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Publication date:
2012

Document Version
Accepted author manuscript, peer reviewed version

AALBORG UNIVERSITY

OPERATION OF MODERN DISTRIBUTION POWER SYSTEMS IN COMPETITIVE ELECTRICITY MARKETS

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PhD Dissertation

Aalborg, September 2012

Department of
ENERGY TECHNOLOGY
E.T.

OPERATION OF MODERN DISTRIBUTION POWER SYSTEMS IN COMPETITIVE ELECTRICITY MARKETS

By

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A Dissertation Submitted to

The Faculty of Engineering, Science and Medicine, Aalborg University

in Partial Fulfillment for the Degree of Doctor of Philosophy

September 2012

Aalborg, Denmark

Aalborg University

Department of Energy Technology

Pontoppidanstraede 101

9220 Aalborg East, Denmark

ISBN:

Printed in Denmark by Aalborg University

Mandatory Page

Thesis title

Operation of Modern Distribution Power Systems in Competitive Electricity Markets

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Weihao Hu

Name and title of supervisor and any other supervisors

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Associate Professor Birgitte Bak-Jensen

List of published papers

[P1] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "The Relationship between Electricity Price and Wind Power Generation in Danish Electricity Markets," in Proc. *IEEE Asia-Pacific Power and Energy Engineering Conference*, Chengdu, China, 28-31, March, 2010.

[P2] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, " Analysis of Electricity Price in Danish Competitive Electricity Market," in *Proc. 2012 PES General Meeting*, San Diego, USA, 22-26, July, 2012.

[P3] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "Stochastic Optimal Wind Power Bidding Strategy in Short-Term Electricity Market," *International Review of Electrical Engineering (IREE)*, vol. 7, no. 1, pp. 186-197, Feb. 2012.

[P4] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "Optimal Load Response to Time-of-Use Power Price for Demand Side Management in Denmark," in *Proc. IEEE Asia-Pacific Power and Energy Engineering Conference*, Chengdu, China, 28-31, March, 2010.

[P5] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "Impact of Optimal Load Response to Real-Time Electricity Price on Power System Constraints in Denmark," in *Proc. International Universities' Power Engineering Conference*, Cardiff, UK, 31, August - 3, September, 2010.

[P6] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "Fuzzy Adaptive Particle Swarm Optimization for Power Loss Minimization in Distribution Systems Using Optimal Load Response," *IET Generation, Transmission & Distribution*, (Status: Submitted).

[P7] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "An Approach to Solve Power System Constraints Using Load Response to Real-Time Electricity Price in Distribution Systems ," in *Proc. the 9th Nordic Electricity Distribution and Asset Management Conference*, Aalborg, Denmark, 6-7, September, 2010.

[P8] Weihao Hu, Chi Su, Zhe Chen, Birgitte Bak-Jensen, "Small Signal Stability Improvement of Power Systems Using Optimal Load Responses in Competitive Electricity Markets," in *Proc. International Universities' Power Engineering Conference*, Soest, Germany, 5-8, September, 2011.

[P9] Weihao Hu, Chunqi Wang, Zhe Chen, Birgitte Bak-Jensen, "Power System Transient Stability Improvement Using Demand Side Management in Competitive Electricity Markets," in *Proc. The International Conference on the European Energy Market*, Florence, Italy, 10-12, May, 2012.

[P10] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "Optimal Operation Strategy of Battery Energy Storage System to Real-Time Electricity Price in Denmark," in *Proc. 2010 PES General Meeting*, Minneapolis, USA, 25-30, July, 2010.

[P11] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "Optimal Operation of Electric Vehicles in Competitive Electricity Markets and Its Impact on Distribution Power Systems," in *Proc. IEEE PES PowerTech 2011*, Trondheim, Norway, 19-23, June, 2011.

[P12] Weihao Hu, Chi Su, Zhe Chen, Birgitte Bak-Jensen, "Optimal Operation of Plug-In Electric Vehicles in Power Systems with High Wind Power Penetrations," *IEEE Transaction on Sustainable Energy, (Status: Revised and Submitted for 3rd Review)*.

[P13] Weihao Hu, Xiaoru Wang, Zhe Chen, "Large Scale Integration of Electric Vehicles into the Power Grid," *Journal of Electric Power Science and Technology*, vol. 26, no. 4, pp. 14-19, Dec. 2011 (in Chinese).

This thesis has been submitted for assessment in partial fulfillment of the PhD degree. The thesis is based on the submitted or published scientific papers which are listed above. Parts of the papers are used directly or indirectly in the extended summary of the thesis. As part of the assessment, co-author statements have been made available to the assessment committee and are also available at the Faculty. The thesis is not in its present form acceptable for open publication but only in limited and closed circulation as copyright may not be ensured.

Acknowledgement

I am very thankful for the financial support provided by the Danish Public Service Obligation (PSO) program under the project 2006-1-6316, “Operation and Control of Modern Distribution Systems”, the Danish Academy of Wind Energy (DAWE) and Aalborg University.

I would like to express my sincere gratitude and appreciation to my PhD supervisors Professor Zhe Chen and Associate Professor Birgitte Bak-Jensen for their kindness, patience, suggestions and encouragement throughout the whole PhD study. Their invaluable support, understanding and expertise have been very important in completing this work.

I would like to thank the project steering committee members, including Stefan Frendrup Sörensen, Niels Andersen and Anders Foosnæs for their invaluable discussions and help with data during the course of this work.

I would like to thank other PhD students in our research group, especially Chi Su, Zhou Liu, Chunqi Wang, Yunqian Zhang, Zakir Hussain Rather, Pietro Raboni and Seyedmostafa Farashbashiastaneh for their helpful discussion. I also would like to thank Professor Xiaoru Wang from Southwest Jiaotong University and Associate Professor Yong Fang from Beijing University of Chemical Technology for their suggestions. I thank all my other friends and colleagues in the Department of Energy Technology for their moral support and encouragement.

Last but not least, I want to thank my parents and my wife for their love and constant support.

Weihao Hu

September, 2012

Aalborg

Abstract

In this dissertation, the characteristics of a distribution system under a dynamic electricity-pricing, load management system and under a large number of power electronic interfaced distributed generation units are investigated. The operation characteristics of a power system with wind turbines, DG units, loads and electricity price are studied. Further, the effect of energy storage systems will be considered, and an optimal operation strategy for energy storage devices in a large scale wind power system in the electricity market is proposed.

The western Danish power system, which has large penetrations of variable wind power production and may represent the future electricity markets in some ways, is chosen as the studied power system. 10 year actual data from the Danish competitive electricity market are collected and analyzed. The relationship among the electricity price, the consumption and the wind power generation in an electricity market is investigated. The formulation of an imbalance cost minimization problem for trading wind power in the Danish short-term electricity market is then described. Stochastic optimization and a Monte Carlo method are proposed to find the optimal bidding strategy for trading wind power in the Danish short-term electricity market in order to minimize the imbalance costs for regulation.

A load optimization method based on spot price for demand side management in Denmark is proposed in order to save the energy costs for 3 types of typical Danish consumers as much as possible. The load optimization to spot price generates different load profiles and reduces the load peaks. These kinds of load patterns have significant effects on power system constraints. A method of achieving power loss minimization in distribution systems by using optimal load response to the electricity price is proposed. A fuzzy adaptive particle swarm optimization (FAPSO) is presented as a tool for the power loss minimization study. Simulation results show that the proposed approach is an effective measure to achieve power loss minimization in distribution systems. Then, three different cases are studied to solve power system constraints, improve power system small signal stability and power system transient stability by deciding an appropriate electricity price.

An optimal operation strategy for a battery energy storage system (BESS) in relation to the electricity price in order to achieve maximum profit of the BESS is proposed. Two kinds of BESS, based on polysulfide-bromine (PSB) and vanadium redox (VRB) battery technologies, are studied. Optimal operation strategies of PEV in the spot market are then proposed in order to decrease the energy cost for PEV owners. Furthermore, the application

of battery storage based on aggregated PEVs is analyzed as a regulation service provider in power systems with high wind power penetrations. The economic benefits of PEVs in both spot market and regulating market are also estimated. Finally, the impacts of different PEV charging/discharging strategies on the spot market price and the interaction between the electricity price and the system demand are presented and discussed.

Dansk Abstrakt

I denne afhandling, er kendetegnene for en distributionssystem under en dynamisk el-pricing, load management system og under en lang række effektelektroniske interface distribuerede produktionsanlæg undersøgt. Drifts karakteristika for en elsystem med vindmøller, GD enheder, belastninger og elprisen er undersøgt. Endvidere vil effekten af energilagringssystemer overvejes, og en optimal drift strategi for energi lagringsenheder i en stor skala vindkraft-system på elmarkedet er foreslået.

Den vestlige danske elsystem, som har store gennembrydninger af variabel vindkraftproduktion og kan repræsentere de fremtidige elmarkeder på nogle måder, er valgt som den studerede elsystemet. 10 år faktiske data fra det danske konkurrencedygtigt elmarked er indsamlet og analyseret. Forholdet mellem elprisen, forbrug og vindproduktion i et elmarked er undersøgt. Formuleringen af en ubalance omkostningsminimering problem for handel vindkraft i det danske kort sigt elmarked derefter beskrevet. Stokastisk optimering og en Monte Carlo metode foreslås at finde den optimale budstrategi for handel vindkraft i det danske kortsigtede elmarked for at minimere ubalancen udgifter til regulering.

En belastning optimering metode baseret på spotprisen for efterspørgselsstyring i Danmark foreslås for at gemme energiomkostningerne for 3 typer af typiske danske forbrugere så meget som muligt. Belastningen optimering til spotpris genererer forskellige belastningsprofiler og reducerer spidsbelastninger. Disse former for belastning mønstre have betydelige virkninger på el-systemet begrænsninger. En metode til at opnå effekttab minimering i distributionssystemer ved hjælp af optimal belastning reaktion på elprisen er foreslået. En fuzzy adaptive partikel sværm optimering (FAPSO) præsenteres som et redskab for effekttab minimering undersøgelse. Simulation resultater viser, at den foreslåede tilgang er en effektiv foranstaltning til at opnå effekttab minimering i distributionssystemer. Derefter tre forskellige undersøgte tilfælde at løse systemadskillelse begrænsninger, forbedre elsystemet lille signal stabilitet og elsystem forbigående stabilitet ved at beslutte en passende elpris.

