10847	5819	23483	12566
14-15	13128	7707	21002	10757
15-16	13988	10521	8939	3533
16-17	11728	5912	9228	4616
17-18	15873	7352	17260	6730
18-19	14100	5730	21985	11243
19-20	12628	5997	12882	4701
20-21	15638	7496	13868	6706
21-22	15255	8912	16105	8065
22-23	20201	12148	9724	3129
23-0	10929	5450	10381	3897

Generator 4 turns the new situation into an advantage by taking more load relative to the reference scenario as seen in Table 4.28. Especially in peaking time intervals, the increase in real load levels is coupled with lower standard deviations. This indicates the higher level of certainty of the average load increase. Generally, difference between the reference scenario and the scenario implementing the price tracking bidding strategy is between 5-10 MW.

As displayed in Table 4.28, the profitability of generator 4 shows a fluctuating performance compared to the reference case. During high demand time intervals 11-21, profit levels are well above the reference case. For other time intervals, profit levels are less compared to the reference case. Even though load assigned to generator increase nearly for all time intervals, the dominant effect of price increase is observed over the profitability. Besides, very high levels of standard deviations (compared to average prices) are seen in some cases, which highlights the inherent high level of uncertainty that makes the average values a weak estimate of the expected profit levels. The situation also indicates the ongoing fierce competition.

Table 4.28. The average real load scheduled to and the profit achieved at generator 4 in the reference scenario and in the Price Tracking based bidding scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Price Tracking Bidding Strategy		The AC-OPF Reference Scenario		The Price Tracking Bidding Strategy	
	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	46.3	13.9	55.7	14.4	11258	8928	16130	12468
1-2	48.2	13.6	49.8	12.4	11262	7876	17011	16420
2-3	45.3	13.5	46.8	12.5	9722	7046	13104	20567
3-4	47.1	14.2	49	13	7840	4120	9598	13607
4-5	46.5	15.8	49.2	13.2	11624	8282	8928	9862
5-6	47.4	15.7	52.1	13.5	11590	7532	13830	13220
6-7	47.4	15	56.7	15	9582	5675	16668	14816
7-8	51	16.4	53.2	14.1	11487	6384	13252	21070
8-9	62.6	18.8	66	17.4	14641	11609	14226	9972
9-10	68	19.7	74.5	19.5	33767	30560	18779	25111
10-11	75.1	20.7	80.6	19.9	12419	7813	23776	25221
11-12	74	19.9	83.4	20.6	26352	23680	29384	26674
12-13	71	19.8	72.2	18.9	21302	16174	27566	39758
13-14	70.9	20.1	78.3	19.9	12220	7818	22231	22943
14-15	65.4	21	73.8	19.2	14205	9675	30563	30136
15-16	64.6	21.7	63.7	17.5	16746	16155	21805	22985
16-17	66.7	23.4	65	18.8	12925	8073	24869	35243
17-18	69.6	23	72	19.8	15961	9828	26045	26795
18-19	70.6	23.2	75.3	21	13463	8647	25777	28137
19-20	75.7	21.5	83.1	20.3	14206	8595	21784	21439
20-21	75.3	19.9	84.5	18.3	16517	10228	22771	20798
21-22	75.1	19.1	84.2	18	16261	10801	18840	13719
22-23	72.5	19.2	81.6	17.8	22065	15081	16966	15552
23-0	65.6	18.1	67.8	15.7	12051	7663	16041	14462

The electricity prices during the planning horizon under the "Combined learning based" bidding strategy are displayed Table 4.29. As can be observed, prices increase substantially in every time interval. Besides, by the combined effect of market share and market power strategies, the standard deviations are lowered compared to the price tracking strategy. The level of standard deviation is still higher than the reference scenario, but low enough to form a healthy expectation for future price levels based on previous data.

Figure 4.44 displays the price behavior under the "combined learning strategy". Prices show a diverging behavior (in other words, the maximum and minimum prices are moving apart from each other, except for the time interval 3). It is conjectured that this situation is due to inelastic demand and to the oligopolistic behavior opportunities arising from the network layout. Accordingly, further control policies are needed to overcome the issue.

Table 4.29. Average electricity sales prices in the reference scenario and under the Combined bidding strategies, for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Combined bidding strategies	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price	Standard Deviation of Price
0-1	143.0	58.5	251.6	101.9
1-2	151.2	53.1	309.5	165.6
2-3	138.2	50.6	183.2	62.7
3-4	122.5	25.5	189.5	61.8
4-5	170.2	52.6	147.2	44.8
5-6	172.9	48.6	177.9	61.2
6-7	151.2	34.8	234.9	93.5
7-8	167.8	38.9	218.5	90.8
8-9	181.8	76.2	233.7	92.6
9-10	345.7	205.3	201.3	83.3
10-11	164.9	45.9	335.9	183.5
11-12	280.2	161.6	343.1	196.4
12-13	238.2	103.7	231.3	116.5
13-14	153.1	48.9	311.9	176.8
14-15	170.6	66.1	379.9	250.3
15-16	193.2	106.6	220.0	113.3
16-17	163.0	45.0	423.3	276.1
17-18	203.7	55.3	304.3	144.3
18-19	178.9	48.8	278.1	121.5
19-20	172.6	53.6	330.1	171.5
20-21	194.6	63.0	247.5	83.7
21-22	186.7	69.6	225.6	93.7
22-23	240.1	94.0	444.7	285.1
23-0	160.5	48.0	163.7	45.7

Figure 4.44. Impact of the combined bidding strategies on electricity prices at the selected time intervals (AC OPF case).

4.2.3. Structural Modifications and Responses

In this section, the impact of various structural changes in the network is investigated. Analysis includes shift of demand between buses, introduction of new generators to the selected buses. Selection of the buses is based on number of connections, the distance to high demand nodes and the distribution of the generation capacity.

Structural modification analysis starts with a demand shift scenario. The demand levels that are displayed in Table 3.10 are modified such that demand of buses 2 and 5 are interchanged to reflect a new demand profile over the network. Power user agents 1 and 4 replaced accordingly (these changes are expected to eliminate the advantageous position of generator 6).

Table 4.30 displays electricity prices under the reference and the demand shift scenarios. The effect of interchanging power users 1 and 4 on the network is observed as decreasing prices at non-peak demand times (17 out of 24 prices declines). The change is especially substantial in low demand time intervals. The increase in prices in peak demand time intervals is insignificant compared to the decline in price at non-peak times.

Figure 4.45 displays electricity price behavior under the demand shift scenario. Price behavior also shows the price decline at the low demand time interval 3-4. The average, maximum, and minimum prices attained show converging behavior around $80, with lower variation compared to the reference scenario. The transition demand time interval 11-12 shows a similar behavior at that of the time interval 3-4, except that the variation is higher in magnitude and distributed more homogenously in the planning horizon.

The resulting price behavior shows the importance of physical location of the demand nodes and the network layout over price formation. This highlights the need of policies for siting the power plants with an eye to overcome monopolistic / oligopolistic behavior in the market. This is crucial for market stability and efficiency.

Table 4.30. Average electricity sales prices in the reference scenario and in the Demand shift scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The Demand Shift (Bus 2-5) Scenario	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5	114.1	34.0
1-2	151.2	53.1	117.6	33.4
2-3	138.2	50.6	103.8	26.6
3-4	122.5	25.5	82.4	20.7
4-5	170.2	52.6	86.4	22.9
5-6	172.9	48.6	108.9	24.2
6-7	151.2	34.8	109.0	33.0
7-8	167.8	38.9	104.9	35.6
8-9	181.8	76.2	152.8	69.6
9-10	345.7	205.3	181.7	85.6
10-11	164.9	45.9	201.0	86.6
11-12	280.2	161.6	119.2	35.9
12-13	238.2	103.7	140.3	56.3
13-14	153.1	48.9	115.1	32.4
14-15	170.6	66.1	165.1	51.2
15-16	193.2	106.6	107.9	28.9
16-17	163.0	45.0	156.7	56.8
17-18	203.7	55.3	189.0	81.6
18-19	178.9	48.8	190.3	61.1
19-20	172.6	53.6	180.3	62.8
20-21	194.6	63.0	212.5	63.8
21-22	186.7	69.6	206.5	99.3
22-23	240.1	94.0	184.0	74.3
23-0	160.5	48.0	142.7	51.8

Figure 4.45. Impact of the demand shift on electricity prices at selected time intervals (AC OPF case).

Table 4.31 displays the average real load scheduled to generator 4, under the demand shift scenario. As can be observed, the average load scheduled to this generator increases significantly in all time intervals. generator 4 now has a more advantageous position on the network (compared to the reference scenario), and it deploys this relative market power to increase its load levels.

Table 4.31. Average real load scheduled to generator 4 in the reference scenario and in the demand shift (bus 2-5) scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The Demand Shift (Bus 2-5) Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	46.3	13.9	113.4	21.4
1-2	48.2	13.6	105.0	20.6
2-3	45.3	13.5	94.5	19.5
3-4	47.1	14.2	106.1	19.7
4-5	46.5	15.8	108.3	20.7
5-6	47.4	15.7	101.3	20.5
6-7	47.4	15.0	102.7	20.8
7-8	51.0	16.4	108.0	20.9
8-9	62.6	18.8	103.8	21.2
9-10	68.0	19.7	118.3	21.9
10-11	75.1	20.7	116.9	22.4
11-12	74.0	19.9	120.1	21.8
12-13	71.0	19.8	108.2	20.4
13-14	70.9	20.1	108.4	21.2
14-15	65.4	21.0	106.5	22.5
15-16	64.6	21.7	120.6	21.6
16-17	66.7	23.4	115.1	22.7
17-18	69.6	23.0	119.6	22.3
18-19	70.6	23.2	117.3	21.0
19-20	75.7	21.5	115.6	21.2
20-21	75.3	19.9	116.8	21.4
21-22	75.1	19.1	119.9	21.8
22-23	72.5	19.2	118.4	20.7
23-0	65.6	18.1	114.8	21.5

Table 4.32 displays the average real load scheduled to generator 6, under the demand shift scenario. As can be observed, the average load scheduled to this generator decreases significantly in all time intervals. Generator 6 loses its advantageous position on the network (compared to the reference scenario) and gradually loses load levels. Figure 4.46 displays the real load levels attained by generator 6 at selected time intervals. The frequency of zero load is higher compared to reference scenario for all time intervals. Besides, average load levels are one-half of the reference scenario levels.

Table 4.32. Average real load scheduled to generator 6 in the reference scenario and in the demand shift scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The Demand Shift (Bus 2-5) Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	123.9	12.0	54.4	11.2
1-2	118.7	11.8	51.5	10.5
2-3	116.9	12.0	58.1	11.5
3-4	113.6	12.8	45.3	9.4
4-5	113.3	12.3	42.3	8.4
5-6	113.7	12.4	47.2	9.9
6-7	114.1	12.5	47.4	10.4
7-8	115.9	12.9	50.8	10.8
8-9	123.4	11.5	62.5	12.5
9-10	125.9	10.5	64.1	13.1
10-11	127.2	9.5	66.8	13.5
11-12	126.8	9.9	66.8	13.2
12-13	126.4	10.0	64.1	11.8
13-14	126.2	10.2	65.4	12.3
14-15	126.5	10.2	72.3	13.1
15-16	126.7	10.1	63.3	12.5
16-17	126.1	9.8	66.4	12.1
17-18	126.1	9.5	66.0	12.7
18-19	127.0	9.0	66.9	12.9
19-20	126.7	9.4	68.3	12.5
20-21	127.7	8.8	69.9	12.7
21-22	127.9	9.0	67.6	12.2
22-23	127.0	9.4	65.9	11.6
23-0	125.1	10.1	63.3	11.9

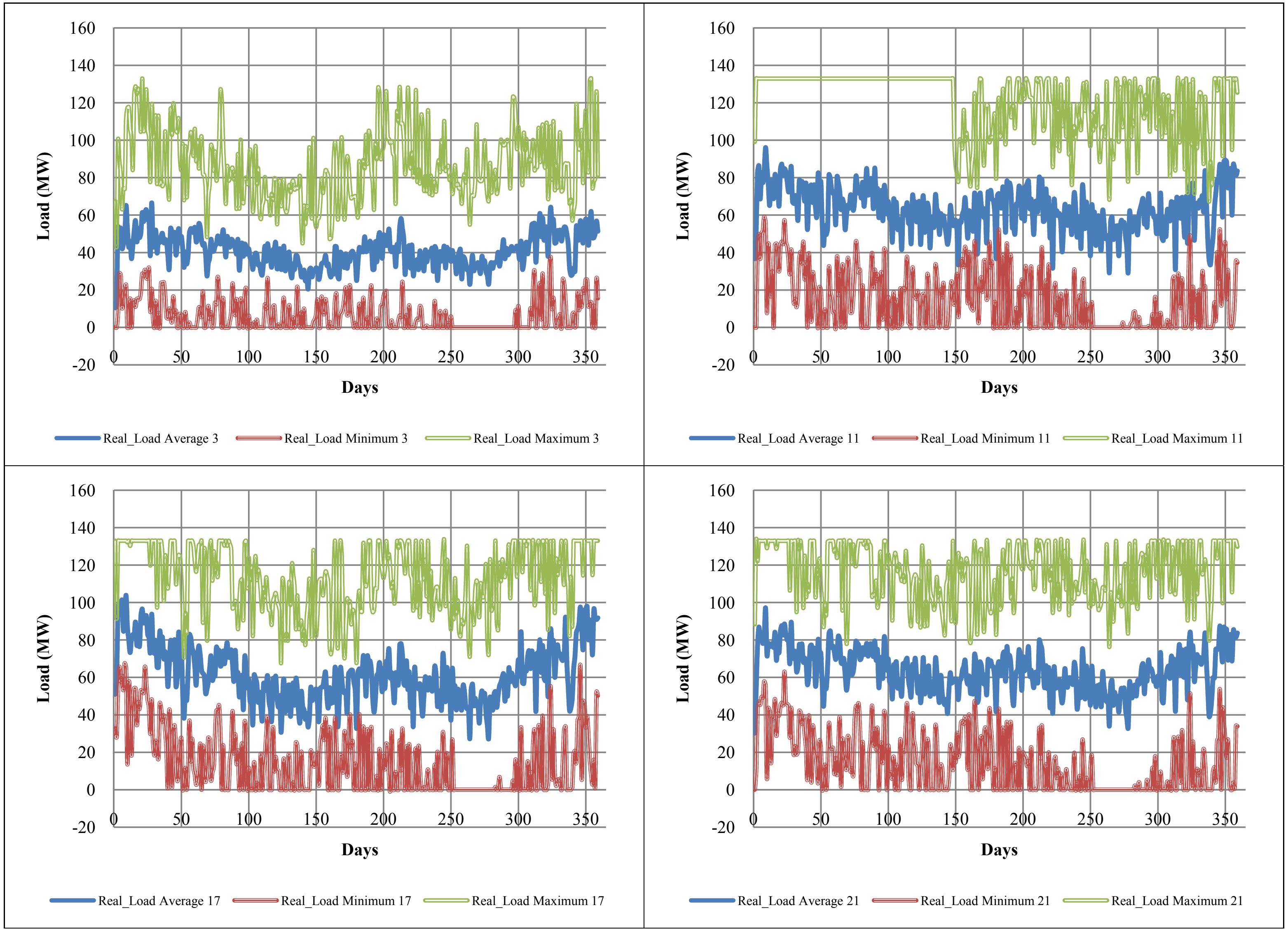

Figure 4.46. Impact of the demand shift (bus 2-5) on real load of generator 6 at selected time intervals (AC OPF case).

The second set of structural changes that are considered deal with the introduction of two different size generators at buses 3 and 6. Table 4.33 displays the descriptions of these scenarios related to new generators on bus 3 and bus 6. Buses 3 and 6 are specifically selected to be able to observe the effect of introducing generators at highly interconnected buses, which are in close proximity to high demand centers. This setting gives the opportunity to better understand the effect of capacity expansion in such buses over price formation and the load schedule. Besides the selection of buses, the impact of the size of the new generator is also investigated by experimenting with two different size units at each bus. The specifications of new introduced generators on bus 3 and 6 are given in Table 4.34.

Table 4.33. Description of scenarios associated with the introduction of new generators at buses 3 and 6.

Scenario Code	***Scenario Details***
NBGB3	New Big Generator on Bus 3
NBGB6	New Big Generator on Bus 6
NSGB3	New Small Generator on Bus 3
NSGB6	New Small Generator on Bus 6

Table 4.34. Technical specifications of the new introduced generators at buses 3 and 6.

Parameters	***Big Generator***	***Small Generator***
Capacity (MW)	100	45
MinLoad (MW)	0	0
Reactive Limits Supply (MVAR)	60	27
Reactive Limits Consume (MVAR)	40	18
NoLoad Energy (MWh)	10	10
Startup Energy (MWh)	2.058	2.058
Minimum Up Time (MWh)	2	2
Minimum Down Time (MWh)	2	2
Primary Resource	Coal	Coal
Connected Bus	3	3

Table 4.35 displays electricity prices under the reference scenario and the described additional generator scenarios (namely, the NBGB3, the NBGB6, the NSGB3, and the NSGB6 scenarios). The observed impacts of introducing a new generator are quite unexpected. At all, time intervals, electricity prices show significant increases especially for near peaking time intervals, with very high levels of variation. At some time intervals

(like 10-11 and 21-22) the price increase is ten folds. In addition, the standard deviation levels are higher than the average prices (such as in time interval 13-14 and 17-18). It is conjectured that this price increase and high variation is due to easier exercising of similar collaborative strategies regarding profit maximization in this environment of more abundant supply and suppliers. This set of structural changes shows that introduction of a new generator may actually lead to unstable electricity prices, due to similar manipulative behavior. The following additional remarks can be made when these scenarios are individually examined

While the NBGB3 scenario features increased price levels, coupled with high variation levels, the magnitudes are moderate compared to other scenarios considered in this set. At all time intervals price levels are high compared to the reference scenario, while the pattern of prices are similar to the reference case, such as higher prices being coupled with high demand intervals.