En optimal drift strategi for et batteri energilager system (BESS) i forhold til elprisen for at opnå størst mulig profit af BESS foreslås. To slags BESS, baseret på polysulfid-brom (PSB) og vanadium redox (VRB) batteriteknologier, er undersøgt. Optimal drift strategier PEV i spotmarkedet derefter foreslået for at reducere energi-omkostninger for PEV ejere. Endvidere er anvendelsen af batteriets storage baseret på aggregerede PEVs analyseret som en forordning tjenesteyder i elsystemer med høje vindkraft gennemføringer. De økonomiske fordele ved PEVs i både spotmarkedet og regulere markedet er også skøn. Endelig er

konsekvenserne af forskellig PEV opladning / afladning strategier på spotmarkedsprisen og samspillet mellem elprisen og systemet efterspørgsel præsenteret og diskuteret.

Abbreviations

BESS	Battery Energy Storage System
CCT	Critical Clearing Time
DCHP	Decentralized Combined Heat and Power Plant
DG	Distributed Generation
DSM	Demand Side Management
Elbas	Balancing Market
Elspot	Spot Market
EV	Electric Vehicle
FAPSO	Fuzzy Adaptive Particle Swarm Optimization
LFC	Load Frequency Control
MC	Monte Carlo
PEV	Plug-in Electric Vehicle
PSB	Polysulfide Bromine
PSO	Particle Swarm Optimization
SCP	Saving Costs Percentage
SQP	Sequential Quadratic Programming
TOU	Time-of-Use
TSO	Transmission System Operator
UCTE	Union for the Coordination of Electricity Transmission
VRB	Vanadium Redox
V2G	Vehicle-to-Grid

Table of Contents

Chapter 1

Introduction

1.1 Background and Motivation

Conventional power systems are dominantly based on large central power plants which supply the energy to the consumers through high voltage transmission systems and low voltage distribution systems. Significant changes are happening in the traditional power systems due to the deregulation of the power system and the integration of distributed generation (DG).

Because of energy shortage and environment pollution, the renewable energy, especially wind energy has attracted more and more attentions all over the world. The wind energy has been widely considered as one of the most rapidly increasing resources among other distributed generation resources [1-5]. By 2020, it is expected that the total wind power generation will supply around 12% of the total world electricity demands [6]. 20% energy should be from renewable sources by 2020 according to the goal of the European Union. The share of electricity from renewable energy sources has to be more than 30% to achieve this target [7]. In Denmark, the wind energy supplies around 20% of the annual electricity demand in 2009, which is the highest among other countries in the world [8]. Wind power is currently the most important renewable energy source in Denmark. The total installed capacity of wind power in Denmark was 3730 MW at the end of September 2010, in which 868 MW was offshore wind power [9]. However, integration of such a lot of wind energy into power grids presents a major challenge to power system operators because of the high uncertainty and variability in the wind power characteristic nature [10].

As the distributed generation is normally placed close to the consumers, the total energy loss through the transmission system and distribution system is significantly reduced. The deployment of DG normally defers the need for grid renewal and DGs could also increase the grid reliability and power quality, such as harmonics and unbalance state [11], [12]. Fig. 1.1 illustrates the evolvement of the Danish power system during the past 20 years. The Danish power system has evolved from a classical centralized power system to a decentralized system of power generation [13], [14]. It can be seen that the number of DG units has increased significantly in Denmark. In 2008, the installed capacity of small power plants and wind turbines was 1829 MW and 3166 MW, respectively [15].

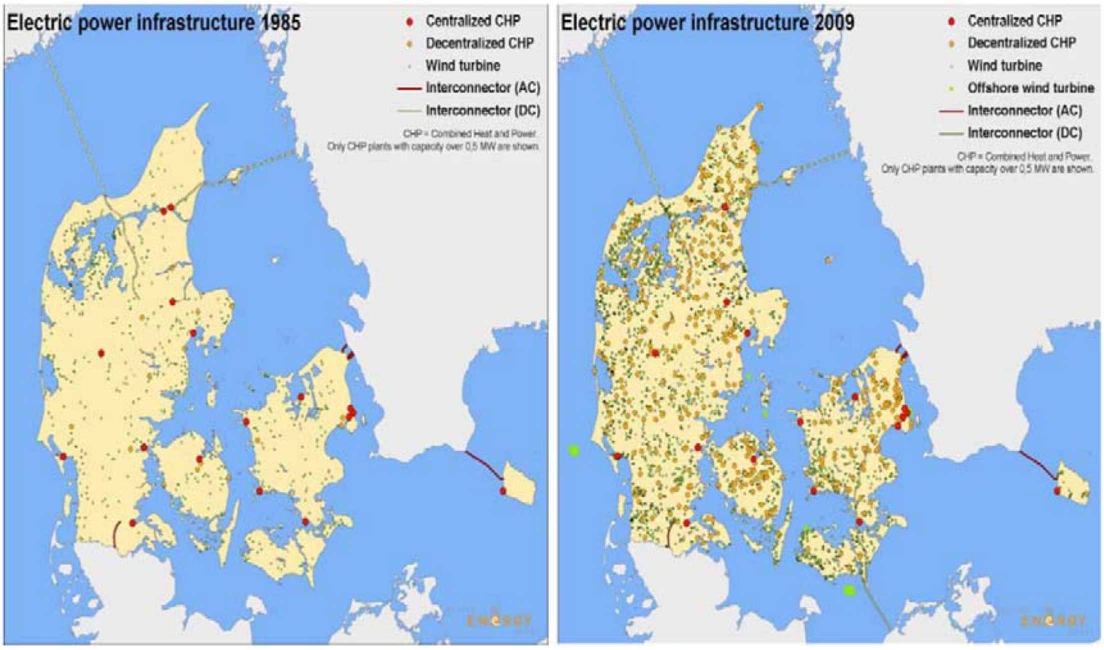


Fig. 1.1. Maps of Denmark showing interconnectors and growth of dispersed generation [13], [14].

Electric power systems are developing towards a market structure from transmission to distribution worldwide, where the economic issue is a main consideration. While the global demand in electrical energy is increasing steadily, the upgrading of national and international power grids is progressing slowly due to the high economic risks of establishing new power stations [16]. The liberalization of the electricity markets has led to the replacement of tariffs by hourly or half-hourly prices in many parts of the world. Economists argue that real-time electricity prices are a powerful way to encourage consumers to behave in an economically optimal way [17-19]. In the deregulated and dynamic electricity markets, there is a strong variability in electricity prices. Load peaks and lacks of generation due to maintenance of generators, power fluctuations from DGs and unexpected outages result in high spot market prices in some periods [20]. Now many consumers in Denmark, especially small businesses and private households, operate on fixed electricity prices contracts. Since the hourly spot market price is available one day ahead, the price could be transferred to the consumers and they may have some motivations to shift their loads from high price periods to the low price periods in order to save their energy costs. This kind of optimal load patterns may have significant effects on the power system normal operation.

The EU's energy policy addresses the transportation sector, requiring a mandatory limit of 120 grams of CO_2/km for new cars by 2012 to reduce the greenhouse gas emissions [21], [22]. Recent developments and advances in battery energy storage systems and power electronics technologies are making the Plug-In Electric Vehicles (PEV) a possible solution in the future. The battery storage of electric vehicles is one of the emerging concepts, which can act as a controllable load or as a generator in the distribution power system. It may allow the power system to be operated in a more flexible, controllable manner [23-30]. Consumers may have some motivations to optimally use their PEVs in order to save energy costs. Therefore, how the PEVs will be operated in relation to the hourly electricity price in competitive electricity markets needs to be studied. The impact of the optimal operation strategy for PEVs together with the optimal load response to spot market price for demand side management on the distribution power system with high penetration of wind power needs to be analyzed and discussed. The aggregated battery based PEVs may also provide power system regulation services in order to get more economic benefits. The application of PEVs as a regulation power provider is investigated by utilizing an aggregated battery storage model in load frequency control (LFC) simulations. The economic benefits of PEVs in both spot market and regulating market should be estimated.

This PhD project is to study the characteristics of a distribution system under a dynamic electricity-pricing, load management system and under a large number of power electronic interfaced distributed generation units. The interactions between the power market and the system operation and control strategies will be fully explored. The operation characteristics of a power system with wind turbines, DG units, loads and electricity price will be studied. Further, the effect of energy storage systems will be considered, and a system optimization for a system with energy storage devices in a large scale wind power system acting in the electricity market will be performed. The western Danish power system, which has large penetrations of variable wind power production and may represent the future electricity markets in some ways, is chosen as the studied power system. The significance of this project includes development of the optimal electricity price for the Danish consumers and development of the optimal operation strategies for Danish power systems with large scale of wind power and energy storage systems.

1.2 Research Objective

This three-year PhD research project "Operation of Modern Distribution Power Systems in Competitive Electricity Markets" was initiated by Department of Energy Technology at Aalborg University in collaboration with Danish Energy Association and the two Danish distribution companies Himmerlands Elforsyning and SEA-VNVE.

This project comprehensively investigates the characteristics of a distribution system under a dynamic electricity-pricing, load management system and a large number of power electronic interfaced DG units. The interactions between the electricity market and the system operation and control strategies will be fully explored. Further, the effect of energy storage systems will be considered, and a system optimization for a system with energy storage devices in a large scale wind power system acting in the electricity market will be performed. Specifically, the objectives of this research study are as follows:

1) To develop models to represent the relationship between a dynamic electricity price and the load characteristics controlled by a load management system.
2) To develop probabilistic models to represent the relation between a dynamic electricity pricing and fuel-free renewable energy based dispersed generation units.
3) To improve the power system operation, such as power loss minimization, power system constraints solving, power system small signal stability improvement and power system transient stability improvement, using demand side management by deciding an appropriate electricity price.
4) To propose an optimal operation strategy for a battery energy storage system and estimate the economic benefits for its owners.
5) To analyze the interaction among electricity price, system load and battery based PEVs.