In the scenario NBGB6 scenario, just like the previous case, price levels show significant increases with very high levels of variation, but the price level is two to three folds higher. On the other hand, price behavior with respect to the daily demand curve shows deviations from the general trend present in the NBGB3 and the reference scenarios. The prices for low demand time intervals (4-5 and 9-10) in the NBGB6 scenario go up to peak demand time intervals' levels unlike the reference and the NBGB3 scenarios. The manipulative behavior is more powerful due to the large generator at the highly interconnected bus 6, which seems to disrupt the general pricing pattern and levels.

The differences between the two scenarios (i.e. introducing large / small generators at the bus) lie at the magnitudes of the responses. Under the NSGB6 scenario, low demand time intervals' prices are lower compared to the NBGB6 case. However, for the peaking and transition demand time intervals, higher prices are observed compared to the NBGB6 scenario. This indicates that with the introduced smaller generator, the strategy of playing for the peaking demand time intervals (which are easier to manipulate for higher premiums) instead of other time intervals becomes crispier because of the more limited capacity.

The impact of introducing a small generator on bus 6, namely the scenario NSGB6, has results similar to that of the NBGB6 scenario in comparison with the reference scenario. The difference between the two cases lies at the magnitudes of the responses. The price levels are lower compared to the NBGB6 scenario for all time intervals. The standard deviations are also lower compared to the NBGB6 scenario but still large with respect to average load levels. Nevertheless, for the peaking time interval 21-22, the price level is comparable to the NBGB6 scenario, indicating the presence of significant level of manipulation. On the overall, compared to the other scenarios regarding bus 3 and bus 6, the NSGB6 scenario leads to the lowest price levels for all time intervals except the reference scenario.

In summary, it is shown that. regarding capacity expansion decisions, introduction of new generators at highly interconnected buses, which are in close proximity of high demand centers are not a good choice for public at large. This is mainly due to the highly interconnected structure of the selected locations, which permits the new entrants developing and exercising market power even though sufficient excess capacity is present in the system. Another interesting observation is the responses of the prices with respect to the size of the new introduced generators. A new small generator on bus 3 leads to higher prices in transient and peaking time intervals, while on bus 6 effect is lower prices at all time intervals. This observation indicates that lower capacity expansion at closer proximity to the higher demand centers (as in case of bus 6), leads to lower market power while multi demand region buses (as in case of bus 3), may affect different strategies for profit maximization.

Figure 4.47 displays electricity price behavior under the NBGB3 scenario. Price behavior in the low demand time interval 3-4 is quite a non-symmetric in the sense that probability of attaining prices lower than the average is higher than that of attaining prices higher than the average. In low demand time intervals, the price behavior is smoother over the planning horizon. In contrast, other time interval considered in the figure features an increasing price behavior over the planning horizon, which indicates that the prices are being pushed up with similar strategies regarding profit maximization (via the learning algorithms designed to take advantage of the inelastic nature of demand).

Figure 4.48 displays electricity price behavior under the NBGB6 scenario. Price behavior is different, which can be characterized by the maximum attained prices which are the highest of all analyzed scenarios except the NSBG6 and the boom and bust behavior leading to high variability in prices (observed by abrupt changes in maximum prices attained).

Figure 4.49 displays electricity price behavior under the NSGB3 scenario. Price behavior shows abrupt changes in the second quarter of the year (especially regarding the maximum prices attained). For time interval 3-4 average prices start to rise to 1000 $ / MWh levels, while for time interval 21-22 average price reaches 2000 $ / MWh levels. When a new generator is introduced at bus 3, under inelastic demand, manipulation potential is greatly increased.

Figure 4.50 displays electricity price behavior under the NSGB6 scenario. Price show abrupt and big changes in the third quarter of the year, regarding the maximum prices attained. Unlike the NSGB3 scenario, at low demand time interval 3-4, average price rose up to 750 $ / MWh, which indicates a fall compared to NSBG3 scenario. For high demand time interval 21-22, average electricity price rose up to 10,000 $ / MWh, indicating a substantial increase in prices. Compared to the reference scenario, general price increase is similar to the NSBG3 scenario, while prices formed at the same time intervals point out serious differences in network formation and manipulative behavior.

Table 4.35. Average electricity sales prices in the reference, NBGB3, NSBGB3, NBGB6 and NSGB6 scenarios for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The NBGB3 scenario		The NBGB6 scenario		The NSGB3 scenario		The NSGB6 scenario	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5	339.7	217.9	1422.4	2152.0	250.5	335.1	391.2	407.6
1-2	151.2	53.1	307.1	307.1	767.9	1022.4	241.2	319.7	516.4	625.1
2-3	138.2	50.6	389.7	229.2	776.5	1013.3	212.1	276.5	333.5	366.6
3-4	122.5	25.5	746.7	432.8	469.0	559.7	233.9	330.4	238.3	251.8
4-5	170.2	52.6	626.5	514.3	1173.2	1629.1	772.1	577.3	256.3	299.0
5-6	172.9	48.6	264.1	348.9	975.7	1237.7	622.9	448.1	294.2	347.3
6-7	151.2	34.8	341.8	263.7	575.4	642.9	776.4	540.1	221.1	237.8
7-8	167.8	38.9	632.3	839.4	626.8	744.5	414.1	445.2	343.6	412.0
8-9	181.8	76.2	687.4	998.8	653.7	782.9	465.6	398.4	429.6	470.4
9-10	345.7	205.3	439.3	296.0	2676.2	4078.0	902.1	693.0	510.8	583.8
10-11	164.9	45.9	1021.6	1009.9	274.2	204.8	1763.2	1229.0	425.5	383.8
11-12	280.2	161.6	840.6	673.5	256.8	159.5	1936.4	1336.1	670.9	843.5
12-13	238.2	103.7	443.2	875.1	696.5	699.9	1285.0	913.7	589.3	770.3
13-14	153.1	48.9	802.0	1227.4	907.6	1039.9	1901.4	1314.5	777.2	955.6
14-15	170.6	66.1	508.2	372.9	3782.6	5660.6	811.4	667.7	459.5	519.8
15-16	193.2	106.6	897.4	1001.7	1406.6	1699.9	544.1	425.8	400.0	424.1
16-17	163.0	45.0	488.3	1245.5	1736.0	2482.1	790.9	567.0	662.3	965.6
17-18	203.7	55.3	413.4	1014.5	1413.7	1940.3	2515.9	1808.3	493.6	621.0
18-19	178.9	48.8	388.2	676.1	1307.6	1765.8	306.7	179.9	316.6	327.0
19-20	172.6	53.6	1256.5	1088.8	1164.1	1538.9	1874.8	1321.9	693.7	978.7
20-21	194.6	63.0	825.6	811.6	1755.9	2431.1	3460.3	2441.9	823.4	1119.8
21-22	186.7	69.6	1046.2	1020.9	2805.3	3987.4	1022.0	759.6	1152.6	1827.7
22-23	240.1	94.0	837.0	1300.5	1812.3	2330.1	718.7	553.3	573.9	705.2
23-0	160.5	48.0	539.1	616.3	996.5	1323.0	994.6	695.8	413.7	547.3

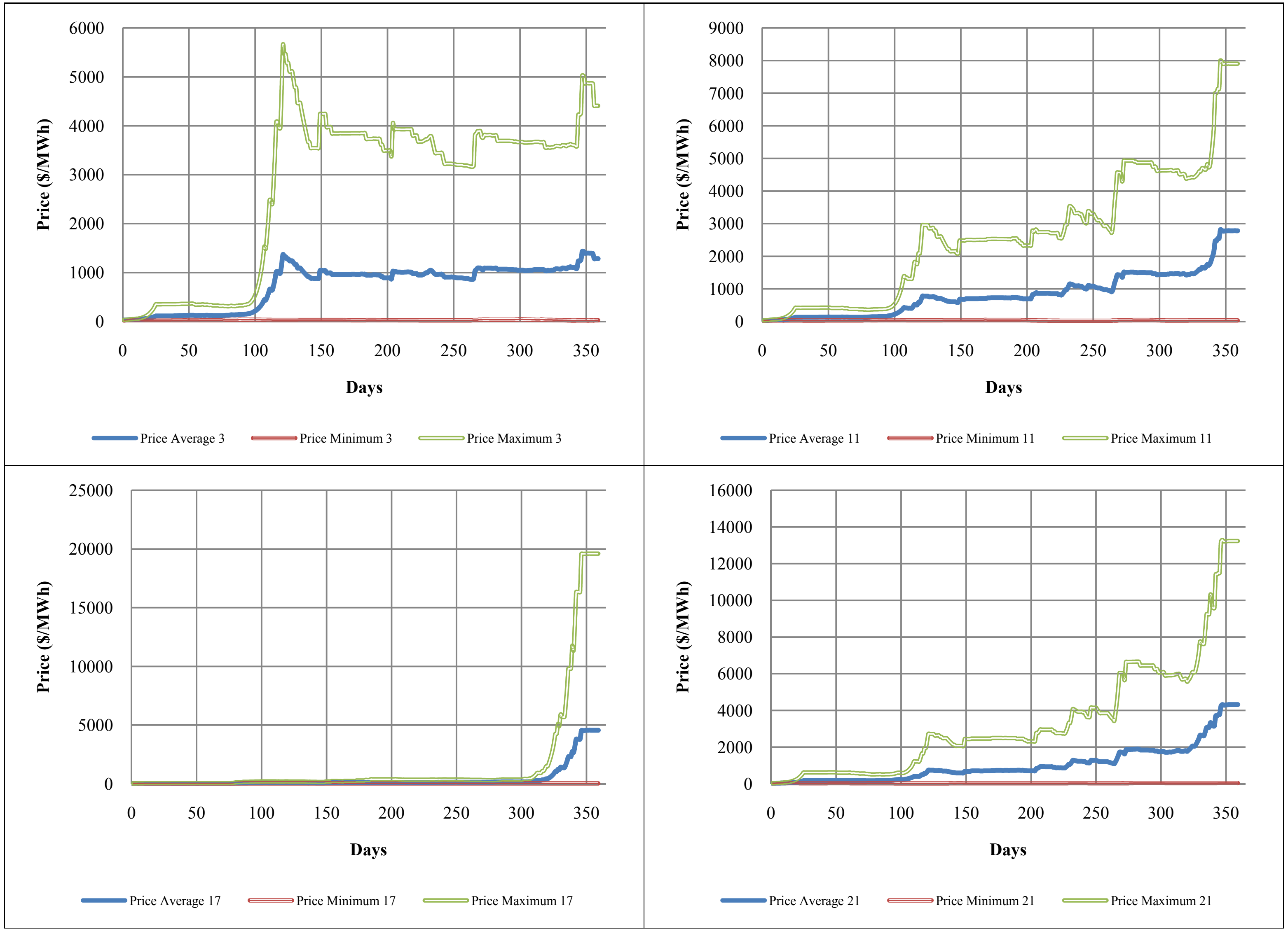

Figure 4.47. Impact of the NBGB3 scenario on electricity prices at selected time intervals (AC OPF case).

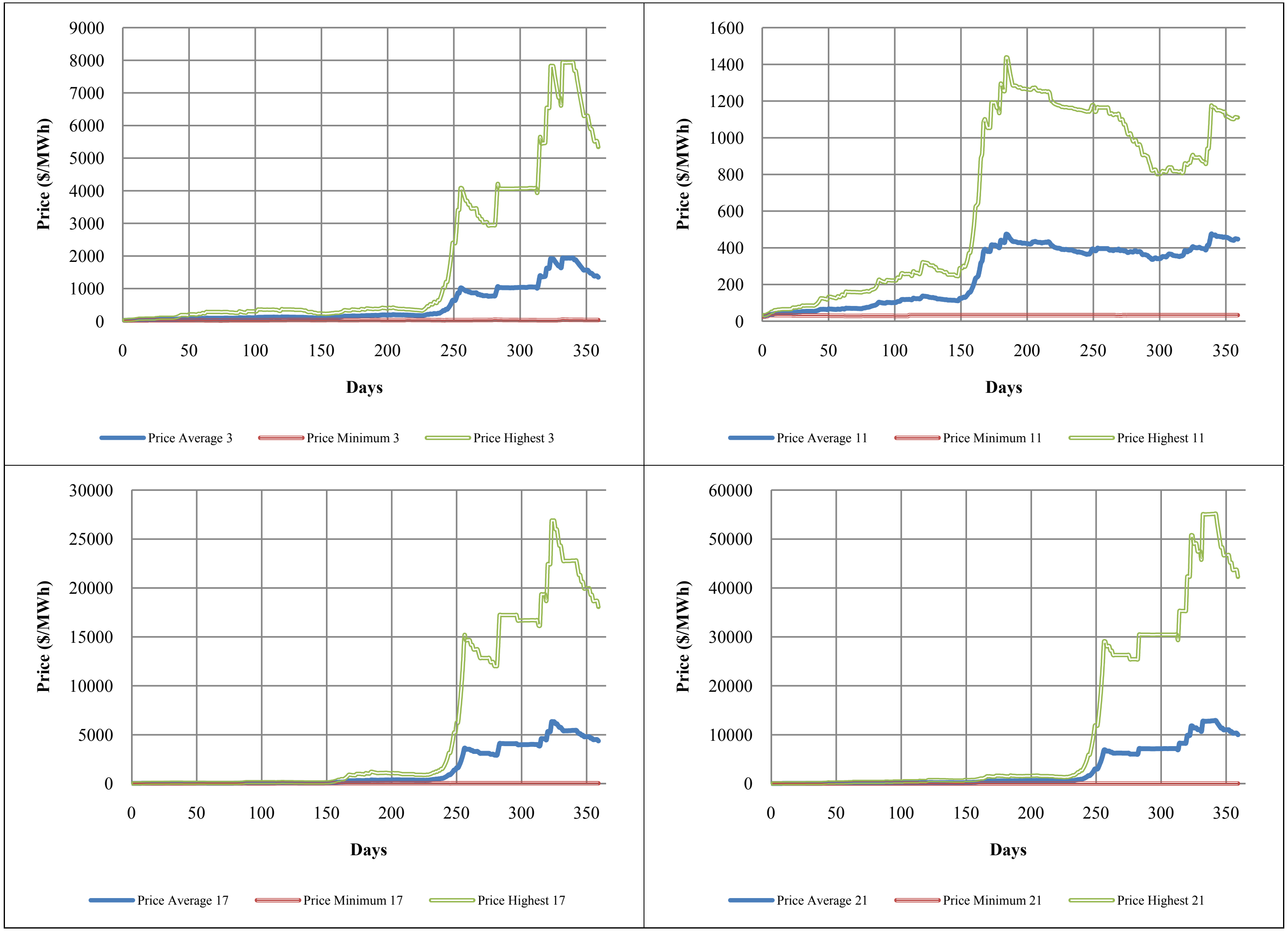

Figure 4.48. Impact of the NBGB6 scenario on electricity prices at the selected time intervals (AC OPF case).

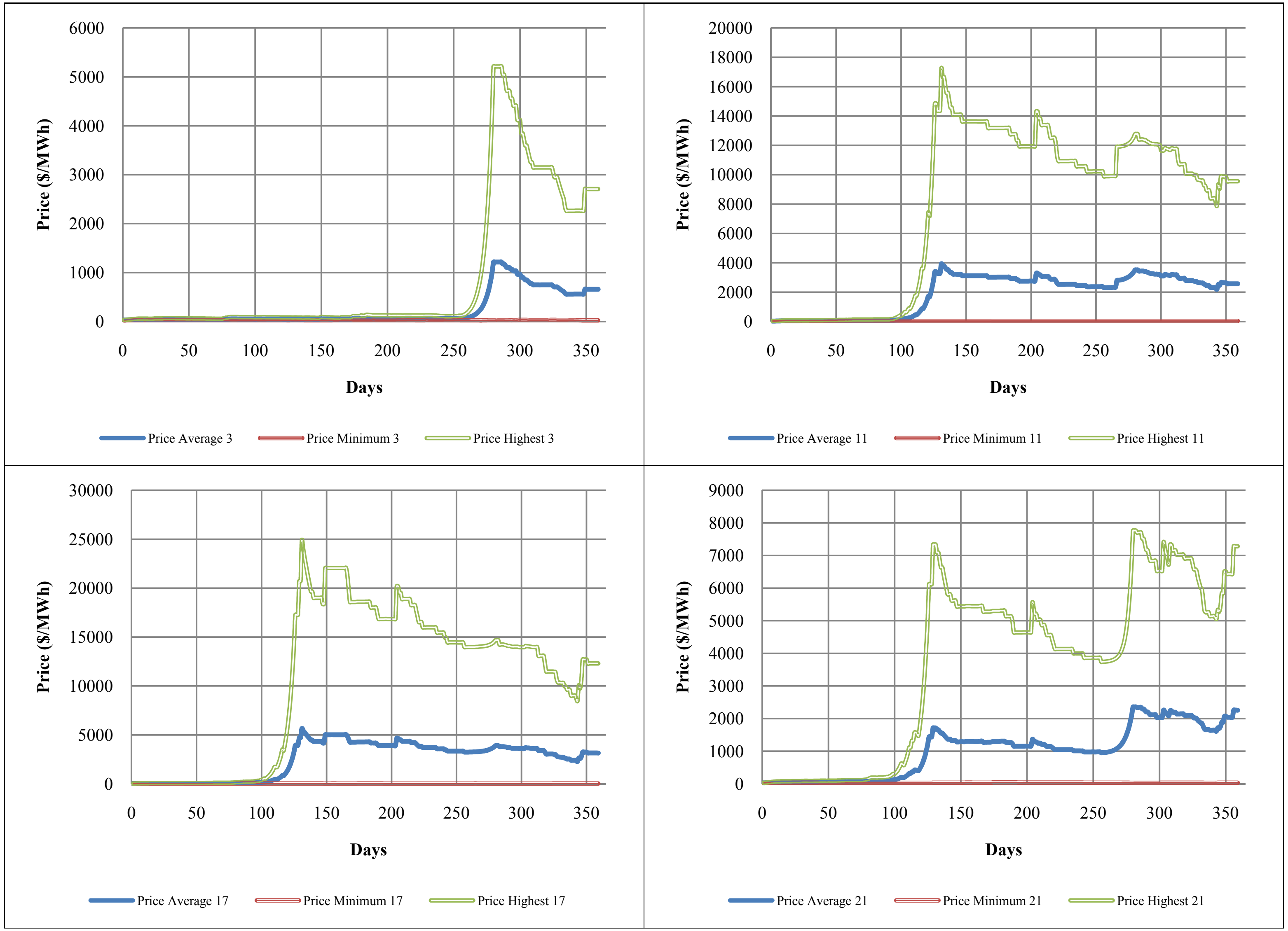

Figure 4.49. Impact of the NSGB3 scenario on electricity prices at the selected time intervals (AC OPF case).

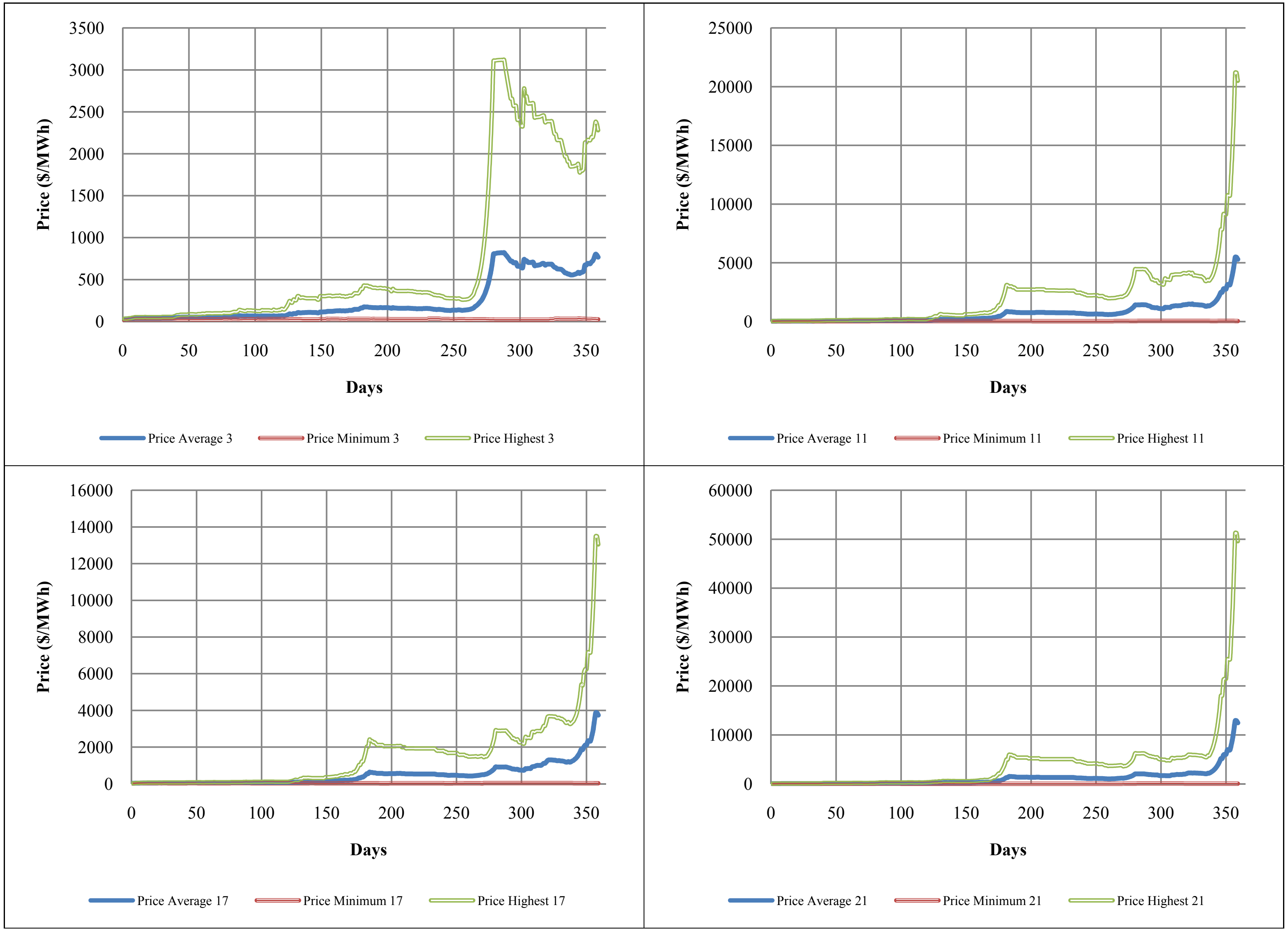

Figure 4.50. Impact of the NSGB6 scenario on electricity prices at the selected time intervals (AC OPF case).

Table 4.36 displays the real load levels of generator 1, under the reference, and the NBGB3, the NBGB6, the NSGB3, the NSGB6 scenarios. As can be observed, under the NBGB3 scenario, generator 1 loses load at low demand time intervals, while gaining load at peaking time intervals. Under the NBGB6 scenario, load loses of generator 1 are even greater compared to the reference and the NBGB3 scenarios. Interestingly, the smaller size generator cases of each bus (namely the NSGB3 and the NSGB6 scenarios) indicate that lower capacity additions diminish the impact of the new generator over generator 1, which is not unintuitive. This analysis also shows that generator 1 is more sensitive to capacity addition on bus 6, while the size of the capacity addition is an important factor regarding the impact of the new generator. Thus, the introduction of the new generator has a negative impact on generator 1 loads and profits in all cases.

Table 4.37 displays the real load scheduled to generator 5 under the reference and the NBGB3, the NBGB6, the NSGB6, the NSBG3 scenarios. Generator 5 is one of the generators that loses real load under the NBGB6 scenario. Except for the time interval 10-11, this generator loses load to the other generators (around 10 to 20MW). Additionally, at all time intervals, the standard deviations of load levels are higher (it is conjectured that this is due to increased competition and increased variability inherent in the new supply structure). In the NBGB3 scenario, the behavior of generator 5 is similar to that of generator 1: loss of load at low demand time intervals, and load gains at peaking time intervals. In scenarios featuring smaller size capacity additions, load loss/gain impacts are lower, which again highlights the importance of level of additional capacity over load and price formation.

As observed in the NBGB3 scenario, generator 5 and generator 8 loses loads in the NSBG3 scenario. Table 4.37 and Table 4.39 display the load levels of generator 5 and generator 8 respectively, in comparison to the reference and other bus 3 and bus 6 related scenarios. The load losses are half of the NBGB3 scenario.

Table 4.36. Average real load scheduled to generator 1 in the reference, NBGB3, NSBGB3, NBGB6 and NSGB6 scenarios for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NBGB3 scenario		The NBGB6 scenario		The NSGB3 scenario		The NSGB6 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	25.2	5.1	20.4	5.0	14.5	3.1	19.3	3.7	17.4	3.4
1-2	16.8	3.5	25.2	5.0	13.4	3.1	16.3	2.7	16.2	3.0
2-3	18.5	3.7	24.2	6.1	14.2	3.0	17.6	3.1	17.9	3.4
3-4	16.0	3.2	21.1	5.8	13.0	3.0	16.8	3.0	14.5	2.7
4-5	15.8	3.1	21.2	5.6	13.7	3.4	15.8	2.9	15.3	2.9
5-6	15.9	3.2	25.2	5.3	13.9	3.5	15.0	2.6	15.0	2.9
6-7	16.0	3.4	24.5	5.6	11.5	3.0	15.5	2.8	16.0	3.3
7-8	16.8	3.5	20.2	6.3	14.8	3.7	16.7	3.1	15.9	3.3
8-9	19.6	4.0	25.6	5.8	17.4	4.1	19.0	3.5	18.6	4.0
9-10	25.7	4.8	26.4	6.0	18.4	4.1	20.5	3.7	20.1	4.2
10-11	22.1	4.0	27.6	5.8	24.9	6.6	24.9	4.6	20.6	4.0
11-12	22.4	4.2	29.2	5.2	20.4	5.0	23.8	4.9	21.4	4.1
12-13	21.5	3.9	27.5	5.4	19.7	4.5	20.6	3.9	23.7	4.5
13-14	21.7	3.9	26.7	6.1	18.2	4.0	20.6	4.0	20.2	4.0
14-15	25.6	4.8	29.9	5.5	18.4	4.0	24.1	5.1	20.5	3.9
15-16	24.6	5.1	26.8	5.4	17.9	4.2	23.7	4.8	20.3	4.1
16-17	22.6	5.4	26.7	5.9	18.5	4.1	21.3	4.8	23.8	4.9
17-18	25.9	5.4	28.2	5.9	21.1	5.3	21.1	4.4	23.9	5.2
18-19	26.1	4.8	31.7	5.2	18.5	4.5	21.3	4.3	21.9	6.3
19-20	22.4	4.1	26.0	6.2	19.0	3.9	21.6	3.9	21.5	4.2
20-21	24.3	5.0	27.1	6.4	19.2	3.8	21.9	3.3	21.8	3.6
21-22	22.6	3.7	30.2	5.6	19.3	3.6	21.7	3.3	21.5	3.7
22-23	22.1	3.6	24.8	5.3	18.3	4.0	24.7	3.8	24.9	4.5
23-0	20.9	4.1	27.9	5.3	18.9	4.3	22.8	4.1	29.1	6.3

Table 4.37. Average real load scheduled to generator 5 in the reference, NBGB3, NSBGB3, NBGB6 and NSGB6 scenarios for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NBGB3 scenario		The NBGB6 scenario		The NSGB3 scenario		The NSGB6 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	67.6	11.5	52.0	11.6	39.3	11.4	57.0	10.6	46.4	11.2
1-2	48.0	10.3	49.9	11.7	39.3	11.8	45.4	9.5	44.2	11.2
2-3	52.7	10.4	48.7	11.4	38.9	11.8	50.5	11.5	47.0	11.4
3-4	46.2	9.8	47.6	11.2	36.3	10.8	46.8	10.4	36.6	9.7
4-5	47.6	10.1	47.2	11.3	39.6	11.7	46.2	10.3	37.8	9.7
5-6	46.7	9.8	44.5	11.0	40.0	11.5	44.6	9.9	38.1	9.9
6-7	47.4	10.0	47.0	11.3	34.2	10.7	45.6	10.6	43.1	11.5
7-8	50.9	11.3	53.1	13.2	44.2	12.5	50.1	10.5	40.3	10.5
8-9	60.5	13.1	60.6	14.0	55.1	14.3	59.8	12.4	53.0	13.8
9-10	73.3	14.0	66.0	15.4	55.4	14.4	66.5	13.5	58.4	14.6
10-11	66.0	13.5	73.8	16.0	71.4	16.9	73.9	13.2	59.4	14.1
11-12	70.7	14.0	69.2	15.5	62.4	15.5	71.8	13.0	61.2	14.4
12-13	66.4	13.1	64.1	14.3	61.0	15.1	64.1	12.6	65.5	14.3
13-14	68.2	13.6	74.1	16.8	56.1	15.1	65.0	13.1	59.1	14.5
14-15	74.2	13.9	70.3	16.1	56.5	15.3	69.3	13.6	58.7	14.3
15-16	71.4	13.9	70.3	16.1	55.9	15.5	69.5	13.5	56.2	13.9
16-17	67.8	13.8	65.9	15.6	55.8	15.8	67.1	14.7	61.9	13.9
17-18	72.9	13.1	72.0	16.3	59.4	17.6	66.9	15.4	64.6	16.6
18-19	74.6	13.2	72.7	16.4	56.9	16.6	68.5	15.8	59.2	17.9
19-20	69.9	12.9	70.7	15.0	59.3	15.6	70.1	14.0	61.3	15.8
20-21	73.0	12.2	79.5	14.8	62.1	14.5	72.0	12.8	64.6	14.2
21-22	70.0	11.5	71.2	14.3	58.8	13.1	70.7	12.1	63.2	13.3
22-23	69.4	12.0	73.8	13.8	56.4	13.8	72.6	11.1	66.4	12.4
23-0	63.5	11.4	66.0	13.8	58.4	14.1	68.6	11.4	73.5	12.4

Table 4.38 displays real load levels of generator 7 under the reference and the NBGB3, the NBGB6, the NSGB3, the NSGB6 scenarios. As can be observed, generator 7 loses real load nearly in all time intervals of the day under the NSBG3 scenario. (The only exception is the afternoon time intervals 12-15, where some insignificant load gains are achieved. Under the NBGB3 scenario, no significant loss of load is observed at non-peaking time intervals, while 2-5 MW load loses are seen at peaking time intervals. Each incremental capacity addition at the bus 3 has lower effect over the generator 7's load levels (comparing the NSGB3 and the NBGB3 scenarios), which points outs a strategy change of the new added generator with increasing size. Under the NBGB6 scenario, generator 7 does not lose significant load at peaking time intervals while load gains are observed at midday time intervals (10-12). When the smaller capacity generator is introduced at bus 6, no significant effect over the load levels of generator 7 can be observed. Thus, due to location and network characteristics, bus 3 is more critical for generator 7 regarding load levels and profitability attained.

Table 4.38. Average real load scheduled to generator 7 in the reference, NBGB3, NSBGB3, NBGB6 and NSGB6 scenarios for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NBGB3 scenario		The NBGB6 scenario		The NSGB3 scenario		The NSGB6 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	36.7	13.6	43.4	16.7	36.3	13.3	23.1	14.2	32.6	18.3
1-2	37.1	13.1	25.3	14.6	34.9	13.5	22.0	14.0	28.5	14.6
2-3	18.5	12.6	21.3	13.0	19.2	12.1	18.2	12.6	18.6	13.5
3-4	22.4	13.5	21.6	12.3	20.6	10.0	14.3	12.6	26.2	14.4
4-5	23.8	13.8	21.4	11.7	21.2	11.4	13.9	6.9	24.6	14.2
5-6	22.2	10.6	20.9	11.9	21.4	11.5	14.9	9.8	25.0	14.5
6-7	22.1	13.6	22.7	12.4	34.4	12.5	17.2	12.9	19.2	10.9
7-8	26.3	14.4	23.3	11.6	20.2	11.1	16.9	11.0	23.0	14.2
8-9	29.2	15.2	27.9	12.3	25.4	11.9	21.0	12.3	30.5	13.4
9-10	34.7	16.3	34.7	16.6	29.9	15.5	26.4	14.9	34.0	15.8
10-11	30.3	15.7	31.4	16.4	41.6	15.4	26.6	15.0	32.9	15.9
11-12	36.8	16.7	35.7	16.9	46.4	15.3	27.0	15.6	35.0	17.3
12-13	31.9	15.9	37.0	16.1	29.7	13.7	40.1	13.8	33.8	16.3
13-14	33.5	16.0	27.7	17.5	32.0	15.1	41.1	14.5	36.3	16.7
14-15	36.3	18.8	30.9	16.3	31.7	16.2	40.0	14.6	34.3	16.5
15-16	40.5	16.5	30.7	16.3	32.0	16.4	24.5	14.8	31.9	16.4
16-17	38.6	16.7	38.1	16.6	29.8	15.1	23.6	14.4	29.3	16.3
17-18	33.0	15.6	25.3	16.9	30.9	16.8	23.3	14.4	35.4	17.0
18-19	34.6	15.5	28.7	15.4	32.5	15.2	26.1	14.8	32.4	15.5
19-20	33.6	15.5	35.5	17.1	33.4	15.6	26.6	15.4	34.9	16.0
20-21	38.4	16.1	29.7	16.0	37.1	16.3	29.7	15.5	38.1	17.2
21-22	34.7	15.8	30.6	15.8	33.8	15.0	28.3	15.1	37.4	16.8
22-23	36.1	15.9	37.8	16.6	33.7	15.0	24.8	14.3	36.0	16.7
23-0	32.5	15.5	32.2	16.2	29.0	14.6	22.8	14.1	28.5	16.2

Table 4.39 displays the real load levels of generator 8 under the reference, and the NBGB3, the NSGB3 and the NBGB6, the NSGB6 scenarios. As can be observed, the introduction of a new generator has negative impact on generator 8 for all scenarios considered regarding bus 3 and bus 6.

Loss of load levels indicate the sensitivity of generator 8 to the new introduced generators. Under the NBGB3 scenario, generator 8 loses load at all time intervals, with loss levels being around 15 MW on average per time interval. In the smaller new generator case, (the NSGB3 scenario), loss level is reduced to 3-10 MW on average per time interval.

The NBGB6 scenario shows that loss levels of generator 8 may rise up to the dramatically high levels of 30 MW in certain time intervals. In the smaller new generator scenario (i.e. the NSGB6 scenario), load loses drop down to the 5-10 MW range. In other words, due to its unfavorable network location and higher production costs, generator 8 is the most disadvantageous generator in the network under the considered capacity expansion scenarios at the most interconnected buses (namely bus 3 and bus 6).

Figure 4.51 displays the real load behavior of generator 8 at selected time intervals under the NSGB3 scenario. The average load levels are relatively small compared to capacity. In low demand time intervals (such as 3-4), average real load is around 20-30 MW. The frequency of attaining zero load levels are also much higher in low demand intervals.

Figure 4.52 displays the real load behavior of generator 8 at selected time intervals under the NBGB6 scenario. The frequency of zero profit intervals is much higher than the reference scenario. Generally, it is under loaded and very close to zero level of utilization. The minimized effect can also be observed in Figure 4.53, which displays the price behavior of generator 8 in the NSGB6 scenario.