1.3 Technical Contribution of the Thesis

The main technical contribution of the thesis is summarized as follows:

1) The relationship among the electricity price, the consumption and the wind power generation in an electricity market is investigated. Stochastic optimization and a

Monte Carlo method are proposed to find the optimal bidding strategy for trading wind power in the Danish short-term electricity market in order to minimize the imbalance costs for regulation.

2) A load optimization method based on spot price for demand side management is proposed in order to save the energy costs as much as possible.
3) A method for achieving power loss minimization in distribution systems by using optimal load response to the electricity price is proposed. A fuzzy adaptive particle swarm optimization is adopted as a tool for the power loss minimization study.
4) A method for power system operation improvement, which includes solving power system constraints, improving power system small signal stability and power system transient stability, using demand side management by deciding an appropriate electricity price is proposed.
5) An optimal operation strategy of a battery energy storage system in relation to the electricity price is proposed in order to achieve the maximum profits for its owners. The application of a battery storage based on aggregated PEVs is used as a regulation service provider in the power system.
6) The interaction among electricity price, system load and battery based PEVs are proposed and discussed.

1.4 Project Limitations

The limitations of this research are as follows:

1) This research focuses on the spot market and regulating market, due to the facts that the intraday balancing market is not very active and only small amounts of energy are traded there.
2) For the time being, these consumers will not have the spot market price as their price, their real expected fluctuation in the price will be much lower due to tax and other tariffs. Therefore, the real consumer behaviors may be different from the optimal ones as discussed in this thesis.
3) The consumers are assumed very sensitive to the electricity price and smart enough to make the optimal decisions in the research.
4) The spot prices are assumed not to change due to the optimal load response and the optimal charge/discharge schedule for PEVs.

5) The operating and maintenance cost of the battery energy storage system (BESS) and its effects on the optimal operation strategy of the BESS are not considered in the research.
6) The other economic benefits of the BESS by providing spinning reserve, frequency regulation and renewable energy support are not evaluated in the research.

1.5 Outline of the Thesis

The PhD dissertation contains eight chapters and appendixes. It is organized as follows:

Chapter 1 Introduction

This chapter gives the background and objective of this thesis. Also the technical contributions and the limitations in the project are discussed.

Chapter 2 Analysis of Danish Electricity Market

In this chapter, the Danish power system, which may represent the future of competitive electricity markets in some ways, is chosen as the studied power system. 10 year actual data from the Danish competitive electricity market are collected and analyzed. The relationship among the electricity price, the consumption and the wind power generation in an electricity market is investigated. The formulation of an imbalance cost minimization problem for trading wind power in the Danish short-term electricity market is then described in the chapter. Stochastic optimization and a Monte Carlo method are proposed in this chapter to find the optimal bidding strategy for trading wind power in the Danish short-term electricity market in order to minimize the imbalance costs for regulation.

Chapter 3 Optimal Load Response to Spot Price and Its Impact on Distribution Systems

In this chapter, a load optimization method based on spot price for demand side management in Denmark is proposed in order to save the energy costs for 3 types of typical Danish consumers as much as possible. The load optimization to spot price generates different load profiles and reduces the load peaks. These kinds of load patterns have significant effects on power system constraints.

Chapter 4 Power loss minimization Using Demand Side Management

The optimal load response to an hourly electricity price for demand side management generates different load profiles and provides an opportunity to achieve power loss minimization in distribution systems. In this chapter, the idea of achieving power loss minimization in distribution systems by using optimal load response to the electricity price is proposed. A fuzzy adaptive particle swarm optimization (FAPSO) is presented as a tool for the power loss minimization study. Simulation results show that the proposed approach is an effective measure to achieve power loss minimization in distribution systems.

Chapter 5 Power System Operation Improvement Using Demand Side Management

The optimal load response to an hourly electricity price for demand side management provides an opportunity to improve the power system operations by adjusting the system loads. Improving power system operation could be achieved by deciding an appropriate electricity price. In this chapter, three different cases are studied to solve power system constraints, improve power system small signal stability and power system transient stability.

Chapter 6 Optimal Operation Strategies for Battery Energy Storage Systems

This chapter presents an optimal operation strategy for a battery energy storage system (BESS) in relation to the electricity price in order to achieve maximum profit of the BESS. Two kinds of BESS, based on polysulfide-bromine (PSB) and vanadium redox (VRB) battery technologies, are studied in the chapter. Optimal operation strategies of PEV in the spot market are then proposed in order to decrease the energy cost for PEV owners. Furthermore, the application of battery storage based on aggregated PEVs is analyzed as a regulation service provider in power systems with high wind power penetrations. The economic benefits of PEVs in both spot market and regulating market are also estimated in this chapter.

Chapter 7 Interaction between Electricity Price and System Demand

The previous chapters analyze the optimal load response and optimal charge/discharge schedule for PEVs in relation to the electricity price in order to save energy costs for PEV owners as much as possible. However, those optimal behaviors affect the electricity price as well. In this chapter, the interaction between the electricity price and the system demand are presented and discussed.

Chapter 8 Conclusions and Future Work

This chapter presents the summary and main findings and conclusions of this thesis. The topics for future work are also discussed in the end.

List of publications

The scientific articles published during the course of this PhD project are listed.

Appendix

The additional and detailed models of simulation components and parameters are listed in the appendix section.

Chapter 2

Analysis of Danish Electricity Market

The Danish power system is currently the grid area in the world that has the largest share of wind power in its generation profiles, with around 20% of its annual consumption generated by wind turbines. The Danish power system, which may represent the future of competitive electricity markets in some ways, is chosen as the studied power system. 10 year actual data from the Danish competitive electricity market are collected and analyzed. The relationship among the electricity price (both the spot price and the regulation price), the consumption and the wind power generation in an electricity market is investigated in this chapter. A short overview of the Nordic electricity market is presented in Section 2.1. The spot market prices are analyzed together with the consumption and the wind power generation in Section 2.2. Section 2.3 presents the relationship among the regulation price, the consumption and the wind power generation. A stochastic optimal wind power bidding strategy is proposed in Section 2.4. Section 2.5 summarizes the main conclusions.

2.1 Nordic Electricity Market

The Nordic countries, i.e. Denmark, Finland, Norway and Sweden, are small in terms of population but the electricity consumption is quite high. In 2001 the total consumption of electricity in the Nordic countries was 393 TWh, which is less than Germany (550 TWh) and France (450 TWh) and slightly higher than the electricity consumption in UK (360 TWh) [31]. The electricity industry of the Nordic countries went through a major restructuring during the 1990s. Norway was the first Nordic country introducing market competition in 1991. Sweden joined the market in 1996, Finland joined the common market in 1998, western Denmark joined in 1999, and in 2000 eastern Denmark also joined the common Nordic market [32], [33]. The Nordic electricity market is a international electricity market. There is one market operator: Nord Pool, and there are currently four transmission system operators (TSOs): Svenska Kraftnat in Sweden, Fingrid in Finland, Statnett in Norway, and Energinet.dk in Denmark [33].

From a technical point of view, the power generation system is fairly mixed in the Nordic countries as a whole, but at the national level the power generation differs significantly. In Norway, almost all power is generated by hydropower, while the share of hydropower generation is around 45% in Sweden, 20% in Finland and zero in Denmark. The share of nuclear power is around 45% in Sweden, 33% in Finland and zero in Denmark and Norway. Power generation based on fossil fuels is quite significant in Denmark and Finland, but close to zero in Norway and Sweden. Wind power generation is very significant in Denmark, but not significant in the other Nordic countries [8]. There are three electricity markets in Denmark, namely the spot market, balancing market and regulating market.

2.1.1 Spot Market (Elspot)

The Nord Pool spot market is the world's first international spot power exchange market, which exchanges the power of Norway, Sweden, Finland and Denmark [34]. The Nord Pool spot market is a day-ahead market where power contracts of a minimum of one-hour duration are traded for delivery in the following day [35]. Purchasing and selling curves are constructed, and the point where they cross determines the spot market price and the volumes being traded during each hour of the next day. The interval between the time when the bids are made and the time when the actual trades take place is at least 12 hours.

2.1.2 Balancing Market (Elbas)

Due to the lengthy time span of up to 36 hours between spot market price-fixing and delivery, participants need market access in the intervening hours to improve their physical electricity balance. The balancing market enables continuous trading with contracts that lead to the physical delivery of the electricity. The balancing market closes one hour before the physical delivery. Its function is in other words to be an aftermarket to the spot market [36]. However, currently, the balancing market is not very active, and only small amounts of energy are traded there [37]. So this chapter focuses on the spot market and regulating market.

2.1.3 Regulating Market

The transmission system operator (TSO) is responsible for the physical balance between production and consumption. The main objective of the regulating market is to serve as a tool for system operators to balance the power generation to the load at any time during real-time operations [38]. There are 2 kinds of bids in the regulating market. The up regulation is for increased generation or reduced consumption and the down regulation is for decreased generation or increased consumption.

2.2 Spot Market

The hourly spot price, the consumption and the wind power generation of Denmark from the year 2001 to the year 2010 can be obtained from Energinet.dk [39], which is the transmission system operator of Denmark. The mean values of the spot price, the consumption and the wind power generation of both western and eastern Denmark for each year are shown in Fig. 2.1. It can be observed that the spot price and wind power generation generally increase during the past 10 years, while the consumption keeps almost the same.

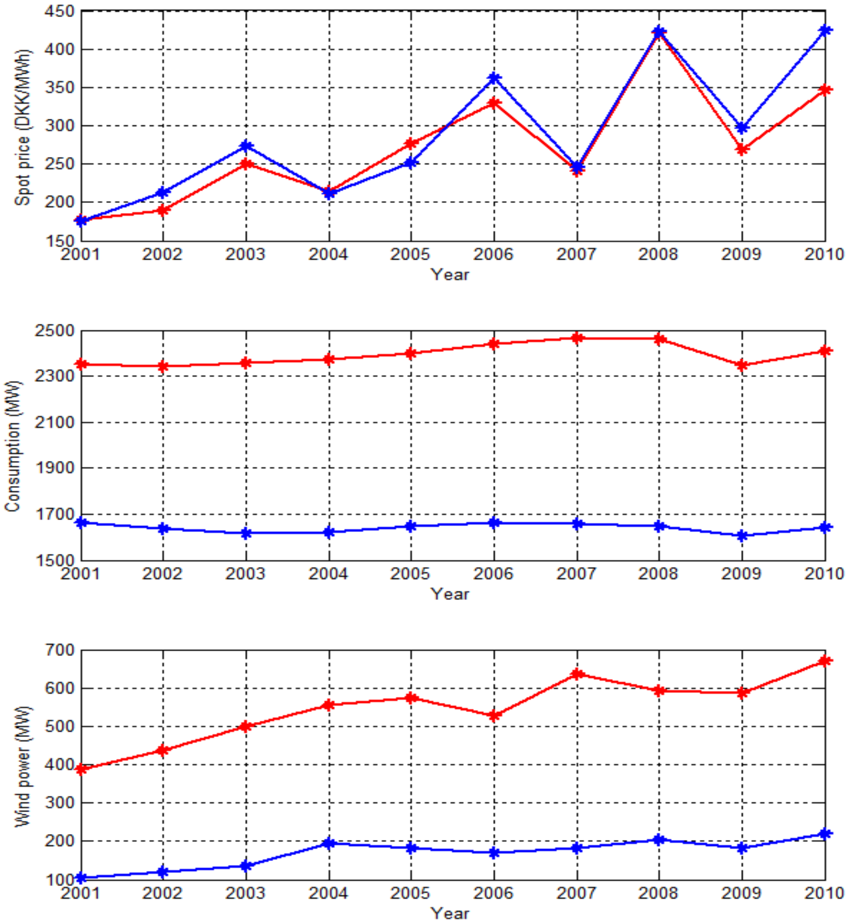


Fig. 2.1. The mean values of the spot price, the consumption and the wind power generation of both western Denmark (red line) and eastern Denmark (blue line) for each year.

Fig. 2.2 illustrates the spot price, consumption and wind power generation of western Demark in the year 2008. The spot price for electricity is volatile, showing unpredictable variations and spikes due to the changes of the generations and demands in the deregulated and dynamic power markets. From this figure, it can also be seen that both the consumption and wind power is higher in winter time and lower in summer time, because the wind speed is higher in winter and a lot of extra light is needed in winter.

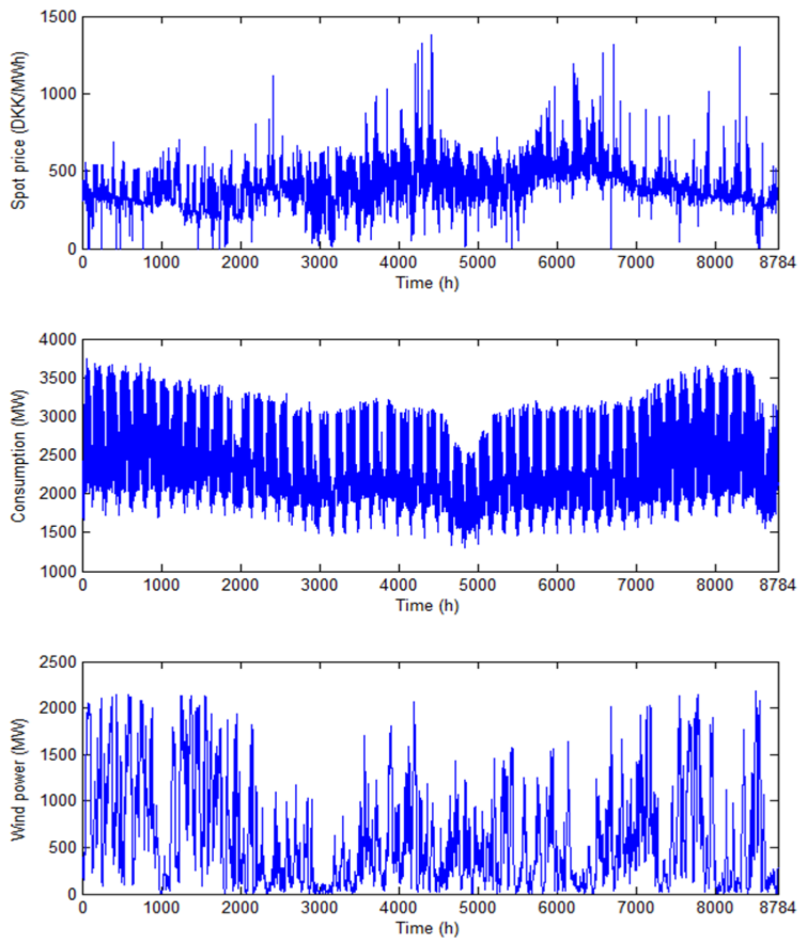


Fig. 2.2. The spot price, consumption and wind power generation of western Demark in the year 2008.

The relationship between the consumption and the spot price is shown in Fig. 2.3 and the relationship between the wind power and the spot price is shown in Fig. 2.4. Each blue circle in the figures represents the consumption and spot price, or the wind power and spot price at each hour. From the linear fitting curve (red line) in the figures, it can be seen that the spot price increases when the consumption increases, and the spot price decreases when the wind power increases. But the relationship among the consumption, the wind power and the spot price is not very clear in these figures.

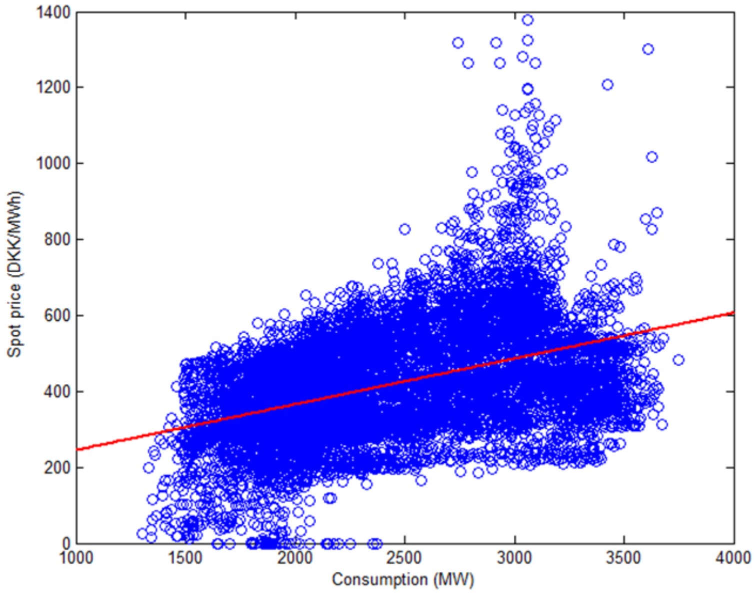


Fig. 2.3. The relationship between the consumption and the spot price (blue circle: consumption and spot price for each hour, red line: linear fitting of the data).

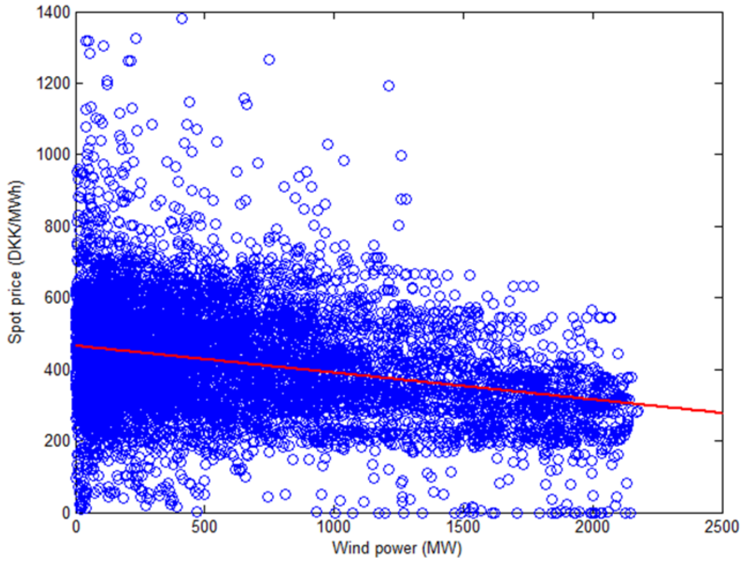


Fig. 2.4. The relationship between the wind power and the spot price (blue circle: wind power and spot price for each hour, red line: linear fitting of the data).

A detailed analysis is done by dividing both the consumption and the wind power into certain intervals. The variation of average spot price with the consumption is shown in Fig. 2.5 and the variation of average spot price with the wind power generation is shown in Fig. 2.6. The 100% wind power generation means that all the installed wind turbines are operated at full capacity. It can be observed that the average spot price generally increases when the consumption of the power system increases, and the average spot price generally decreases when the wind power generation in the power system increases. But the relationship among the consumption, the wind power and the spot price is quite nonlinear. The spot price increases slowly at high consumption periods and the spot price increases rapidly at low consumption periods. Similarly, the spot price decreases slowly at low wind power generation periods and the spot price decreases rapidly at high wind power generation periods.

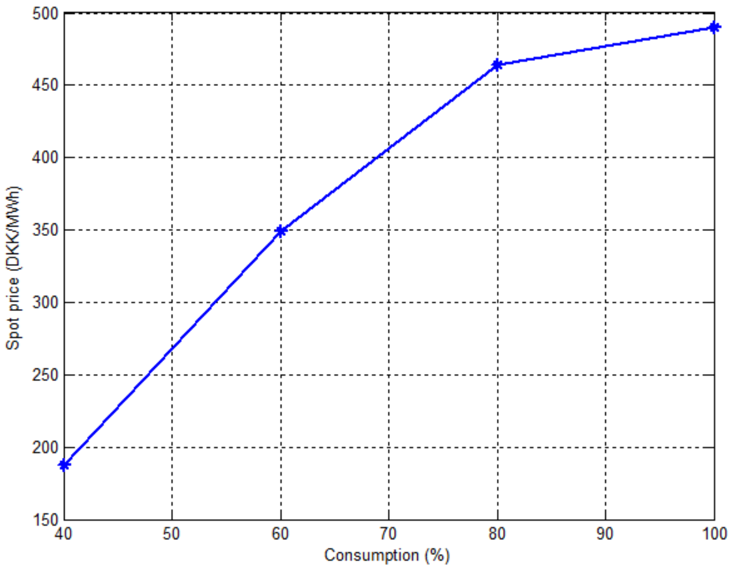


Fig. 2.5. The variation of spot price with the consumption.