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Table 4.39. Average real load scheduled to generator 8 in the reference scenario, NBGB3, NSBGB3, NBGB6 and NSGB6 scenarios for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NBGB3 scenario		The NSGB3 scenario		The NBGB6 scenario		The NSGB6 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	35.9	11.7	27.5	11.7	37.9	12.3	23.3	9.6	35.6	12.4
1-2	40.7	12.1	25.5	10.7	37.4	11.6	22.4	9.4	33.4	11.4
2-3	40.1	12	25.7	12.2	30.9	10.2	21	8.8	25.9	10.9
3-4	42	12.7	28.6	12	34.4	11.1	22.9	8.8	30.2	10.8
4-5	40.5	13.3	29	11.9	32.5	10.9	19	8.5	31.2	10.9
5-6	41	13	27.7	11.4	35.7	11.8	19.3	8.7	31.4	11.1
6-7	41.2	13.2	28.1	13	35.9	12.5	19.4	8.3	27.5	11.2
7-8	44.8	13.7	30.5	12.7	38.9	12.9	20.8	9.1	32.7	12.1
8-9	49.9	14.7	34.3	14.4	43.8	13.9	26.1	11	38.4	13.6
9-10	48	14.3	37.1	14.8	46.1	14.6	30.7	12	41.4	14.1
10-11	54.9	16.5	35.4	14	42.4	13.1	20.7	9.1	41.7	14.4
11-12	56.3	17	37.6	15.2	43.5	14.3	25.1	10.7	43.8	14.8
12-13	54.5	16.2	35.9	14.1	42.4	13.9	26.3	11.4	38	13.5
13-14	55.2	16.2	33.6	13.9	42.3	13.7	30.2	11.8	40.7	14.3
14-15	49.7	16.3	35	13.9	39	13.9	30.8	11.8	41.7	14.2
15-16	48.7	18	35.2	14.4	41.7	13.9	30.2	11.8	40.8	14
16-17	49.5	18.2	34.4	14	45.8	14.8	30.9	12	39.4	14.1
17-18	51.3	18.1	36.1	14.9	47.8	16.5	30.2	12	38.1	14.2
18-19	52.9	17.4	35.3	16.3	48	16.8	31	12.9	41.1	15.3
19-20	57.1	17.1	38.7	16.8	48.6	16.4	32	12.6	43.8	15.9
20-21	57.3	16.8	33.7	14.3	48.8	15.4	32	12.5	44.9	15.4
21-22	57.3	15.9	35.9	13.6	47.9	14.8	31.6	12	44.2	14.7
22-23	56.3	16	31.9	13.3	42.9	14.4	30.1	11.7	37.3	14
23-0	52.3	15.1	30.4	12.7	40.9	13.7	25.2	10.7	30.1	12.3

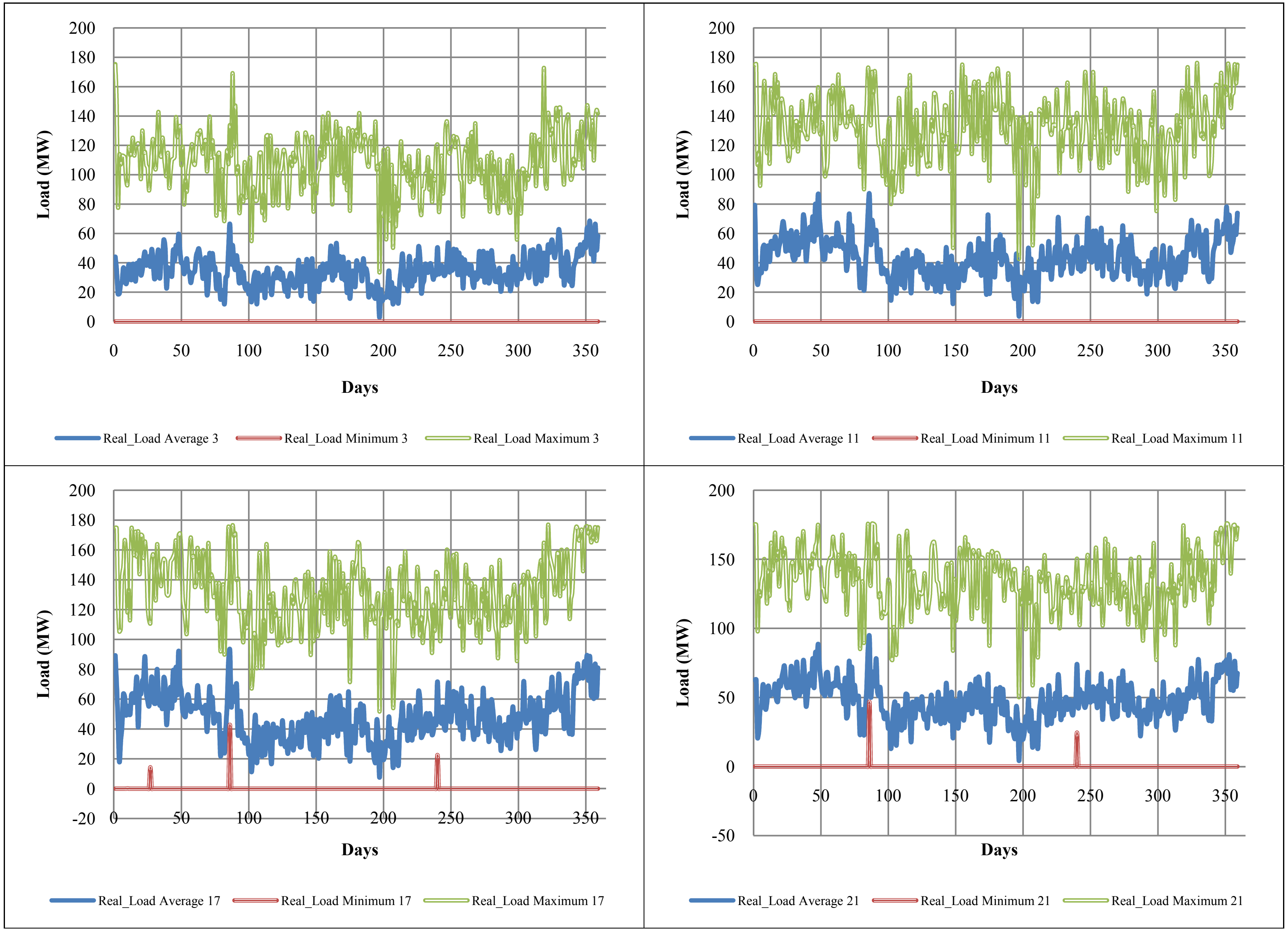

Figure 4.51. Impact of the NSGB3 scenario on real load behavior of generator 8 at the selected time intervals (AC OPF case).

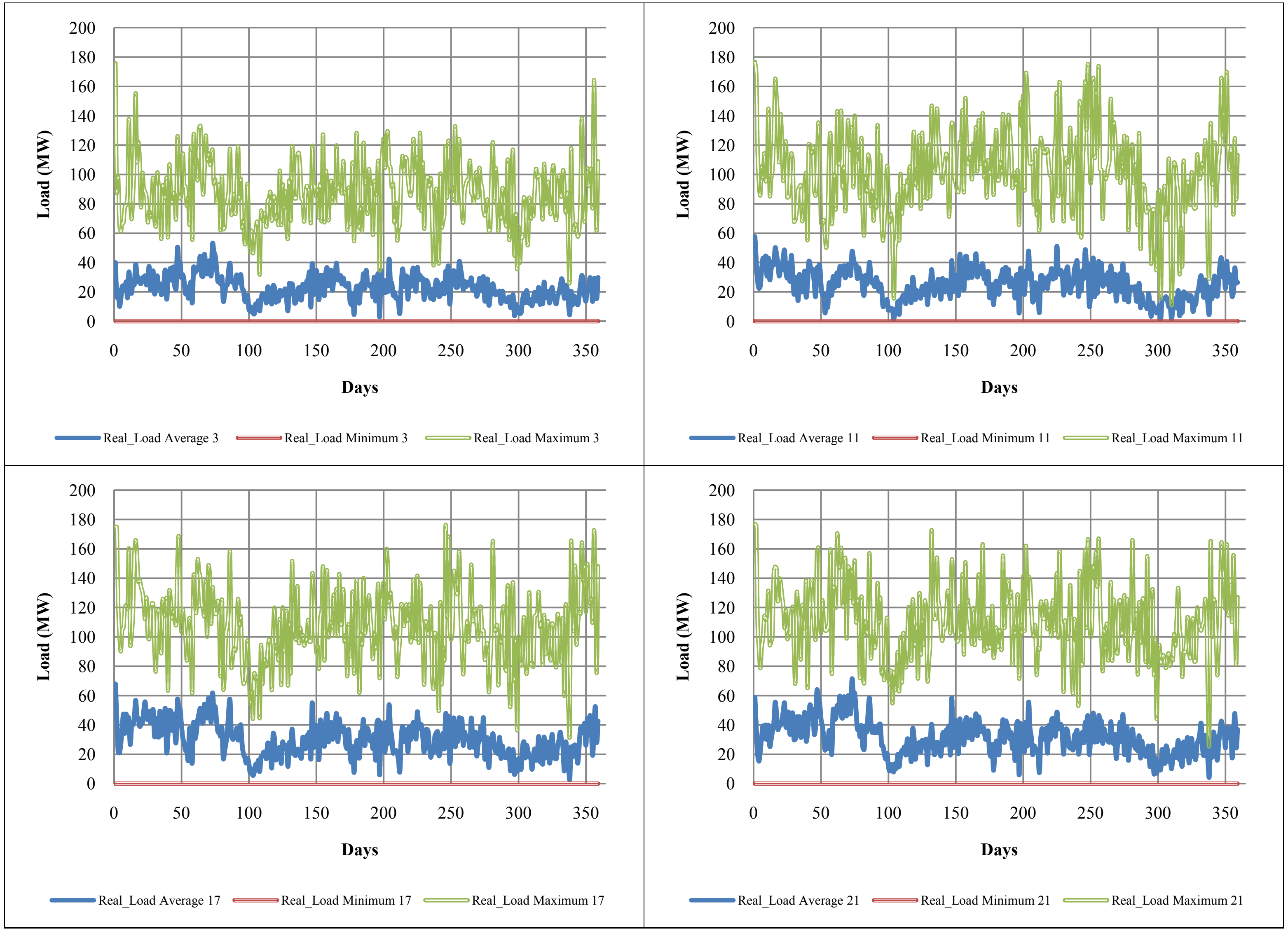

Figure 4.52. Impact of the NBGB6 scenario on real load behavior of generator 8 at selected time intervals (AC OPF case).

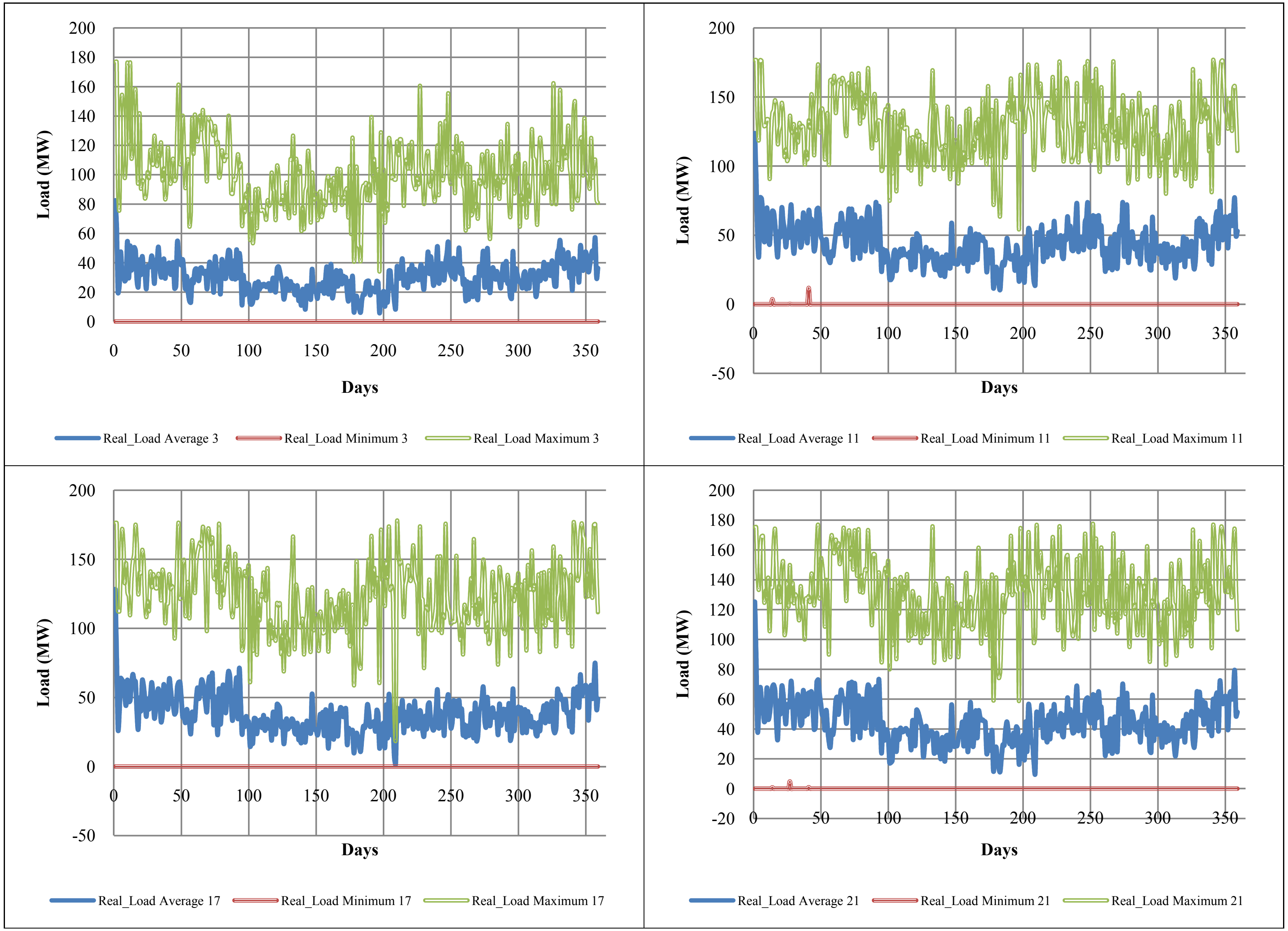

Figure 4.53. Impact of the NSGB6 scenario on real load behavior of generator 8 at the selected time intervals (AC OPF case).

The real load levels of the new generator are displayed in Table 4.40. It can be observed that load levels are responsive to changing demand levels, while the average load levels stay in the 15-36 MW band under the NBGB3 scenario. Load levels under the NBGB6 scenario are responsive to the only two portion of the day (not responsive on hourly time interval basis). The time interval featuring low load (50-55 MW) is the 0-9 time interval (which also features relatively low demand), while the time interval in which the new generator has a significant load (60-75 MW) is the 9-23 time interval. The utilization levels realized are between 50 MW and 75 MW for an average day. Additionally, the realized load variation is quite expected: low (high) demand leads to low (high) load levels. Under the NSGB3 scenario, load levels of the new generator are almost halved (compared to the NBGB3 scenario). The load pattern is also different, peak load being observed in time interval 14-15 and lowest load being observed in time interval 5-6. New generator load levels under the NSGB6 scenario follow a pattern similar to the daily load curve. The average load levels change in 25-30 MW interval. Load levels are two thirds of capacity, which is 45 MW. Generator’s load level range under the NBGB6 and the NSGB6 is higher compared to the NBGB3 and the NSGB3, respectively, indicating disadvantageous location of bus 3 scenario in terms of load assignment for new generators.

Table 4.40. Average real load scheduled to the new generator in the NBGB3, NSGB3, NBGB6 and NSGB6 scenarios for all time intervals (AC-OPF case).

	The NBGB3 scenario		The NBGB6 scenario		The NSGB3 scenario		The NSGB6 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	27.2	8.9	55.9	13.1	14.5	4.9	26.9	6.7
1-2	25.4	8.7	57.1	13.1	10.8	4.4	25.9	6.4
2-3	25.3	8.5	54.7	12.5	15.1	3.7	29.1	5.8
3-4	15.6	9.4	48.6	13.0	11.6	3.8	22.9	6.1
4-5	15.4	9.5	53.9	13.2	13.5	4.1	25.1	6.3
5-6	17.2	8.6	55.9	13.6	9.8	3.9	24.8	6.1
6-7	15.3	9.1	56.1	14.0	10.6	4.4	25.6	6.1
7-8	19.9	9.4	58.4	14.0	10.3	4.1	24.4	6.3
8-9	19.5	10.4	59.6	12.7	13.1	4.6	27.5	6.8
9-10	22.3	12.5	59.7	13.5	15.8	5.1	29.1	6.7
10-11	30.9	10.3	76.8	11.7	18.7	4.8	29.2	6.8
11-12	24.4	11.5	68.3	12.8	18.7	5.0	30.2	6.8
12-13	24.9	9.0	65.0	13.2	17.7	4.7	30.4	6.6
13-14	35.5	9.9	60.2	13.5	18.1	5.0	29.1	7.1
14-15	30.1	11.4	60.4	13.8	20.2	4.6	29.3	7.1
15-16	28.5	10.6	60.2	13.5	18.2	5.0	28.9	6.9
16-17	33.4	9.6	60.2	13.5	14.3	4.7	30.8	6.4
17-18	32.1	9.0	65.1	13.0	13.8	4.8	30.6	6.5
18-19	30.1	12.0	60.0	13.8	15.2	4.9	29.1	6.6
19-20	26.7	13.5	61.0	13.7	15.7	5.1	30.0	6.2
20-21	36.8	10.9	62.5	13.7	17.3	5.3	30.6	6.4
21-22	27.8	10.3	61.1	13.1	16.6	5.1	30.4	6.8
22-23	35.5	11.0	60.2	13.6	18.2	4.9	31.7	6.2
23-0	30.0	9.3	64.1	13.3	17.7	4.7	34.2	5.6

Profitability of the new generator under the NBGB3 scenario is displayed in Table 4.41. As can be observed, the profitability is high due to very high price levels attained. However, standard deviations are one or two folds of the corresponding time interval average load, which makes the average profit levels an unhealthy indicator of financial performance.