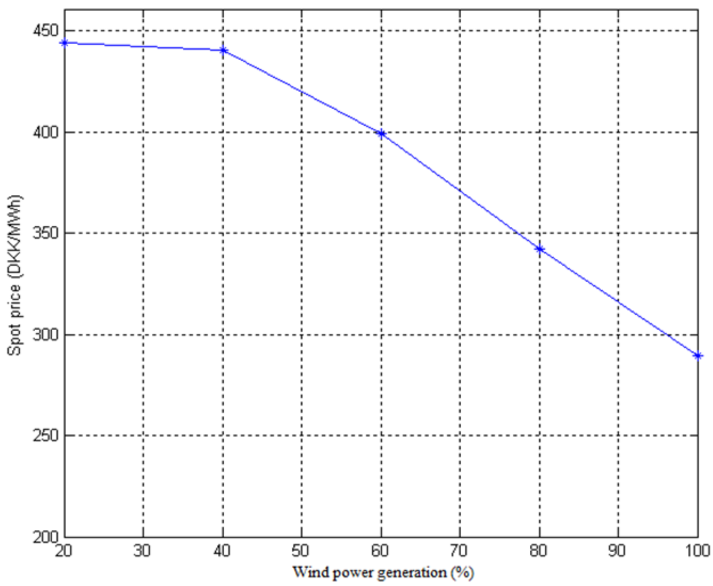
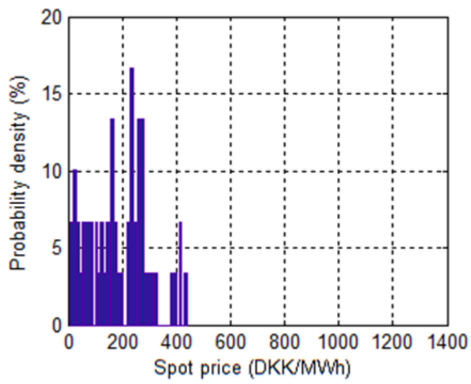
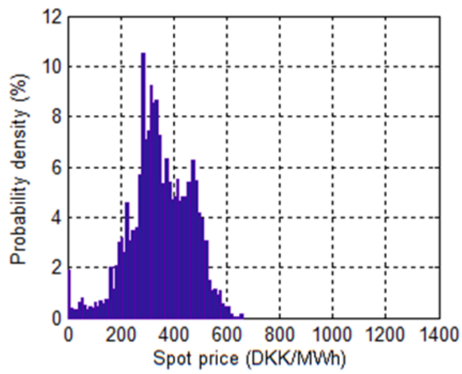


Fig. 2.6. The variation of spot price with the wind power generation.

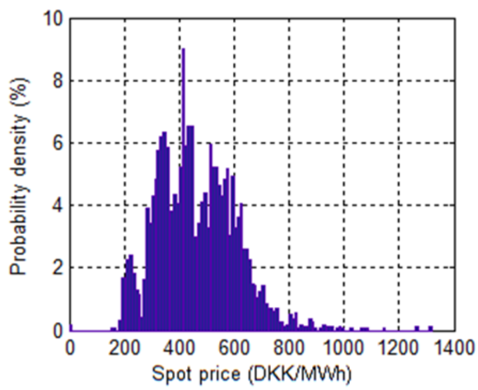
The statistical analysis is then adopted in order to obtain a more detailed relationship among the consumption, the wind power and the spot price in Denmark. Fig. 2.7 illustrates the probability density of the spot price for different consumption percentages. It can be observed that the figure moves to the right side when the consumption increases, which also indicates that the mean value of the spot price increases when the consumption increases. Furthermore, when the consumption is higher, the probability density of the high spot price is higher. It can also be noticed that when the consumption is lower, the probability density of the zero price is higher due to the total generation may be higher than the total consumption during the periods.



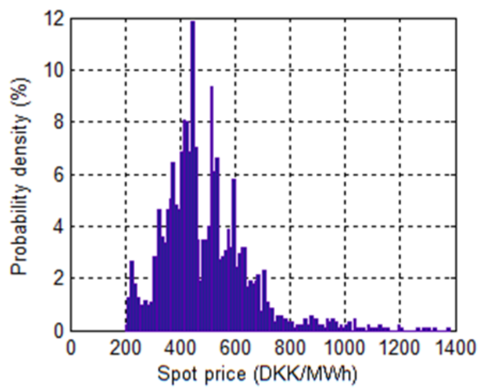
(a) 0%~40%



(b) 40%~60%



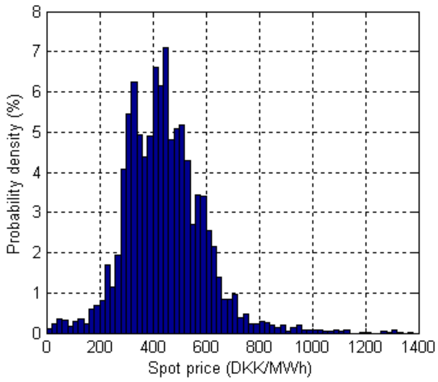
(c) 60%~80%



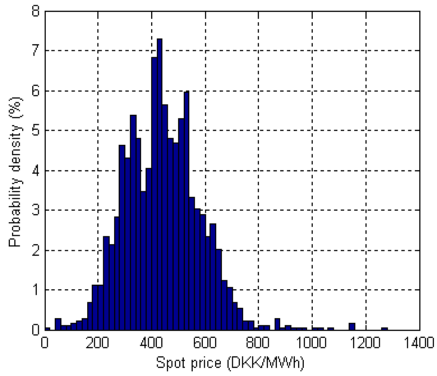
(d) 80%~100%

Fig. 2.7. The probability density of the spot price for different consumption percentages.

Fig. 2.8 illustrates the probability density of the spot price for different wind power generation. It can be also seen that the mean value of the spot price decreases when the wind power generation increases. When the wind power generation is higher, the probability density of the high spot price is lower. It can be noticed that when the wind power generation is higher, the probability density of the zero price is much higher due to the very low marginal prices of the wind power generation. Furthermore, from 30th, November, 2009, the Nord Pool decides to lower the minimum price from 0 to -200 EUR/MWh in order to increase the effectiveness of the market by forcing power generators to consider reducing their generation or having to pay for generating electricity [40]. Danish wind power owners are normally trading their energy in the spot market purely using the wind conditions. With the negative prices, wind turbine owners may be forced to monitor the electricity price as well [40].



(a) 0%~20%



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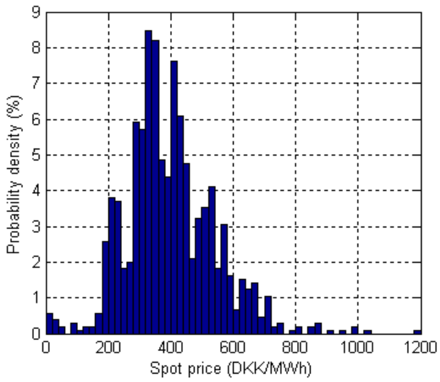

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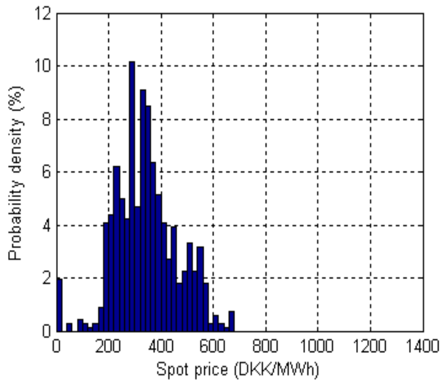
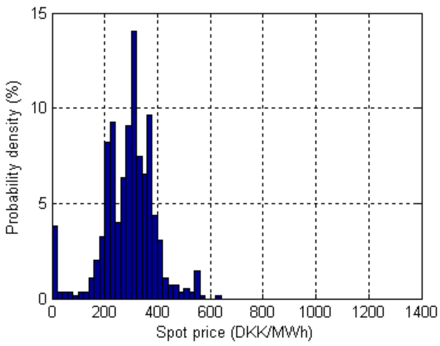


(d) 60%~80%



(e) 80%~100%

Fig. 2.8. The probability density of the spot price for different wind power generation.

2.3 Regulating Market

The regulating market is a tool for system operators to balance the power generation and the consumption at any time during real-time operations. The up regulation is for increased generation or reduced consumption and the down regulation is for decreased generation or increased consumption. Both the up regulation price and the down regulation price of Denmark from year 2001 to year 2010 can be obtained from Energinet.dk [39]. The mean values of the spot price, the up regulation price and the down regulation price of both western Denmark (upper figure) and eastern Denmark (bottom figure) for each year are shown in Fig. 2.9. It can be observed that the spot price, the up regulation price and the down regulation price generally increase during the past 10 years. The up regulation price is always higher than the spot price in order to encourage the generators to generate more power and the loads to consume less power. The down regulation price is always lower than the spot price in order to encourage the loads to consume more power and the generators to generate less power.

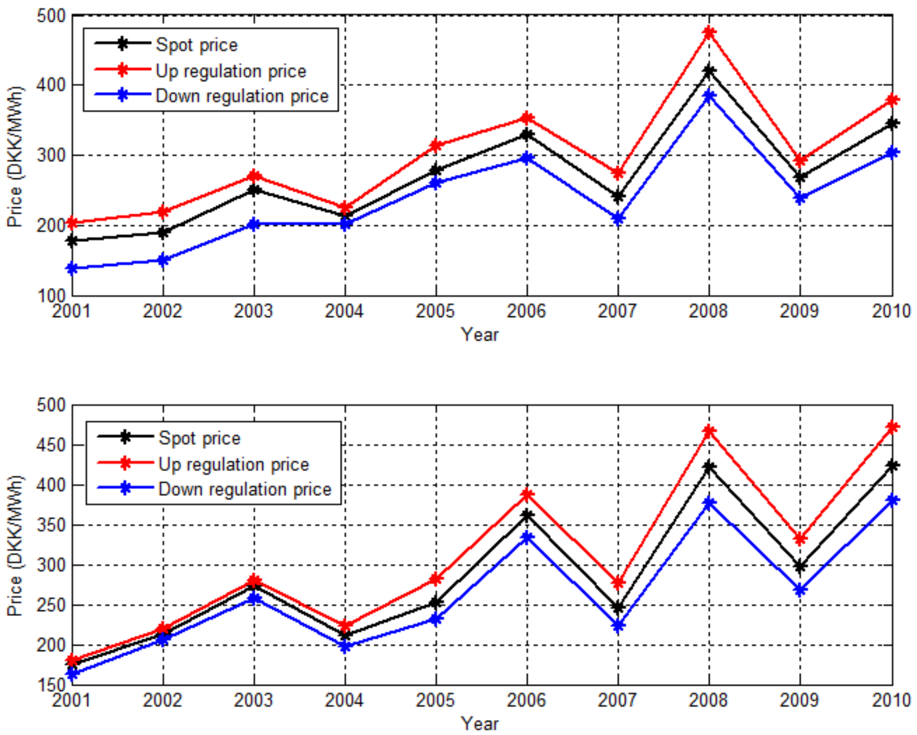


Fig. 2.9. The mean values of the spot price, the up regulation price and the down regulation price of both western Denmark (upper figure) and eastern Denmark (bottom figure) for each year.

Fig. 2.10 illustrates the spot price and the regulation price of western Demark in some periods of year 2008. It can be noticed that the fluctuation range of the regulation price is bigger than the range of the spot price. The deviation of the regulation price to the spot price may be written as

$$\Delta p_{down} = p_{down} - p_{spot} \tag{2.1}$$

$$\Delta p_{up} = p_{up} - p_{spot} \tag{2.2}$$

where Δp_{down}, Δp_{up} are the deviation of the down regulation price to the spot price and the deviation of the up regulation price to the spot price, respectively, p_{down}, p_{up} are the down regulation price and the up regulation price, respectively, p_{spot} is the spot price. The deviation of the down regulation price and the up regulation price is shown in Fig. 2.11.

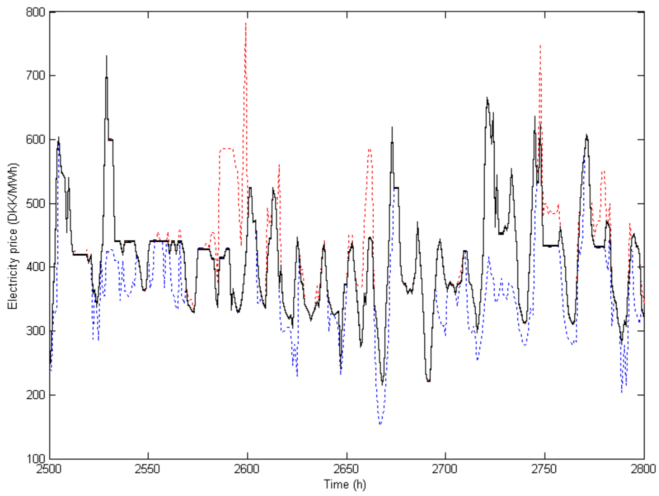


Fig. 2.10. The regulation price of western Demark in some periods of year 2008 (black line: spot price, blue line: down regulation price, red line: up regulation price).

Fig. 2.12 illustrates the variation of the down regulation price and the up regulation price with the consumption. It is indicated that the regulation price generally increases when the consumption of the power system increases. The deviation of the down regulation price and the up regulation price with the consumption is also shown in Fig. 2.12 (bottom one). At low consumption periods, Δp_{down} is higher than Δp_{up}, because the power system needs less generation and more demand in this period. At high consumption periods, Δp_{up} is higher than Δp_{down}, because the power system needs more generation and less demand in this period.

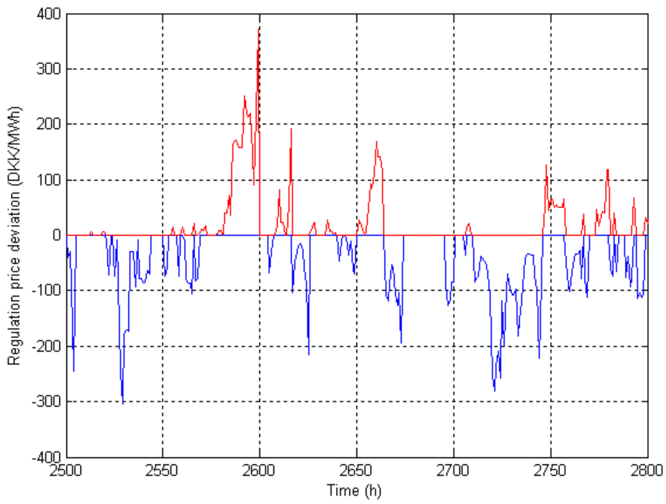


Fig. 2.11. The deviation of the regulation price (blue line: deviation of the down regulation price, red line: deviation of the up regulation price).

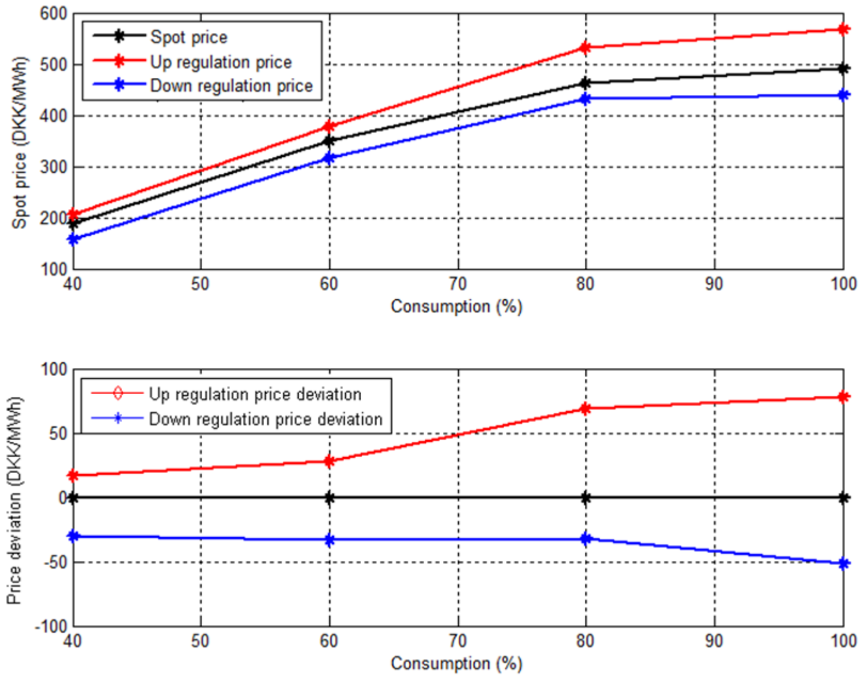


Fig. 2.12. The variation of regulation price with the consumptions (upper figure) and the variation of deviation of the regulation price with the consumptions (bottom figure).

Fig. 2.13 illustrates the variation of the down regulation price and the up regulation price with the wind power generation. It can be seen that the regulation price generally decreases when the wind power generation in the power system increases. The deviation of the down regulation price and the up regulation price with the wind power generation is also shown in Fig. 2.13 (bottom one). At low wind power generation periods, Δp_{up} is high and Δp_{down} is low, because the power system needs more generation and less demand in this period. At high wind power generation periods, Δp_{up} is low and Δp_{down} is high, because the power system needs less generation and more demand in this period.

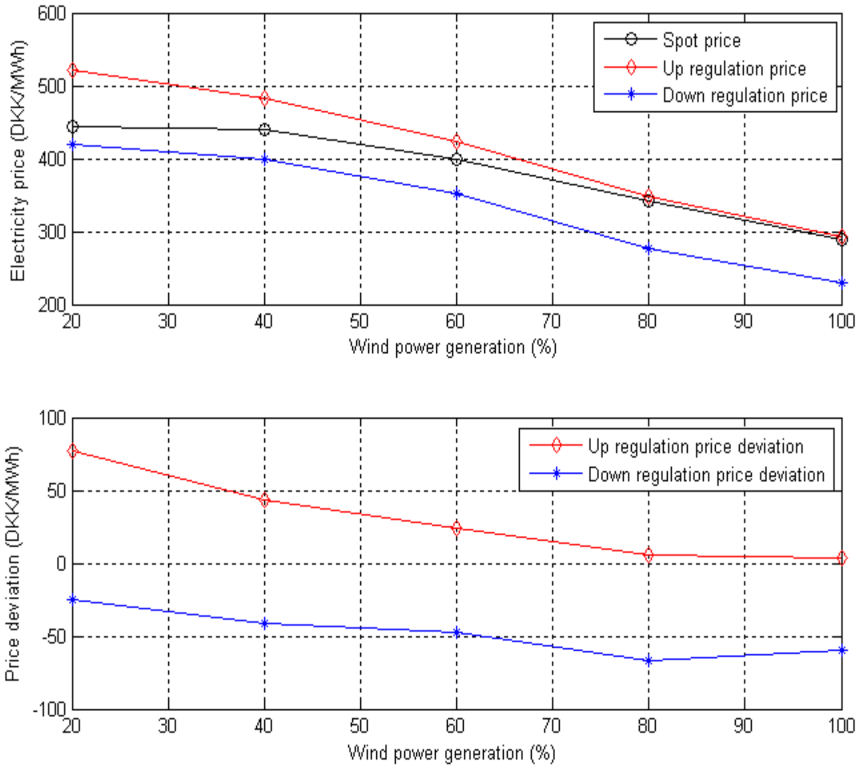
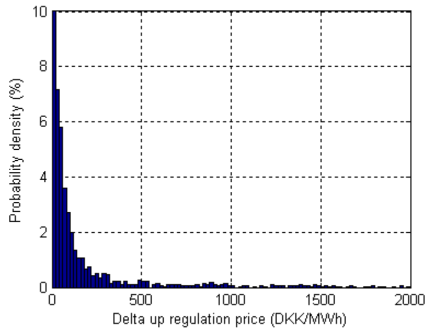
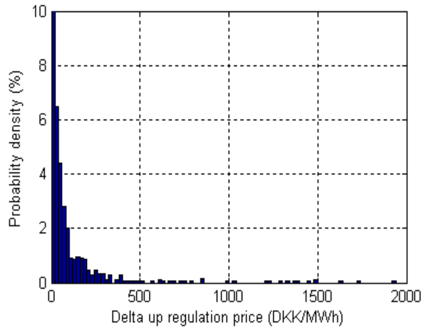


Fig. 2.13. The variation of regulation price with the wind power generation (upper figure) and the variation of deviation of the regulation price with the wind power generation (bottom figure).