Under the NBGB6 scenario, profitability of the new generator is high due to the very high price levels attained. Table 4.40 indicates that these high profits (which are two to three times average profit levels compared to the NBGB3 scenario) can be explained by the changes in load assignments. Especially high demand time intervals 14-22 and the time interval 9-10 feature profit increases up to ten folds. This mainly shows the effect pricing over profit levels. The new generator succeeded in both load assignment and price increasing compared to the NBGB3 scenario. Besides, standard deviation levels are very high, which makes the expected profit levels an unhealthy indicator of financial performance. This situation is very similar to that of the NBGB3 scenario result.

Profit levels of the new generator under the NSGB6 scenario are lower than that of the NSGB3 case. Even though load levels assigned are two times higher compared to the NSGB3 scenario, lower prices cut down this success in financial terms. In most time intervals price levels are lower than the NSBG3 scenario. Peak profitability is attained in time interval 21-22 due to the highest price attained (which is the only time interval featuring higher price than the NSBG3 scenario) over all time intervals, while lowest profitability is observed in time interval 6-7. High standard deviations still exists showing the continuation of high uncertainty regarding profitability. Comparison with the NBGB6 scenario reveals that capacity downsizing diminishes profits accordingly unlike the bus 3 cases.

Table 4.41. Profit of the new generator in the NBGB3, NSGB3, NBGB6 and NSGB6 scenarios for all time intervals (AC-OPF case).

	The NBGB3 scenario		The NBGB6 scenario		The NSGB3 scenario		The NSGB6 scenario	
Hours	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	14227	14592	104544	196756	5792	10779	9248	12276
1-2	13105	23772	54023	91540	5701	11298	11469	19228
2-3	15134	15747	54298	90428	5159	9577	7437	11385
3-4	26794	29155	31472	50660	5314	10887	4545	6340
4-5	24929	36711	84212	149557	21227	22249	5581	9417
5-6	10539	26890	69144	112224	17606	16978	5562	8707
6-7	12964	18801	38131	57639	22735	22869	4057	5884
7-8	29832	64163	42090	64968	10957	15420	6597	10326
8-9	35171	77177	46018	69969	12888	14062	10660	15120
9-10	19842	21936	201121	373000	26619	25512	14033	20418
10-11	53423	77367	18986	17067	53115	51929	11686	12392
11-12	41909	48373	16618	13157	58480	59756	20189	32871
12-13	25678	72486	48689	60665	37982	36516	16839	28404
13-14	44735	101612	65949	91711	57301	56789	21968	34624
14-15	23226	27943	289760	521223	23992	24180	12018	16861
15-16	47262	71787	104595	152958	15563	14880	10978	14394
16-17	31623	105960	132574	229590	23224	21939	19344	37708
17-18	26320	84514	106484	176951	78107	83085	14789	24486
18-19	21372	57873	97744	159728	8647	7886	8077	9811
19-20	65261	85160	86968	140330	56799	56682	21837	38678
20-21	44631	60618	130137	220717	105084	108470	25019	43092
21-22	55919	75658	209464	365244	30700	28949	37477	72788
22-23	47479	100531	133096	209173	21285	20688	16922	26503
23-0	26283	47524	72709	119605	29772	32569	11276	19193

The profitability of the new generator under the NSGB3 scenario is displayed in Table 4.41. The new generators' main strategy in this case is to manipulate prices so that even with the size disadvantage high profit levels are attainable. One can sense this strategy by checking the Table 4.35 and Table 4.40. This strategy compromising very low levels of load assignments lead to profit levels that is comparable to the NBGB3 scenario. Besides, high standard deviations indicate high uncertainty following the strategy, but not more than the NBGB3 scenario levels.

The third set of structural changes considered concern the introduction of a standard size generator at the buses 21 and 28. Table 4.42 displays the descriptions of those scenarios related to new generators at bus 21 and bus 28. The selection of bus 21 and bus 28 is done in order to see the effect of introducing generators at remote buses, which are far away from high demand centers. This setting gives the opportunity to observe the effect of capacity expansion in such buses over prices and load assignments. The technical specifications of the new introduced generators at bus 21 and 28 are given in Table 4.43.

Table 4.42. Description of scenarios associated with the introduction of new generators at buses 21 and 28.

Scenario Code	***Scenario Details***
NGB21	New Generator on Bus 21
NGB28	New Generator on Bus 28

Table 4.43. Technical specifications of the new introduced generators at buses 21 and 28.

Parameters	***Generator***
Capacity (MW)	45
MinLoad (MW)	0
Reactive Limits Supply (MVAR)	27
Reactive Limits Consume (MVAR)	18
NoLoad Energy (MWh)	10
Startup Energy (MWh)	2.058
Minimum Up Time (MWh)	2
Minimum Down Time (MWh)	2
Primary Resource	Coal
Connected Bus	3

Table 4.44 displays the prevailing electricity prices under the reference, the NGB21 and the NGB28 scenarios. The impact of introducing a generator on bus 21, namely the NGB21 scenario, creates a more competitive environment compared to the previous structural changes considered. Electricity prices decrease compared to the reference scenario in six time intervals 4-5, 5-6, 7-8, 15-16, 22-23 and 23-0. In the remaining time intervals some price increases are observed, but they are insignificant except in periods of peak demand. This is mainly due to the breaking of the former oligopolistic market structure around bus 21, and the need for lower prices to gain higher load levels from the highest demand bus 5.

Introducing a generator on bus 28, namely the NGB28 scenario, leads to the most competitive environment (with respect to the structural changes considered so far). In all time intervals, prices decrease compared to the reference scenario. The decrease of the prices is coupled with lower standard deviations in price variations. It is conjectured that collaborative behavior (i.e. generator agents following independent but similar bidding strategies) has not emerged in this scenario because of the disadvantageous position of the new generator (i.e. being far away from high demand centers, with the many buses in between introducing numerous constraints on load flow in reaching the high demand buses). Without a lower bid, compared to other generators', it is not preferable to dispatch load to the new generator.

Figure 4.54 displays electricity price behavior under the NGB21 scenario. In low demand time intervals price behavior is smooth over the planning horizon. In contrast, the peak demand time intervals feature increasing price trends over the planning horizon. This indicates that prices are being pushed-upwards through independent but similar bidding strategies of generators which capture and manipulate the inelastic nature of demands.

Figure 4.55 displays electricity price behavior under the NGB28 scenario. For all time intervals price behavior is smooth over the planning horizon. It is conjectured that this is because of the fierce competition between the new generator and the existing generators, due to network placement (common demand buses served): accordingly, sudden and high price changes become less likely and the price behavior gets smoother.

Table 4.44. Average electricity sales prices in the reference, NGB21 and NGB28 scenarios for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5	169.6	66.1	93.9	26.5
1-2	151.2	53.1	202.5	69.5	74.7	18.2
2-3	138.2	50.6	157.5	62.4	86.7	16.4
3-4	122.5	25.5	147.9	55.9	108.7	30.1
4-5	170.2	52.6	113.3	41.5	127.5	27.6
5-6	172.9	48.6	129.0	57.8	105.0	20.5
6-7	151.2	34.8	162.1	72.1	87.5	15.1
7-8	167.8	38.9	162.0	81.1	92.1	17.1
8-9	181.8	76.2	169.4	73.2	100.4	23.8
9-10	345.7	205.3	366.3	258.6	153.3	47.6
10-11	164.9	45.9	333.1	259.5	91.7	24.2
11-12	280.2	161.6	278.7	185.2	131.7	51.7
12-13	238.2	103.7	240.5	148.8	118.8	32.5
13-14	153.1	48.9	389.1	186.9	168.2	71.4
14-15	170.6	66.1	201.4	111.5	108.3	35.6
15-16	193.2	106.6	189.2	100.4	155.9	53.8
16-17	163.0	45.0	213.9	153.3	123.8	37.3
17-18	203.7	55.3	316.9	181.3	129.6	41.8
18-19	178.9	48.8	346.7	221.8	134.9	39.2
19-20	172.6	53.6	248.7	126.9	131.3	43.7
20-21	194.6	63.0	258.8	139.8	190.8	61.9
21-22	186.7	69.6	240.9	121.8	188.3	77.5
22-23	240.1	94.0	158.8	72.1	185.9	78.4
23-00	160.5	48.0	132.8	53.6	104.6	34.8

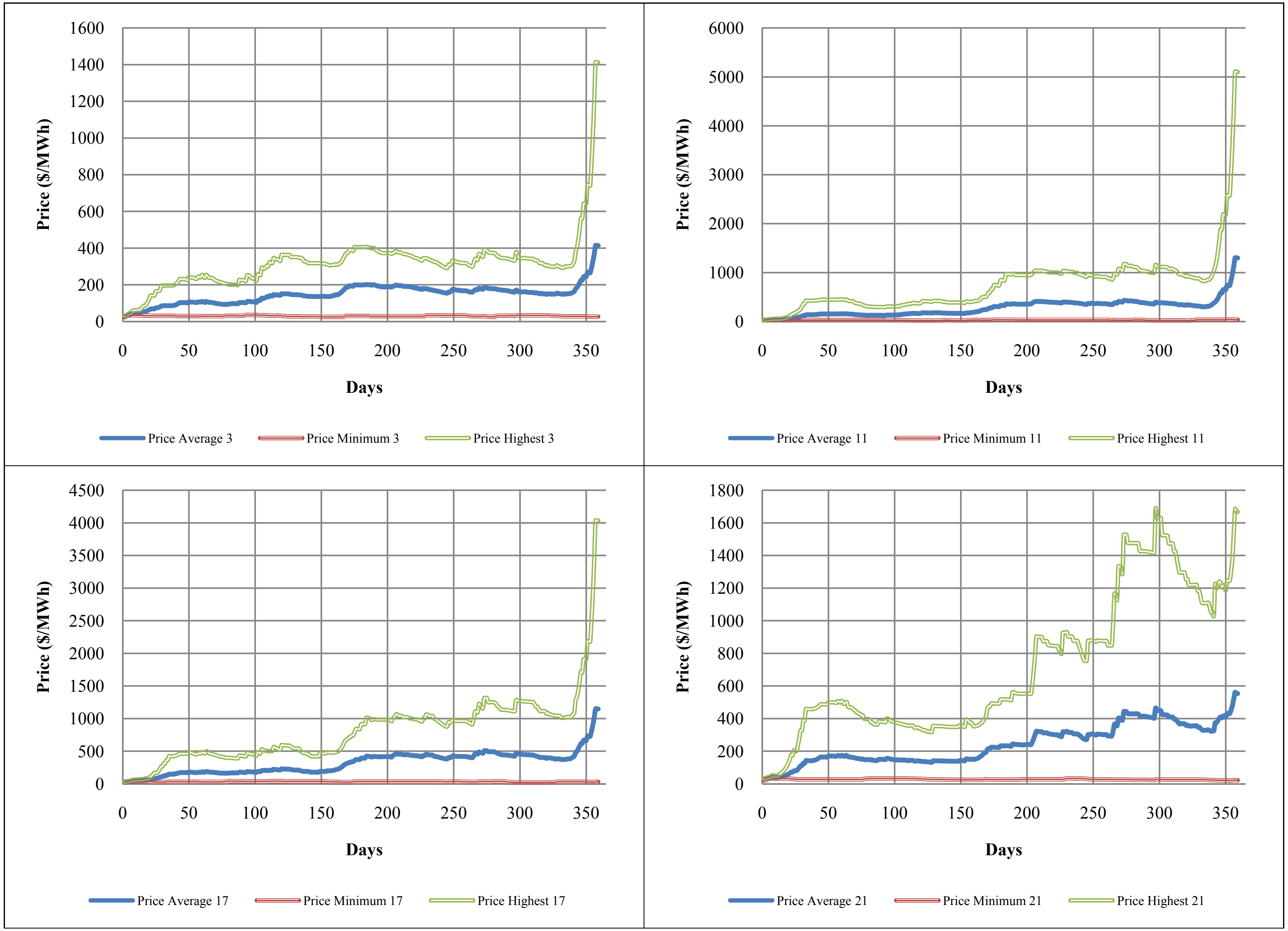

Figure 4.54. Impact of the NGB21 Scenario on electricity prices at the selected time intervals (AC OPF case).

Figure 4.55. Impact of the NGB28 Scenario on electricity prices at the selected time intervals (AC OPF case).

Table 4.45 displays real load levels of generator 1 in the reference, the NGB28 and the NGB21 scenarios. The NGB28 scenario is the only one where generator 1 loses significant levels of real load nearly for all time intervals. The introduction of the new generator seems to break the market power of the agents in the network. Figure 4.56 displays the real load profile of generator 1. The frequency of zero load level is much higher compared to the reference and any other scenario considered so far. This is due to the closeness of demand buses both to generator 1 and to the new generator. The new generator breaks the local market power of generator 1 and introduces competition to the region. Even though peak time load levels scheduled to generator 1 have changed under the NGB21 scenario, no significant load change can be observed in the non-peak periods. This indicates that the demand centers served via bus 30 and bus 21 are decoupled.

Table 4.45. Average real load scheduled to generator 1 in the reference, the NGB21 and the NGB28 scenarios for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	25.2	5.1	16.8	3.2	11.9	3.2
1-2	16.8	3.5	15.4	3.1	13.2	3.3
2-3	18.5	3.7	15.6	3.2	11.9	3.0
3-4	16.0	3.2	14.0	3.0	11.5	2.9
4-5	15.8	3.1	15.3	3.1	12.0	3.6
5-6	15.9	3.2	15.2	3.1	11.9	3.3
6-7	16.0	3.4	15.1	3.2	10.1	2.9
7-8	16.8	3.5	14.7	3.4	11.0	3.1
8-9	19.6	4.0	25.6	7.0	16.5	4.4
9-10	25.7	4.8	19.1	3.8	15.7	4.0
10-11	22.1	4.0	23.8	4.7	16.2	4.0
11-12	22.4	4.2	20.2	4.0	16.7	3.9
12-13	21.5	3.9	19.6	3.9	15.6	3.8
13-14	21.7	3.9	22.5	4.8	15.5	3.8
14-15	25.6	4.8	26.6	5.7	19.0	4.7
15-16	24.6	5.1	26.0	5.8	15.6	4.1
16-17	22.6	5.4	19.1	4.1	15.7	4.2
17-18	25.9	5.4	20.1	4.7	16.0	4.6
18-19	26.1	4.8	20.5	4.6	16.7	5.0
19-20	22.4	4.1	23.8	4.9	16.7	4.1
20-21	24.3	5.0	24.8	4.3	16.9	3.5
21-22	22.6	3.7	21.0	3.6	20.5	3.9
22-23	22.1	3.6	27.4	4.4	16.3	4.2
23-0	20.9	4.1	25.0	4.8	15.5	4.5

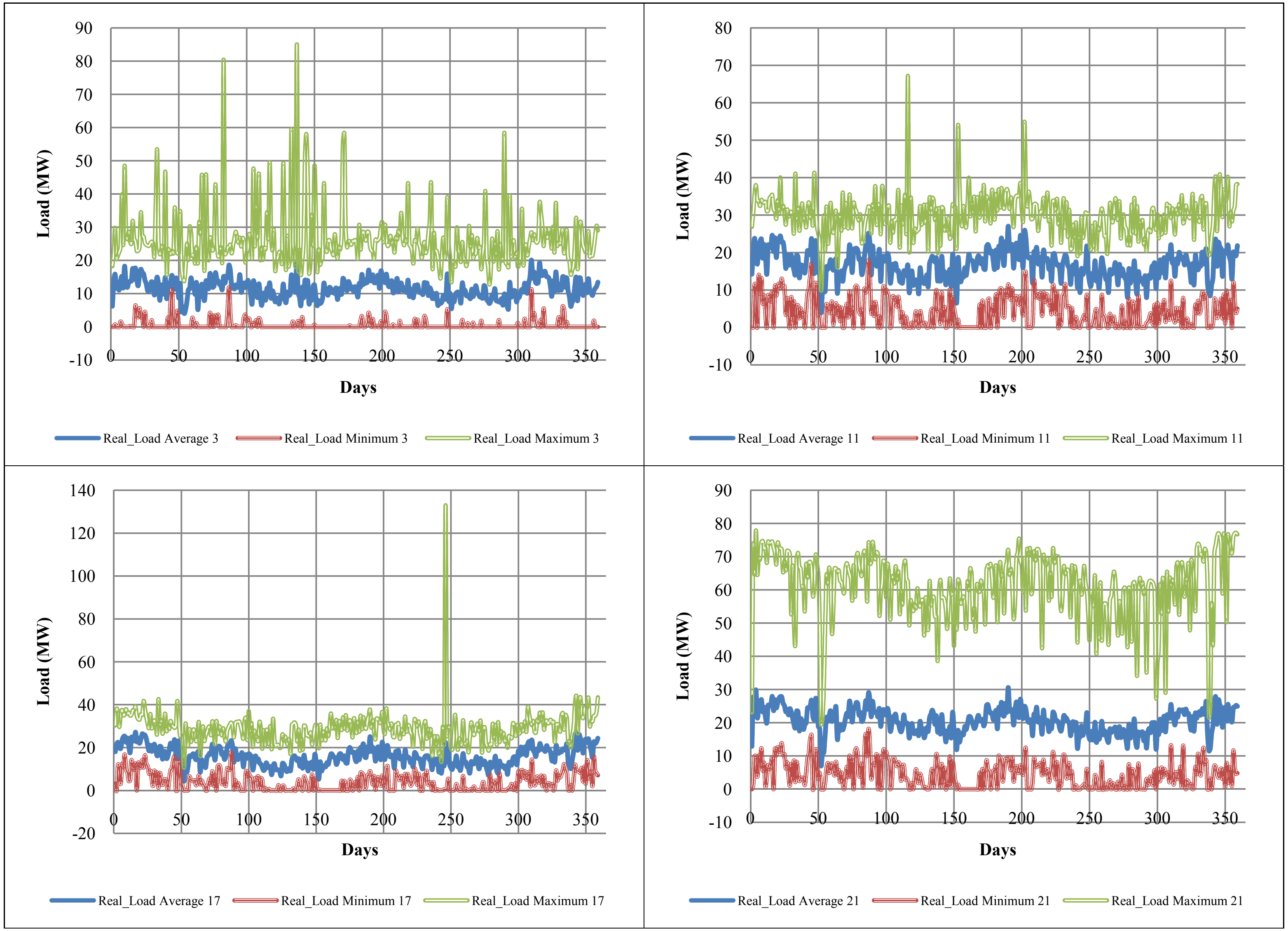

Figure 4.56. Impact of the NGB28 scenario on real load behavior of generator 1 at the selected time intervals (AC OPF case).

Table 4.46 displays the real loads of generator 5 in the reference, the NGB21 and the NGB28 scenarios. Under the NGB28 scenario, except for time intervals 4-6 and 21-22, the generator loses load and the standard deviation increases even at these low real loads. It is conjectured that with decreasing load levels, need for more market share leads to lower bid prices. Under the NGB21 scenario, lower load levels are significant at low demand time intervals, while at transition time intervals significant load gains are observed (such as time interval 8-9). Variance in the load levels is higher compared to the reference scenario, but lower than that of the NGB28 scenario. Regional market power effect of the new generator is higher in the NGB28 scenario, while the effect is significant in both scenarios.

Table 4.46. Average real load scheduled to generator 5 in the reference scenario, in the NGB21 scenario and in the NGB28 scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	67.6	11.5	46.7	11.2	44.6	11.1
1-2	48.0	10.3	44.8	10.8	47.7	10.4
2-3	52.7	10.4	45.1	10.9	44.3	10.6
3-4	46.2	9.8	40.1	10.4	44.4	10.6
4-5	47.6	10.1	42.6	11.0	50.4	12.7
5-6	46.7	9.8	41.1	11.1	50.2	12.2
6-7	47.4	10.0	40.7	12.0	39.1	10.6
7-8	50.9	11.3	39.6	11.2	43.3	11.5
8-9	60.5	13.1	70.0	15.5	60.3	13.8
9-10	73.3	14.0	57.1	14.4	60.6	14.4
10-11	66.0	13.5	65.7	14.6	59.4	14.4
11-12	70.7	14.0	60.1	14.6	63.2	14.7
12-13	66.4	13.1	57.1	13.8	57.5	14.2
13-14	68.2	13.6	62.7	14.3	60.8	14.5
14-15	74.2	13.9	70.5	14.6	65.4	13.8
15-16	71.4	13.9	67.6	15.0	60.7	14.4
16-17	67.8	13.8	56.2	15.0	58.4	14.8
17-18	72.9	13.1	60.3	15.8	61.6	16.5
18-19	74.6	13.2	62.6	15.6	63.3	16.5
19-20	69.9	12.9	68.5	14.0	63.0	15.1
20-21	73.0	12.2	70.6	13.3	65.0	14.3
21-22	70.0	11.5	61.1	12.0	71.5	12.7
22-23	69.4	12.0	69.5	11.7	62.2	13.6
23-0	63.5	11.4	65.7	12.1	56.5	13.4

Table 4.47 displays the real load scheduled to generator 7 under the reference, the NGB21 and the NGB28 scenarios. Generator 7 is one of the exceptions in terms of load

gains / loses pattern over demand periods. Generator 7 gains load in peak demand time intervals (such as 21-0); however, in other time intervals it loses load in general. This generator succeeds increasing its load in peak demand times, while it cannot withstand competition and abundance of supply in other portions of the day. Generator 7 increases load levels significantly under the NBG28 scenario. Nearly for all time intervals, significant load increases are seen, but especially for the transient and the peaking time intervals. This scenario shows how two generators with distinct serving areas may reduce the market power of better located rivals (generator 6 at bus 5) by gaining extra load at peak demand periods. (generator 7 and new generator located at bus 1 and bus 28 respectively.).

Table 4.47. Average real load scheduled to generator 7 in the reference scenario, in the NGB21 scenario and in the NGB28 scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	36.7	13.6	25.0	13.7	44.6	14.4
1-2	37.1	13.1	23.3	13.0	23.3	13.8
2-3	18.5	12.6	22.6	14.0	24.2	13.2
3-4	22.4	13.5	23.1	13.0	23.4	13.1
4-5	23.8	13.8	20.6	13.4	21.9	12.9
5-6	22.2	10.6	20.7	13.7	21.3	12.9
6-7	22.1	13.6	34.1	13.2	38.7	13.1
7-8	26.3	14.4	36.3	12.6	41.0	13.5
8-9	29.2	15.2	23.8	15.5	28.5	14.2
9-10	34.7	16.3	30.6	16.5	37.7	15.8
10-11	30.3	15.7	31.5	16.8	34.1	15.7
11-12	36.8	16.7	30.6	16.5	38.5	16.9
12-13	31.9	15.9	29.6	16.4	35.9	16.0
13-14	33.5	16.0	30.1	16.3	38.3	16.6
14-15	36.3	18.8	28.1	15.7	33.7	16.1
15-16	40.5	16.5	30.0	18.0	37.6	16.7
16-17	38.6	16.7	29.6	16.3	35.4	16.4
17-18	33.0	15.6	32.9	17.2	37.0	15.5
18-19	34.6	15.5	35.4	17.5	39.3	16.3
19-20	33.6	15.5	34.6	17.3	37.0	15.4
20-21	38.4	16.1	34.6	17.2	39.3	15.7
21-22	34.7	15.8	46.3	15.0	38.0	14.6
22-23	36.1	15.9	45.4	15.4	39.3	15.7
23-0	32.5	15.5	44.2	15.9	32.4	15.1

Table 4.48 displays the real load scheduled to generator 8 under the reference, the NGB21 and the NGB28 scenario. In the NGB21 scenario, generator 8 loses 2 to 15 MW load depending on the time interval. Highest load loss is observed in time interval 22-23, while minimum loss is in time interval 9-10. Load losses are less significant for the peaking times interval 16-18. In the NGB28 scenario, lost load levels are not significant as the NGB21 scenario, variance of the average load levels are less compared to the reference and the NGB21 scenarios. This is an indicator of the coupling of the demand centers that are served by new generator on buses 28 and 21 with respect generator 8's main market area. The physical placement of the buses considered is a good bases supporting the findings observed.

Table 4.48. Average real load scheduled to generator 8 in the reference scenario, in the NGB21 scenario and in the NGB28 scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	35.9	11.7	42.0	12.5	39.7	11.0
1-2	40.7	12.1	39.9	11.7	38.4	10.6
2-3	40.1	12.0	34.6	11.4	34.9	11.0
3-4	42.0	12.7	37.2	11.1	34.5	10.9
4-5	40.5	13.3	36.0	11.0	28.6	8.5
5-6	41.0	13.0	36.0	10.9	31.0	9.5
6-7	41.2	13.2	33.4	9.5	32.2	10.0
7-8	44.8	13.7	36.4	10.7	35.7	10.8
8-9	49.9	14.7	34.6	10.7	39.4	11.9
9-10	48.0	14.3	46.9	14.4	48.0	12.9
10-11	54.9	16.5	45.8	14.4	50.1	13.4
11-12	56.3	17.0	48.5	14.7	50.9	13.6
12-13	54.5	16.2	47.9	14.2	48.3	13.1
13-14	55.2	16.2	43.1	14.1	47.9	13.1
14-15	49.7	16.3	41.9	13.9	45.6	12.8
15-16	48.7	18.0	42.6	14.0	48.3	13.1
16-17	49.5	18.2	47.3	14.7	48.2	13.2
17-18	51.3	18.1	49.1	15.5	49.1	13.7
18-19	52.9	17.4	50.5	15.6	50.4	13.9
19-20	57.1	17.1	45.6	14.9	51.1	13.8
20-21	57.3	16.8	46.6	14.4	51.2	13.2
21-22	57.3	15.9	45.4	13.8	44.5	12.7
22-23	56.3	16.0	38.0	13.2	47.6	13.1
23-0	52.3	15.1	36.1	13.1	46.7	13.3

Real load levels of generator 9 under the reference, the NGB21 and the NGB28 scenarios are displayed in Table 4.49. Under the NGB21 and the NGB28 scenarios, loss of load characteristics are very similar to the case of generator 8. Lost load levels are significant at low demand time intervals while they diminish at peaking time intervals. Since the technical characteristics of generator 8 & 9 are very similar (i.e. same capacities, same minimum up and down times etc.), the difference in load levels is mainly due to their placement in the network and closeness to the demand centers.

Table 4.49. Average real load scheduled to generator 9 in the reference scenario, in the NGB21 scenario and in the NGB28 scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	29.3	9.1	36.2	11.3	34.3	10.2
1-2	32.9	9.6	34.4	10.9	34.3	9.9
2-3	32.3	10.0	29.7	10.0	30.7	9.6
3-4	34.6	10.4	32.5	11.1	30.5	9.9
4-5	34.8	10.4	28.8	10.5	26.8	9.7
5-6	34.5	9.8	28.3	10.6	28.8	9.4
6-7	34.5	9.7	26.1	10.2	29.9	9.3
7-8	36.2	10.1	29.9	10.2	32.8	9.8
8-9	40.6	11.1	27.0	10.8	36.2	10.5
9-10	40.1	11.1	39.1	12.0	42.5	11.7
10-11	44.7	12.4	38.7	11.8	43.0	12.1
11-12	45.7	12.7	42.0	12.5	44.8	12.1
12-13	44.5	12.4	41.1	12.2	41.7	11.7
13-14	44.7	12.2	36.1	11.7	42.2	11.8
14-15	39.7	11.3	34.4	11.4	38.7	11.5
15-16	40.1	12.2	32.9	11.5	42.4	11.8
16-17	41.1	13.3	39.9	12.9	42.2	12.4
17-18	41.1	12.1	42.5	13.4	43.2	12.4
18-19	41.9	11.0	42.9	13.3	43.8	12.2
19-20	45.4	11.4	39.1	12.7	44.6	11.5
20-21	45.2	11.7	40.4	12.1	44.6	11.4
21-22	45.8	11.6	38.6	11.5	42.2	11.1
22-23	45.2	11.6	30.9	10.9	42.4	10.9
23-0	41.9	11.3	29.5	10.9	41.2	11.1

The real load levels of the new small generator under the NGB21 and the NGB28 scenarios are displayed in Table 4.50. It should be emphasized that, load level changes are not in line with the daily demand curve in the NGB21 scenario. That is, increasing demand does not lead to higher load levels for the generator. This indicates that the competitive auction process pushed this generator out of the supply pool, especially in the second peak demand time interval 17-18. The average load levels during the day, which are in the 23-33 MW bandwidth, utilize two thirds of the generator's capacity, of 45 MW. Accordingly, this generator is better utilized compared to bus 3 and bus 6 cases, investigated in the NSBG3 and the NSBG6 scenarios, respectively. The utilization levels are also better than that of the NGB28 scenario.

Table 4.50. Average real load scheduled to the new generator in the NGB21 scenario and in the NGB28 scenario for all time intervals (AC-OPF case).

	The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0-1	25.4	5.6	23.8	5.7
1-2	24.4	5.6	23.5	5.5
2-3	24.6	5.5	21.6	5.1
3-4	22.6	5.7	20.9	5.1
4-5	25.3	5.5	23.4	5.0
5-6	24.8	5.4	23.5	5.0
6-7	27.7	5.2	20.1	5.1
7-8	25.3	5.2	21.4	5.3
8-9	31.4	5.0	22.4	5.5
9-10	26.6	5.8	24.3	6.2
10-11	29.8	5.6	23.3	6.0
11-12	28.2	5.7	25.3	6.5
12-13	27.6	5.6	23.9	6.0
13-14	28.1	6.0	24.4	6.4
14-15	31.3	5.4	24.9	5.9
15-16	30.9	5.5	23.9	6.4
16-17	26.6	5.7	23.4	6.1
17-18	28.5	6.2	24.0	6.3
18-19	29.1	6.4	24.6	6.5
19-20	30.0	6.0	24.2	6.3
20-21	30.9	5.5	24.5	6.2
21-22	30.2	5.3	26.3	6.1
22-23	33.0	4.7	24.3	6.2
23-0	32.8	4.7	21.9	5.8

Under the NBG28 scenario, average load levels change in the 22-27 MW interval, which is about one-half of the generator's capacity of 45 MW. Generator utilization levels are not satisfactory due to the limited demand in the region (buses 28 and 30 region). Additionally, even with the low load levels attained, generators' load levels' variance is equal or higher than that of the NGB21 scenario, which indicates high uncertainty of load and low market power potential on bus 28.

The profitability of the new generator under the NGB21 and the NGB28 scenarios is displayed in Table 4.51. Under the NGB21 scenario, profit levels are lower than that of the new generator in the NSGB3 and the NSGB6 scenarios, due to low prices. Peak profitability is attained in the time interval 9-10, while lowest profitability is observed in the time interval 4-5. However, again the standard deviations in peak time intervals are higher than the average levels, indicating the high uncertainty present for profitability. On the other hand, the standard deviation of second highest profit time interval, (which is very close to the peak profit level), is considerably smaller implying that the mean profit at that time interval is attainable with less uncertainty. The price pattern through the periods and load dispatch pattern through the day (as two main components of profit) form a profit distribution that does not follow the daily load curve (i.e. peak profitability attained in time interval 13-14, not in the 17-18 or 21-22 peaking demand intervals).

Profit levels of the new generator under the NGB28 scenario are lower than those in the other new generator cases considered, mainly due to lower electricity prices attained. Peak profitability is seen in the time interval 20-22, while lowest profitability is observed in the time interval 6-7. However, the variability in profitability is lower than those in other new generator cases.

Table 4.51. Profitability of the new generator in the NGB21 scenario and in the NGB28 scenario for all time intervals (AC-OPF case).

	The NGB21 Scenario		The NGB28 Scenario	
Hours	Average Hourly Profit ($)	Standard Deviation of Hourly Profit	Average Hourly Profit ($)	Standard Deviation of Hourly Profit
0-1	4586	3149	2417	1048
1-2	4911	3084	1745	652
2-3	3602	2283	1891	778
3-4	3362	2112	2265	1409
4-5	2578	1642	2795	1425
5-6	2943	2049	2293	1099
6-7	4069	2953	1796	712
7-8	4165	3061	1844	777
8-9	4827	2895	2395	1136
9-10	12086	11373	4094	2121
10-11	11316	11379	2368	1047
11-12	9176	8107	3575	2201
12-13	7454	6295	3148	1502
13-14	12078	8359	4658	2970
14-15	6372	4722	2933	1500
15-16	6004	4461	4174	2258
16-17	6793	6814	3217	1702
17-18	10072	8139	3481	1773
18-19	11248	9699	3622	1703
19-20	8073	5767	3522	2012
20-21	8501	6162	5232	2925
21-22	7889	5481	5224	3508
22-23	4945	3355	4997	3401
23-0	3875	2569	2680	1498

The last set of structural changes investigated concern scenarios introducing new generators at the highest demand bus, namely bus 5. Table 4.52 displays the descriptions of these scenarios. These scenarios are selected to better understand the impact of a large generator (powerful agent) versus the impact of two smaller generators (weaker agents) operating at the same location. This setting also gives the opportunity to observe the effect of structural changes at the highest demand bus in the network. The specifications of the new generators considered at bus 5 are displayed in Table 4.53.

Table 4.52. Description of scenarios associated with the introduction of new generators at bus 5.

Scenario Code	***Scenario Details***
NSGB5	New Small Generator on Bus 3
SPLTB5	Split of Generator on Bus 5 (Generator 6)

Table 4.53. Technical specifications of the new introduced generators at bus 5.

Parameters	***NSGB5***	***SPLTB5***
Capacity (MW)	45	66
MinLoad (MW)	0	0
Reactive Limits Supply (MVAR)	27	40
Reactive Limits Consume (MVAR)	18	26
NoLoad Energy (MWh)	10	10
Startup Energy (MWh)	2.058	2.058
Minimum Up Time (MWh)	2	2
Minimum Down Time (MWh)	2	2
Primary Resource	Coal	Coal
Connected Bus	5	5

Table 4.54 displays the electricity prices under the reference, the NSGB5 and the SPLTB5 scenarios. As can be observed, under the NSGB5 scenario, electricity prices decrease in only four time intervals (4-5, 5-6, 6-7 and 7-8). Additionally, the lower prices are coupled with higher standard deviations that create more uncertainty in those price levels. Additionally, the comparison of the prices between the NSBG5 and SPLTB5 scenarios indicates that in the time interval 0-9 (which is the low-demand time interval), prices in scenario NSBG5 are lower than that of the SPLTB5 scenario. For other time intervals, prices in the NSBG5 scenario are higher in general.

Prices under the SPLTB5 scenario are higher compared to the reference scenario except for very few time intervals such as 11-12. Another interesting point is that prices of the reference scenario lie in between the NSGB5 and the SPLTB5 scenario’s prices.

The above observations suggest two different trends emerging at the considered scenarios. Under the NSGB5 scenario, new generator focuses on increasing the prices as much as it can with the market power it has captured by being close to the highest demand point. This strategy is meaningful since, with the limited capacity, playing for price is more profitable and sustaining the achieved profit levels is easier than maximizing the load levels assigned. However, at elevated prices, even for the most inflexible generator, shutting down and starting up costs are negligible compared to the price levels, introducing new actors into the competition and forming a feedback mechanism holding the prices at the proposed levels. Under the SPLTB5 scenario, competition between the similar units installed pulls down prices at non-peaking time intervals (with respect to the reference scenario). However, low prices are not profitable for inflexible units to be open right before peaking time intervals. Accordingly, flexible generators exercise the power of their technical advantage and are able to increase the prices to higher levels.

Table 4.54. Average electricity sales prices in the reference scenario, the NSGB5 scenario and the SPLTB5 scenario for all time intervals (AC OPF case).