The probability density of the deviation of the up regulation price Δp_{up} and the deviation of the down regulation price Δp_{down} for different wind power generation are shown in Fig. 2.14 and Fig. 2.15. It can be observed that Δp_{up} decreases when the wind power generation increases and Δp_{down} increases when the wind power generation increases. This is due to the fact that the power system is more likely to need more loads and less generations when the wind power generation increases. Furthermore, when the wind power generation is lower, the probability density of the very high up regulation price is higher. When the wind power generation is higher, the probability density of the very low down regulation price is higher.



(a) 0%~20%



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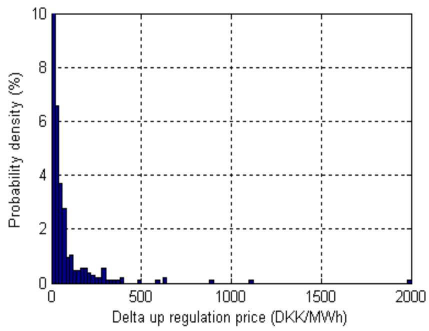
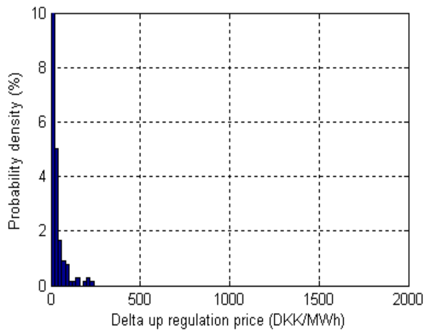
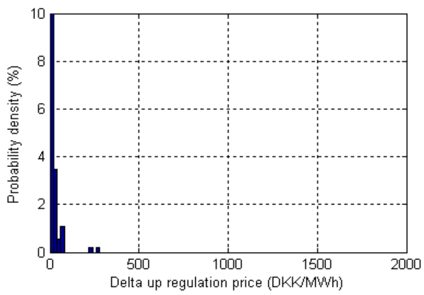


(c) 40%~60%

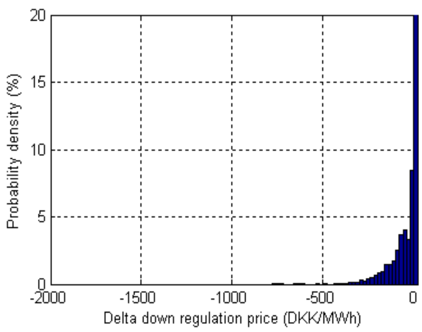


(d) 60%~80%



(e) 80%~100%

Fig. 2.14. The probability density of the deviation of the up regulation price Δp_{up} for different wind power generation.



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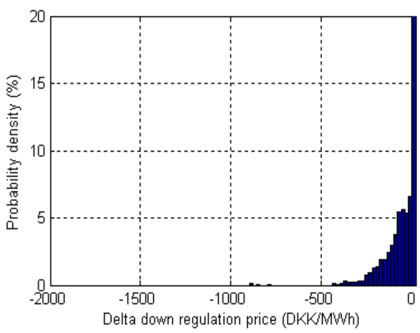

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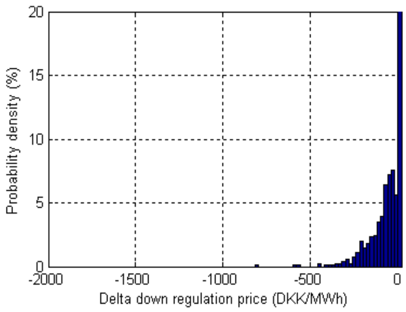

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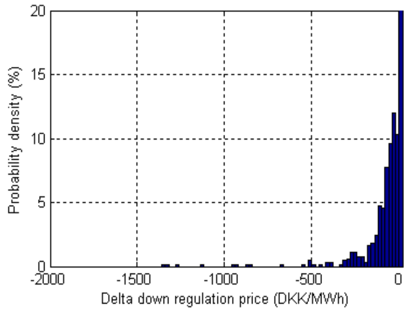

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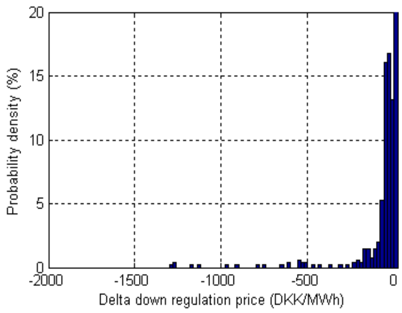


(e) 80%~100%

Fig. 2.15. The probability density of the deviation of the down regulation price Δp_{down} for different wind power generation.

Fig. 2.16 illustrates the probability of the activated regulation with the wind power generation. It can be seen that at low wind power generation, the probability of up regulation is high and the probability of down regulation is low, which means that the power system is more likely to need more generation and less loads. At high wind power generation, the probability of up regulation is low and the probability of down regulation is high, which means that the power system is more likely to need less generation and more loads.

In the regulation market of Denmark, the wind power owners pay an imbalance cost if the actual wind power generation deviates from the bidding amount. The imbalance cost is calculated based on the regulation price and the imbalance wind power between the bid wind power and the actual wind power generation. If up regulation is activated, the up regulation price is paid by the wind power owners for negative imbalance wind power, which means the bid wind power is higher than the actual wind power generation, while the wind power owners with positive imbalance wind power are paid according to the spot price. If down regulation is activated, the down regulation price is paid by the wind power owners for positive imbalance wind power, which means the bid wind power is lower than the actual wind power generation, while the wind power owners with negative imbalance wind power are paid according to the spot price [35], [38]. Generally speaking, when the actual wind power generation helps the regulation process of the power system, the wind power owners are paid according to the spot price. Otherwise, the wind power owners are penalized with the regulation price. The imbalance cost paid by the wind power owners is shown in Table 2.1.

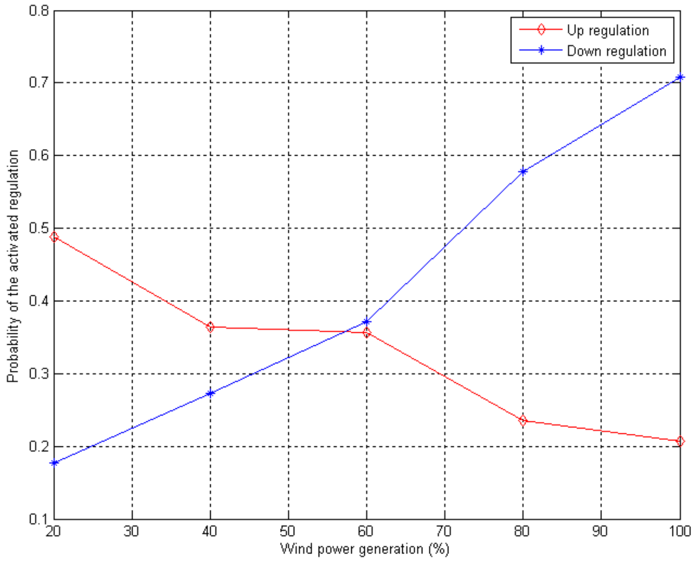


Fig. 2.16. The probability of the activated regulation with wind power generation (blue asterisk line: down regulation, red diamond line: up regulation).

Table 2.1. The imbalance cost paid by the wind power owners.

Wind power imbalance	The regulation process of the power system	
	Up regulation	Down regulation
Positive	p_{spot}	p_{down}
Negative	p_{up}	p_{spot}

These relationships between the electricity price and the wind power generation may be useful for the wind power generation company to make a better bidding strategy so that the imbalance cost of trading wind power in the electricity market can be reduced. For example, at low wind power generation periods, the wind power generation company may bid less wind power than the forecasted value in the spot market so that a high up regulation price is avoided. A 20 MW wind farm in western Denmark is used as a study case in the section. A low wind speed day (1st, July, 2008) is chosen as the first study case. The forecasted wind energy and the actual wind energy are shown in Fig. 2.17. The persistence forecast method, which is one of the most simple wind forecast methods [41], is adopted in this case. In the persistence wind forecast method, the forecasted wind energy for hour *t* equals to the actual wind energy at hour *(t-1)*.

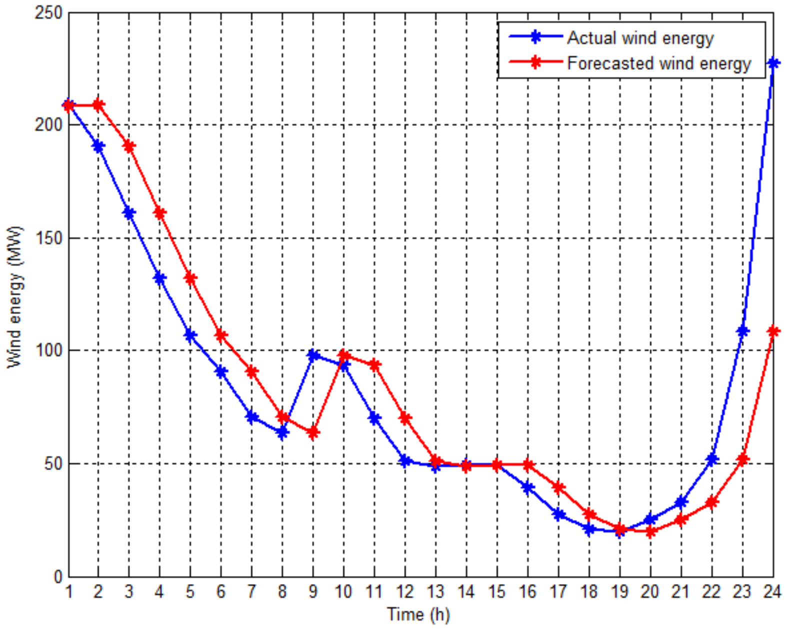


Fig. 2.17. The forecasted wind energy (red line) and the actual wind energy (blue) in a low wind speed day.