	The AC-OPF Reference Scenario		The SPLTB5 scenario		The NSGB5 scenario	
Hours	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price	Average Price ($ / MWh)	Standard Deviation of Price
0-1	143.0	58.5	195.5	102.7	208.5	117.9
1-2	151.2	53.1	157.2	70.7	209.6	105.2
2-3	138.2	50.6	188.0	72.2	230.0	127.9
3-4	122.5	25.5	132.2	61.0	221.8	116.2
4-5	170.2	52.6	98.0	31.5	147.2	69.0
5-6	172.9	48.6	111.3	42.3	212.5	113.6
6-7	151.2	34.8	96.8	46.3	212.7	110.0
7-8	167.8	38.9	125.9	63.4	177.6	81.5
8-9	181.8	76.2	193.8	96.6	177.6	81.3
9-10	345.7	205.3	252.0	153.1	213.1	95.0
10-11	164.9	45.9	295.0	188.5	160.2	71.7
11-12	280.2	161.6	252.6	158.9	170.2	85.3
12-13	238.2	103.7	331.5	201.3	154.0	64.4
13-14	153.1	48.9	315.5	194.0	242.4	131.5
14-15	170.6	66.1	304.6	178.5	212.7	104.4
15-16	193.2	106.6	221.4	120.0	216.8	105.9
16-17	163.0	45.0	240.6	145.7	265.8	154.1
17-18	203.7	55.3	270.8	148.4	273.8	176.1
18-19	178.9	48.8	272.6	152.4	210.8	111.8
19-20	172.6	53.6	311.5	191.2	295.5	179.8
20-21	194.6	63.0	194.7	114.0	245.7	143.8
21-22	186.7	69.6	269.0	163.8	337.7	183.2
22-23	240.1	94.0	329.9	200.1	119.0	47.3
23-0	160.5	48.0	188.3	123.2	101.9	42.3

Figure 4.57 displays electricity price behavior under the SPTB5 scenario. Price behavior indicates highly volatile structures in the low demand time interval 3-4, which converges to $100 levels close to the end of the planning horizon. For all time intervals, price behavior shows abrupt price level changes which stay at the new level until the end of planning horizon. The maximum price levels indicate higher variation until the end of the simulation.

Figure 4.58 displays electricity price behavior under the new small generator on bus 5 scenario. Price behavior feature a boom and bust characteristic in low demand time intervals, which converges to $200 levels close to the end of the planning horizon. For all time intervals price dynamics exhibit a sudden price level change in the second quarter of the year. For time intervals 11-12 and 21-22, prices stay constant at the new level until the end of the planning horizon. The high price levels attained also contain high variation.

Table 4.55 displays the real load scheduled to generator 4 under the reference, the SPLTB5 and NSGB5 scenarios. As can be observed, in the NSGB5 scenario generator 4 loses 2 to 25 MW load (to other agents) depending on the time interval. Highest loss is observed in time interval 10-11, while minimum loss occurs in time interval 1-2. This is an expected result since the overall increase in system capacity, would decrease the load levels of the existing generators as long as they do not have a special market power due to some technical advantage or network location. In the SPLTB5 scenario, generator 4 increases real load levels as can be observed from Table 4.55. Even though no capacity change is present in the system, the competition between generators on bus 5 seems to open the way for taking extra load compared to the reference scenario. This situation is a good example of how a single or multiple unit generation with the same capacity may have different effects regarding load scheduling.

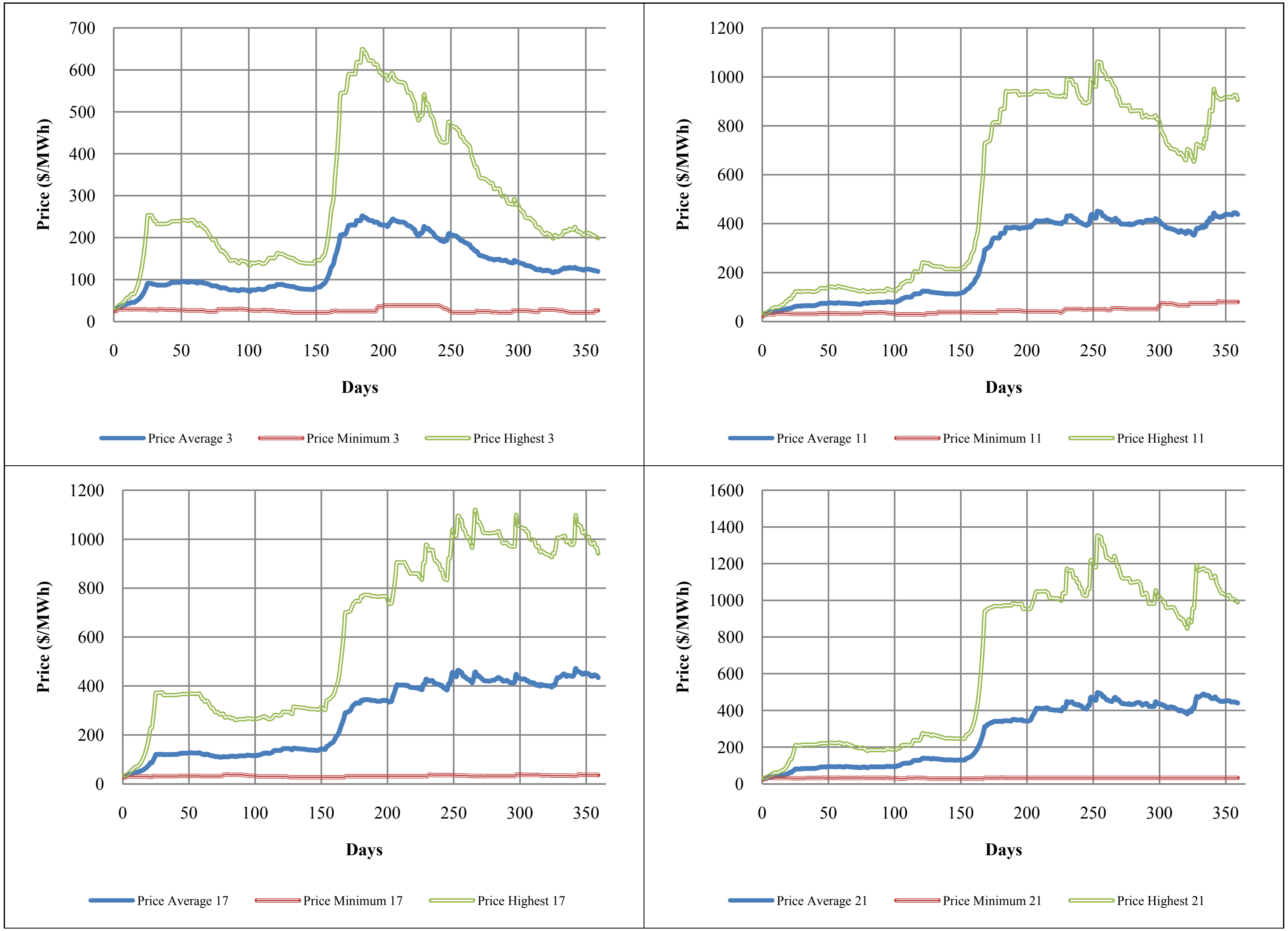

Figure 4.57. Impact of the SPLTB5 scenario on electricity prices at the selected time intervals (AC OPF case) .

Figure 4.58. Impact of the NSGB5 scenario on electricity prices at the selected time intervals (AC OPF case).

Table 4.55. Average real load scheduled to generator 4 in the reference scenario, in the SPLTB5 scenario and in the NSGB5 scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The SPLTB5 scenario		The NSGB5 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0	46.3	13.9	49.8	15.2	47.6	13.5
1	48.2	13.6	52.7	14.5	47.9	14.4
2	45.3	13.5	45.4	12.7	42.2	13.6
3	47.1	14.2	46.5	14.6	41.4	13.8
4	46.5	15.8	42.6	13.8	43.5	14.4
5	47.4	15.7	45.8	13.7	44.0	13.4
6	47.4	15.0	43.8	13.1	42.2	13.3
7	51.0	16.4	51.2	14.3	46.8	14.0
8	62.6	18.8	64.1	17.6	52.0	15.4
9	68.0	19.7	73.4	19.2	49.0	14.4
10	75.1	20.7	76.2	19.8	51.1	14.6
11	74.0	19.9	76.4	19.7	54.5	14.8
12	71.0	19.8	72.1	19.5	45.9	13.8
13	70.9	20.1	72.9	19.9	47.0	14.5
14	65.4	21.0	74.3	20.5	52.7	17.3
15	64.6	21.7	73.4	20.4	52.5	17.0
16	66.7	23.4	72.7	21.0	48.5	15.2
17	69.6	23.0	74.3	21.8	54.1	16.2
18	70.6	23.2	77.6	20.7	54.8	15.6
19	75.7	21.5	78.0	19.4	55.1	14.9
20	75.3	19.9	80.6	18.0	56.8	15.2
21	75.1	19.1	74.8	17.1	58.6	16.7
22	72.5	19.2	71.7	18.0	52.8	15.3
23	65.6	18.1	60.3	16.7	47.1	14.5

Table 4.56 displays the real load scheduled to generator 6 in the reference, the SPLTB5 and the NSGB5 scenarios. While the generator’s load is near full capacity at all time intervals in the reference scenario, under the SPLTB5 scenario, average load levels are always less than half of the levels in the reference scenario. In other words, in the SPLT5 scenario, when the total load scheduled to bus 5 is considered, some loss of load is observed. This situation indicates that same capacity under a single management is able to get more loads than multi-management cases.

Under the NSGB5 scenario and with the new structure brought about by the introduction of a small generator, it is observed that generator 6 loses around 2-15 MW load at all time intervals. Direct competition with the new generator at the same bus negatively affects generator 6’s load levels, as would be expected in the real world.

However, it should be noted that the loss of load is not as high as the new generator's load gain. Accordingly, the total power scheduled to bus 5 increases.

Table 4.56. Average real load scheduled to generator 6 in the reference scenario, in the SPLTB5 scenario and in the NSGB5 scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The SPLTB5 scenario		The NSGB5 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0	123.9	12.0	59.5	7.0	110.1	13.1
1	118.7	11.8	57.5	6.9	103.5	12.7
2	116.9	12.0	56.5	7.0	103.6	12.2
3	113.6	12.8	54.0	7.6	102.2	12.1
4	113.3	12.3	56.2	7.3	100.6	12.6
5	113.7	12.4	55.2	7.7	99.4	13.1
6	114.1	12.5	57.1	7.2	100.7	13.6
7	115.9	12.9	58.0	7.2	104.1	14.2
8	123.4	11.5	59.6	6.8	113.5	13.9
9	125.9	10.5	61.6	6.0	114.0	14.8
10	127.2	9.5	62.0	5.6	122.7	11.1
11	126.8	9.9	62.1	5.6	122.2	11.3
12	126.4	10.0	61.8	5.6	121.6	10.8
13	126.2	10.2	61.3	5.9	122.0	10.8
14	126.5	10.2	61.7	5.8	119.4	12.1
15	126.7	10.1	61.5	6.0	118.7	12.1
16	126.1	9.8	61.4	5.8	120.1	11.8
17	126.1	9.5	61.4	5.6	120.2	12.1
18	127.0	9.0	61.7	5.3	120.7	12.0
19	126.7	9.4	61.6	5.4	120.9	11.6
20	127.7	8.8	62.9	4.8	122.4	10.7
21	127.9	9.0	62.6	4.9	121.2	11.0
22	127.0	9.4	61.7	5.4	121.7	10.8
23	125.1	10.1	62.4	5.2	119.9	10.8

Figure 4.59 displays the price behavior of generator 6 in the NSGB5 scenario for the selected time intervals. Average load levels are lower than the reference scenario. Even for the peaking time intervals, the frequency of minimum load being at zero level is significantly higher indicating the loss of market power due to the new structure.

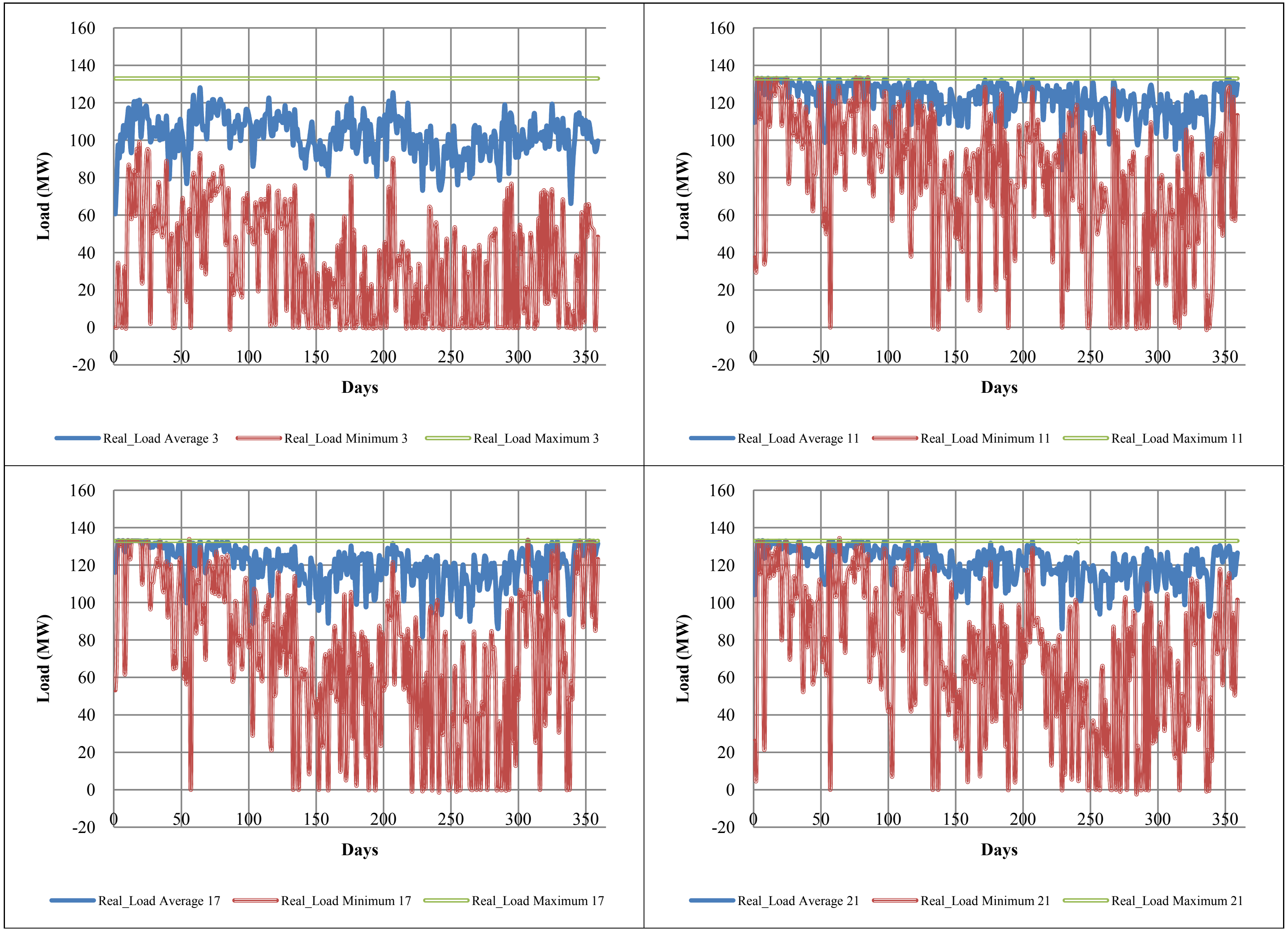

Figure 4.59. Impact of the NSGB5 scenario on real load behavior of generator 6 at the selected time intervals (AC OPF case).

Table 4.57 displays the real load scheduled to generator 7 under the reference, the SPLTB5 and the NSGB5 scenarios. During most time intervals generator 7 gains 2-20 MW load in the SPLTB5 scenario. The highest gains are seen around peak demand times. Some insignificant losses are also observed during non-peak time intervals. The real load gains indicate that increased competition on bus 5 (without any increase in the system capacity), causes generator 7 to gain additional load through its location and cheap resource (coal) advantages.

Under the NSGB5 scenario, it is observed that generator 7 loses load in low demand time intervals (between 0 - 9), while featuring significant load gains in midday time intervals, compared to the reference scenario. This situation occurs mainly due to the technical characteristics of this generator: on the hand, it has advantage of having a cheap primary resource, while, on the other hand, it is the least flexible generator in the network. So, it can only make effective use of its resource advantage, when it is able to boost up its generation level, which can only occur when demand is above a certain threshold. Thus, the resulting load levels seems to be intuitive.

Table 4.58 displays the real load scheduled to generator 8 under the reference, the SPLTB5 and the NSGB5 scenarios. In the NSGB5 scenario, generator 8 loses 3 to 16 MW load depending on the time interval. Highest loss is observed in time interval 22-23, while minimum loss occurs in time interval 5-6. The capacity increase over the network is a key disadvantage for this generator, since it uses oil as energy resource, which is the most expensive resource present in the system. Thus, the capacity expansion at the highest demand bus reduces the market power of this generator considerably. Under the SPLTB5 scenario, generator 8 loses power like in the NSGB5 scenario with a lower level of load loss. The situation is more complicated compared to the NSGB5 scenario. Introduction of additional competition on bus 5 leads to an increase in generator 7's load level which has the lowest marginal production cost, thus reducing the local market power of higher marginal cost producers. Generator 8 suffers from this situation as well.

Table 4.57. Average real load scheduled to generator 7 in the reference scenario, in the SPLTB5 scenario and the NSGB5 scenario for all time intervals (AC-OPF case)..

	The AC-OPF Reference Scenario		The SPLTB5 scenario		The NSGB5 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0	36.7	13.6	29.7	14.8	21.6	13.3
1	37.1	13.1	27.0	13.7	22.7	13.7
2	18.5	12.6	24.8	13.5	20.4	11.3
3	22.4	13.5	39.4	15.0	20.3	13.6
4	23.8	13.8	34.4	13.3	19.0	13.3
5	22.2	10.6	24.5	13.3	20.6	13.4
6	22.1	13.6	30.2	15.5	24.2	15.9
7	26.3	14.4	24.9	14.1	21.3	13.5
8	29.2	15.2	34.3	15.1	25.1	14.5
9	34.7	16.3	39.1	16.2	58.9	13.2
10	30.3	15.7	40.8	16.6	41.7	14.2
11	36.8	16.7	41.1	17.2	43.3	14.7
12	31.9	15.9	38.1	15.7	57.8	14.1
13	33.5	16.0	40.8	16.9	39.9	13.5
14	36.3	18.8	38.9	16.8	44.2	14.4
15	40.5	16.5	37.2	17.1	45.2	15.0
16	38.6	16.7	38.0	16.9	44.5	15.9
17	33.0	15.6	40.0	16.4	45.1	15.2
18	34.6	15.5	38.7	15.9	46.6	15.3
19	33.6	15.5	43.2	16.7	47.1	15.3
20	38.4	16.1	39.5	17.1	37.5	16.3
21	34.7	15.8	40.5	15.7	37.5	17.0
22	36.1	15.9	42.9	16.2	38.8	19.4
23	32.5	15.5	44.8	17.1	35.7	20.8

Load levels of the new generator, under the SPLTB5 and NSGB5 scenarios, are displayed in Table 4.59. The levels are nearly the same as the other splitted generator, namely generator 6. However, compared to the reference scenario, the total load of these splitted generators is not equal to the original instance. This indicates that the loss of load on bus 5 is due to the competition between those units. This is an expected outcome since two small generators cannot behave like a single unit(having their aggregate capacity) to gain more load. However, the location advantage of bus 5 does not permit further load loses at higher demand levels.

Table 4.58. Average real load scheduled to generator 8 in the reference scenario, in the SPLTB5 scenario and the NSGB5 scenario for all time intervals (AC-OPF case).

	The AC-OPF Reference Scenario		The SPLTB5 scenario		The NSGB5 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0	35.9	11.7	37.3	12.0	41.1	13.1
1	40.7	12.1	40.5	11.7	40.9	13.0
2	40.1	12.0	38.5	11.5	34.8	11.6
3	42.0	12.7	37.4	11.6	34.3	11.5
4	40.5	13.3	32.6	10.8	36.8	11.9
5	41.0	13.0	37.0	11.7	38.3	12.7
6	41.2	13.2	33.3	11.4	36.9	12.4
7	44.8	13.7	40.4	12.3	39.4	12.8
8	49.9	14.7	45.6	13.3	44.1	14.3
9	48.0	14.3	51.0	14.2	40.6	13.9
10	54.9	16.5	51.9	14.3	39.6	13.9
11	56.3	17.0	51.9	14.3	44.3	14.5
12	54.5	16.2	50.3	14.0	38.8	13.9
13	55.2	16.2	50.3	14.1	38.1	13.7
14	49.7	16.3	50.2	14.3	43.2	14.7
15	48.7	18.0	50.6	14.2	43.0	14.6
16	49.5	18.2	49.3	14.2	39.9	14.2
17	51.3	18.1	50.5	15.0	44.5	15.6
18	52.9	17.4	51.2	15.6	44.8	15.8
19	57.1	17.1	52.9	15.7	45.1	15.5
20	57.3	16.8	53.5	15.3	44.8	14.2
21	57.3	15.9	47.2	13.6	46.6	15.0
22	56.3	16.0	45.3	13.3	39.7	15.4
23	52.3	15.1	37.7	12.1	38.3	15.6

Under the NSGB5 scenario, the new generator at bus 5 attains load levels of 25 MW and higher in low demand time intervals, while having 35 MW and higher load levels in transient and peaking time intervals. Considering its 45 MW capacity, load levels are satisfactory. Nevertheless, this situation also indicates that further capacity increases would not result in higher load levels, since 95% utilization levels observed in the reference scenario is lowered to 80-85% for generator 6 and 60-70% for the new generator. This indicates a higher level of competition with a further capacity increase, may show an opportunity that can lead to lower prices due to fierce competition. However, it should be pointed out that instead of small units, moderate and large size units may be more appropriate, as smaller units are more capable in price manipulations leading to price and profit increases - as was observed in other scenarios, such as the NSGB3, and the NSGB6 scenarios.

Table 4.59. Average real load scheduled to the new generator, in the SPLTB5 scenario and the NSGB5 scenario for all time intervals (AC-OPF case).

	The SPLTB5 scenario		The NSGB5 scenario	
Hours	Average Real Load (MW)	Standard Deviation of Real Load	Average Real Load (MW)	Standard Deviation of Real Load
0	58.5	6.8	29.0	6.6
1	56.1	7.0	26.2	6.3
2	55.5	6.8	26.4	6.2
3	52.0	7.7	25.9	6.5
4	55.7	6.9	24.2	6.8
5	54.2	7.5	24.4	6.6
6	55.8	7.2	25.0	6.8
7	56.5	7.4	27.0	6.7
8	58.3	7.1	32.2	6.7
9	60.4	6.4	33.4	6.4
10	60.8	6.1	38.1	5.6
11	61.0	6.0	37.7	5.7
12	60.6	6.0	37.0	5.5
13	60.0	6.4	37.2	5.5
14	60.3	6.3	36.0	6.0
15	60.3	6.3	35.5	6.2
16	60.2	6.2	36.6	5.7
17	60.0	6.4	36.2	6.6
18	60.5	5.9	36.6	6.6
19	60.3	5.9	37.1	6.0
20	61.9	5.1	38.2	5.0
21	61.7	5.2	37.4	5.1
22	60.6	5.6	38.0	4.9
23	61.5	5.4	36.1	5.5

5. CONCLUSION AND FURTHER STUDY

In this thesis, a mathematical model is developed to investigate and better understand the implications of a competitive and regulated power market (under transmission line and production technology based constraints) on electricity prices, sustainability, availability, and supply security. An integrated simulation / optimization approach is used in the modeling and analysis of the decentralized electricity market. The primary electricity supply / demand issue tackled is “day ahead hourly market balancing” based on the available transmission network, estimated demand profiles and supply bids offered by the electricity providers present in the system. For this purpose, an integrated agent based simulation model and network flow optimization models (linear and nonlinear) are developed to mimic bidding and oversee / optimize electricity flows, while enforcing technological and other constraints. In the simulation model generators try to maximize their profits under the existing market conditions and technical constraints, while their decision making mechanisms are designed in a way to benefit (learn from) their previous actions. The System Operator (SO) collects hourly bids (of specific amount of electricity production at specific prices) from generators and accepts the bids starting from lowest price until the period’s demand is satisfied, so that all demand is satisfied at minimum cost of generation and transmission. The SO oversees a predefined set of power generators and a power transmission network, while pursuing cost minimization through generation scheduling and power flow decisions. The characteristics and capacities of the generators and transmission lines are represented through two alternative network flow optimization models, one linear and another non-linear.

Within this framework, various hourly and daily bidding strategies (of individual generator agents) are developed and tested, and further policy analysis is carried out under various settings of market parameters, such as demand heterogeneity, supplier number, size and distribution over the network. In this context, new generators are introduced at various locations in the network to see the possible effects over price formation and agent behavior.

The current study is an attempt to close the gap in the literature on electricity market modeling with self-learning autonomous agents over a transmission network. The network is treated such that full AC OPF constraints are implemented with an exact solution approach. The developed modeling scheme is employed to observe and compare location, size and type of decisions associated with new generation facilities and their effects on prices. Regarding the placement of a new entrant, various technological configurations are implemented to better understand the effect of selected technologies. Other novel features of the model include the introduction of different hourly bidding strategies and transmission fee implementations, which are compared and investigated through scenarios. The key observations and conclusions reached are as follows.

Table 5.1. Comparison of descriptive information for two modeling approaches.

	Linear Network	AC-OPF
# of Demand Components	Single (Real)	Two (Real and Reactive)
Simulation Time (each run)	5 min	40 min
Number of Constraints	70	149
Type of Constraints	All linear	All non-linear
Closeness to reality	Not Much	Yes

Table 5.1 summarizes the main underlying differences of the AC-OPF and the linear network approaches. The number of demand components and constraints, together with the characteristics of the constraints, increases the complexity of the integrated simulation / optimization accomplished as is reflected by the run times. The increased complexity however brings the simulation / optimization model closer to the real world it represents.

First, it should be noted that, the effect of the transmission network on market price formation is minimal in the linear network case. The price remains in the 20-70 $ / MWh range, which is very close to the marginal cost of production of the electricity producing technologies. Besides, the transmission capacity is not very crucial in the linear case. The flexibility of the optimization for the flow of electricity is high enough so that disturbance over the prices is minimal as long as excess capacity is present within the system. Transmission fee has a vital role in market formation. An increase in the transmission directly increases the electricity production costs; selecting the most cost effective producers are selected repetitively in the optimization. Those producers exercise market power as much as they can to maximize profit, thus pushing prices upward.

Implemented bidding strategies, namely the Market Share based bidding strategy, the Market Power bidding strategy and the Price Tracking bidding strategy, turned out to have different effects at different time intervals. The Market Share bidding strategy is found to be especially effective at low demand time intervals where low marginal cost producers dominate the market. These producers exercise market power with their influential market share and this affects the pricing mechanism considerably. The Market Power bidding strategy, on the other hand, is found to be effective at peaking demand time intervals, where the gap between the capacity and demand narrows considerably. The Price Tracking bidding strategy is seen to be effective at all time intervals, which is surprising since the market is competitive in any sense by its excess production capacity and unlimited transmission capacity. This indicates the possible dramatic outcomes of a market structure with good macro indicator in a deregulated electricity market.

Regarding the AC-OPF case, due to the nature of the AC, the network structure (and limitations) have considerable effect on market price formation. This situation is better observed on average electricity sale prices. The resulting prices are higher for each time interval (as compared to the linear network model). In the base run, the average electricity price changes between 120 and 350 $ / MWh depending on the time interval. This wide price range indicates the capability of the modeling approach in capturing real life possibilities with the price of increased complexity in terms of coding and increased computational time as pointed out in Table 5.1. In this case, unlike the linear network approach, lowering of the transmission capacity has significant effect on price formation. In low demand time intervals, due to low energy needs, network capacity is rarely fully utilized, exhibiting no noticeable effect over prices. However, in the peak and transition time intervals, when the line capacity utilization is much higher, the pricing mechanism is affected by higher local market power potential of generators close to demand. Unlike the linear case, even if excess production capacity is present within the system, due to the nature of the AC, the central planner cannot effectively use the excess capacity to maintain the desired supply / demand balance.

Transmission fee is also found to be one of the parameters in the AC-OPF case that responds in reverse direction compared to the linear network approach. Lowering the transmission fee leads to manipulative behavior among the agents leading to higher prices compared to the base case. Setting the transmission fee to higher levels forces the generators that are far from demand centers to lower their bids, so that they will have a better chance of getting awarded load assignments throughout the day by the SO. Since the nature of AC effects the producers that are far from the demand in a negative manner, higher transmission fees let no way for the outside generators other than cutting their prices.

The Market Share bidding algorithm is observed to be effective at all time intervals. It is found that the generators that are producing less than their capacity lower their bid prices in order to increase market share. This pulls down prices to level nearly equal to the linear case. This finding, leads to two possible policy design concerns: first, market design should motivate the generators for maximizing their market share leading to lower prices and volatility; second, this situation indicate how the linear approach and AC-OPF diverge at load schedule and assignment leading to reverse effects.

The Market Power bidding strategy produces results similar to the linear network approach while the Price Tracking bidding strategy exhibits a different behavior than the linear case. For price tracking bidding strategy, at low demand intervals significant price decreases are observed, followed by extraordinary high prices at peak demand time intervals. Generators motivated by the high prices at peak demand intervals compete to take load in advance (in prior transition periods) in order to be in operational state at peak demand intervals. This behavior lowers prices considerably at time intervals close to peak times, thus introducing an interesting dynamics triggered by high peak time prices.

Under the AC-OPF model, various network structures are experimented with in order to see the important aspects of the network affecting the price dynamics. First, the location of high demand centers are moved to compare outcomes with the base case. It is observed that, as a result of interchanging demand pattern on two buses, the market power of certain influential generators diminish, making the market more efficient. This indicates that physical closeness to high demand centers and technological advantages affect the local market power potential of generators. It indicates the importance of demand heterogeneity and generator siting as essential factors in price dynamics.

Next, the introduction of a new small or moderate sized generator over the network, at a highly interconnected or at a remote node, is investigated. Interestingly, it is found that the introduction of a new generator does not necessarily make the market more competitive or efficient. The selection of location and capacity affects price dynamics. Diverging behavior of generators may even lead to a manipulation of the market if right is not carried out. Decisions should cover the selection of size as; small, medium or large based on the current network structure; including resource selection, which will effect the flexibility of the generator. Siting of the generator should also be investigated to balance the local market power of generators by accounting the transmission line capacities, demand centers' locations and locations of other generators present in the system.

It is also observed that locations that have many connections and / or easy to transmit power are good positions for manipulating prices; generators sited at such locations make use of the advantageous position to push prices up as much as possible (Bus 3 and Bus 6 based scenarios). The size of the generator is another important parameter affecting the outcome. Placing a large generator in a location that is close to high demand centers or which can easily transmit power to many demand buses may decrease the prices at certain time intervals. Locating a relatively small generator pushes prices to an upper level for profit maximization, using the local market power of the location. New generators at locations distant to demand centers are more suitable candidates for lowering prices in the system since they have to overcome local market power of existing generators and compensate transmission costs with the bids they offer. Small size generators is proven to be wrong decision for buses that are highly interconnected and in close proximity to demand centers. Big sizes are more appropriate in such cases. Siting to the remote buses diminishes the importance of size but larger sizes are favorable for price stability.

Finally, it is found that splitting a dominant generator at a highly interconnected location does not necessarily lead to lower prices. The competition between new agents with less capacity may open the way for another generator that has more capacity but was suppressed by the initial, unsplitted generator. Even though the splitted generators lose load to the next powerful generator, they still use the power of the advantageous bus and push prices up to maximize profit. Prices are distorted so significantly that profits increase for both generators, in spite of lower generation levels.

In summary, this study showed and underlined the importance of transmission network, location of demand centers, and siting of generators for the successful design of a deregulated electricity market. It has been shown that the design of an electricity market is far more complex than just having excess production capacity to meet demand. Physical network parameters have dramatic effects over price levels and stability. Additionally, the behavior of the generators have significant effect over market price formation, as pointed out by the market share,the market power and the price tracking based bidding strategies. For an efficiently functioning, competitive electricity market, careful system design, giving due consideration to physical network parameters including demand location and generator siting is inevitable.

From the investor / generator viewpoint, the picture is somewhat different. Since the general objective of the generators is to maximize profit, this target is seen to be achieved by two strategies. The first strategy is to maximize the assigned load levels so that the gap between the cost of production and price is fully accounted as profit. The second strategy is to manipulate the prices, through well designed bidding strategies, so that the gap between the electricity price and production cost is maximized. In this study it is shown that siting of the generator in the network, selection of its size and technology are the main strategical decisions in a decentralized competitive power market.

Siting of the generator is a key strategic factor since it determines the market power of the generator for different time intervals. A generator may be very advantageous at a certain bus at transient time intervals just because of technological flexibility since all other close neighborhood generators can be very inflexible due to their inherent technical parameters. In this case, such a generator’s market power will enable it to push up prices until a remote comparable rival’s disadvantageous situation is compensated by the price increases and its active competition stabilizes the prices. NSGB3 is a good example of the situation, where the prices are elevated until remote generators balanced the prices at those high levels. Such a flexible generator located at a remote bus, far from demand centers has to overcome transmission loses, costs and network constraints, in order to market its electricity production. In such a case, the primary strategy will be to maximize load assignments, which inevitably induces the generator to offer lower bids and accept lower profitability.

Another important parameter for the investor is the difference between high demand load and low demand load intervals and the length of transient period for this load change at the close proximity of candidate bus for the new generator. This may increase the value of technological flexibility of the new generator or diminish this technological advantage due to other flexible rivals or daily demand curve. The locations permitting the price manipulation, such as highly interconnected buses, for profit maximization should be selected accordingly for better profit performance. Other profitable conditions may be the buses with higher quality transmission line permitting smoother flow to the high demand centers with lower electricity loss. Such case will also put the generator to an advantageous position in the market, allowing partial power for manipulative behavior.

Regularity authority should analyze each candidate bus for capacity expansion with possible opportunities for investors. Authority should classify the buses clearly indicating the ones permitting manipulative pricing behavior based on this thesis outcome. After this classification the installation permits should be prioritized such that capacity expansion plans developed contains mainly buses that are permitting profit maximization only by increasing load levels. In this case capacity expansion will yield more smooth and stable prices in the market.

5.1. Further studies

The current simulation / optimization framework focuses on the supply side of the market structure. The management and analysis of the demand side is still an open research area. Price elasticity of demand, financial accounting of reactive power are some of the aspects that may be studied under the developed optimization simulation framework.

Another interesting topic that may be studied with the developed infrastructure is the transmission cost accounting and related nodal pricing strategies. The effect of possible policies for electricity pricing including but not limited to local marginal pricing, regional pricing, loss load pricing and many other pricing strategies can be investigated. Congestion management is another interesting area to study over the current structure. Policies to prevent congestion may be tested and the relevant effects can be captured accordingly.

Besides, the transmission network extension options can be tested. The effect of line capacity expansion and / or new line construction is an important research area for the deregulated electricity market. In addition, transmission line congestion management and local marginal pricing are worth to investigate. In this context, various scenario analyses for both demand distribution and network structure can be tested by altering the current setup.

Another interesting study may be the application of intensive renewable energy generation and smart grid network principles. Renewable energy, such as wind or solar and small scale co-generation have power outputs that are all primarily stochastic in nature. Such a system could necessitate an enlarged AC-OPF model for correcting the potential deviations from the day ahead schedule, which would increase the complexity of the simulation / optimization framework significantly.

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