Conventionally, the wind power generation companies choose the forecasted wind energy as the bid wind energy in the short-term electricity market. This case is referred as the original case in the section. In the low wind speed day, the deviation of the up regulation price Δp_{up} is higher than the deviation of the down regulation price Δp_{down} (see Fig. 2.13-2.15). If the wind power generation companies are aware of these relationships between the electricity price and the wind power generation discussed in the previous sections, they may choose to bid 10% less than the forecasted wind energy in order to avoid to be penalized with a high up regulation price. This case is referred as the new case in the following parts. Fig. 2.18 illustrates the imbalance costs for the original case and the new case. It can be observed that the imbalance cost for the regulation decreases when the new bidding strategy is used for trading the wind power in the short-term electricity market. The total imbalance cost in the studied day decreases from 208 DKK for the original case to 101 DKK for the new case, which corresponds to 51.4 % imbalance cost reduction in the low wind speed day. Similarly, the total imbalance cost decreases for about 76.2% in a high wind speed day (15th, January, 2008), when the wind power generation companies choose to bid 10% more than the forecasted wind energy in order to avoid to be penalized with a high down regulation price. So it may be concluded from the simulation results that the findings of this chapter may help wind power generation companies to make a better bidding strategy so that the imbalance cost of trading wind power in the electricity market could be reduced.

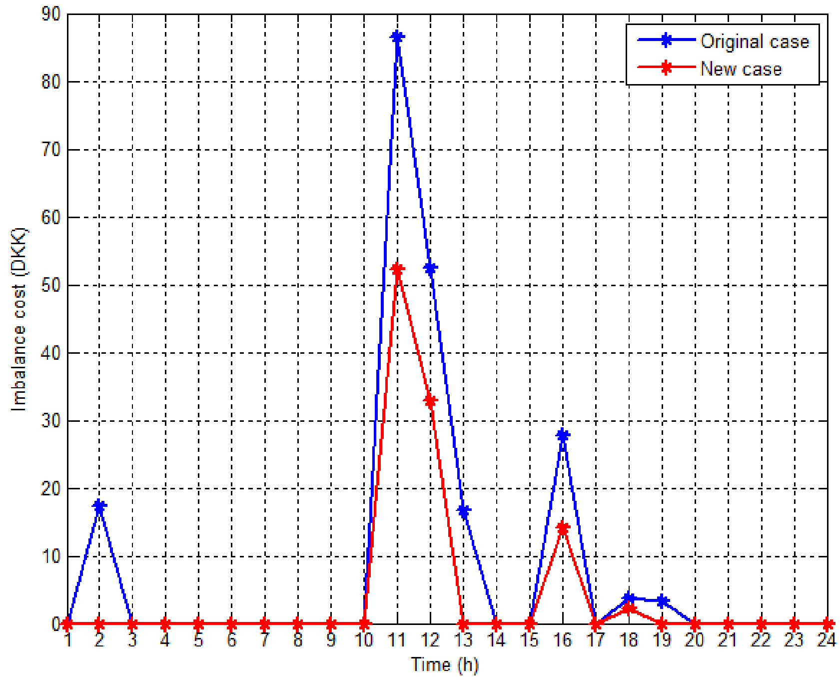


Fig. 2.18. The imbalance cost for the regulation for the original case (blue line) and the new case (red line) in a low wind speed day.

2.4 Stochastic Optimal Wind Power Bidding Strategy

Due to the fluctuating nature and non-perfect forecast of the wind power, the wind power owners are penalized for the imbalance costs of the regulation as discussed in the previous section, when they trade wind power in the short-term liberalized electricity market. Therefore, in this section a formulation of an imbalance cost minimization problem for trading wind power in the short-term electricity market is described, to help the wind power owners optimize their bidding strategy. Stochastic optimization and a Monte Carlo method are adopted to find the optimal bidding strategy for trading wind power in the short-term electricity market in order to deal with the uncertainty of the regulation price, the activated regulation of the power system and the forecasted wind power generation. The Danish short-term electricity market and a wind farm in western Denmark are chosen as study cases due to the high wind power penetration here. Simulation results show that the stochastic optimal bidding strategy for trading wind power in the Danish short-term electricity market is an effective measure to maximize the revenue of the wind power owners.

2.4.1 Problem Formulation of Wind Power Bidding Strategy

The revenue of a wind power owner in an hour can be formulated as

$$R = p_{spot}E_{b,spot} + p_{bal}E_{b,bal} + p_{reg}E_{im} \tag{2.3}$$

where R is the revenue of a wind power owner, p_{spot} , p_{bal} are the spot price and the balancing market price, respectively, $E_{b,spot}$, $E_{b,bal}$ are the amount of bid wind energy in the spot market and the balancing market, respectively, p_{reg} is the regulation price and E_{im} is the amount of imbalance wind energy. Due to the fact that only small amounts of energy are traded in the balancing market and the balancing market price equals to the spot market price for around 80% of the time in the year, the revenue of a wind power owner in an hour can be approximated as

$$R = p_{spot}E_b + p_{reg}E_{im} \tag{2.4}$$

where E_b is the sum of bid wind energy in the spot market and the balancing market. The imbalance wind energy in an hour is defined as

$$E_{im} = E_a - E_b \tag{2.5}$$

where E_a is the actual wind power generation.

As discussed in Section 2.3, if up regulation is activated and the wind power owner has negative imbalance wind energy, the wind power owner is penalized with the up regulation price. In this case, the revenue of the wind power owner in an hour may be given by

$$R = p_{spot}(E_a - E_{im}) + p_{up}E_{im} = p_{spot}E_a + (p_{up} - p_{spot})E_{im} \tag{2.6}$$

With the definition of the deviation of the up regulation price to the spot price (Eq. (2.1)), the revenue of the wind power owner in an hour can be rewritten as

$$R = p_{spot}E_a - (-\Delta p_{up}E_{im}) \tag{2.7}$$

If down regulation is activated and the wind power owner has a positive imbalance wind energy, the wind power owner is penalized with the down regulation price. In this case, the revenue of the wind power owner in an hour may be given by

$$R = p_{spot} E_a - (-\Delta p_{down} E_{im}) \tag{2.8}$$

If up regulation is activated and the wind power owner has a positive imbalance wind energy, or down regulation is activated and the wind power owner has a negative imbalance wind energy, the wind power owners are paid according to the spot price. In these 2 cases, the revenue of the wind power owner in an hour may be given by

$$R = p_{spot} E_a \tag{2.9}$$

So Eq. (2.4) can be reformulated such that the revenue R of a wind power owner results from the combination of the income from selling the actual wind power generation E_a at the spot price, minus the imbalance cost for the regulation. It may be rewritten as

$$R = p_{spot} E_a - C_{im} \tag{2.10}$$

The imbalance cost for the regulation C_{im} is given by

$$C_{im} = \begin{cases} -\Delta p_{up} E_{im} & \text{(up regulation) \& } (E_{im} < 0) \\ -\Delta p_{down} E_{im} & \text{(down regulation) \& } (E_{im} > 0) \\ 0 & \text{(up regulation) \& } (E_{im} > 0) \\ 0 & \text{(down regulation) \& } (E_{im} < 0) \end{cases} \tag{2.11}$$

In Eq. (2.10) the first component $p_{spot} E_a$ of the revenue for the wind power owner is the dominating component, which corresponds to the income received by the wind power owner if the wind power is forecasted perfectly. Furthermore, since the bid wind energy E_b only appears in the second component of the revenue for the wind power owner, maximizing the revenue may be translated to minimizing the imbalance cost for the regulation C_{im} for the wind power owner. So the objective of the wind power owner is to achieve a minimum imbalance cost for the regulation by deciding the optimal bid wind energy.

Because the power consumption and generation in Denmark is relatively small in the Nordic electricity market and the variation range of the optimal bid value of wind energy are small [37], it is assumed that the spot price and the regulation price are not changed by the optimal bidding strategy for trading wind power in the short-term electricity market of Denmark.

2.4.2 Stochastic Optimization

Stochastic optimization is adopted to find the optimal bidding strategy for trading wind power in the Danish short-term electricity market in order to deal with the uncertainty of the regulation price, the activated regulation of the power system and the forecasted wind power generation. The flow chart of the stochastic optimization algorithm for the imbalance cost minimization is shown in Fig. 2.19. In this section, the wind energy is forecasted using the persistence forecast method [41]. The probability density of the forecasted error for the wind power generation will be obtained in the next sub-session. Then the bid wind energy is initialized based on the forecasted wind energy. In order to deal with the uncertainty of the regulation price, the activated regulation of the power system and the forecasted wind power generation, the Monte Carlo (MC) method is used in the stochastic optimization. The regulation price and the activated regulation of the power system are generated based on the probability densities of the regulation price and the activated regulation in the Danish electricity market, which have been discussed in Section 2.3. The actual wind energy is also generated based on the probability density of the forecasted error for the wind power generation, which will be discussed in the next section. In the MC method, 1000 sets of data of the regulation price, the activated regulation and the actual wind energy are generated based on the zone of the wind power generation. The imbalance cost for the regulation for each hour can then be calculated according to Eq. (2.11).

The sequential quadratic programming method represents the state of the art in nonlinear programming methods [42]. This method makes a lot of iterations in order to find the optimization results under the constraints. At each iteration an approximation is made of the Hessian matrix of the Lagrangian function using a Quasi-Newton updating method [43]. This is then used to generate a quadratic programming sub-problem whose solution is used to form a search direction for a line search procedure [44]. At each iteration 1000 sets of data, which include the regulation price, the activated regulation and the actual wind energy, are generated based on their probability density in order to deal with their uncertainties. The sequential quadratic programming method makes a lot of iterations until the stop criterion is satisfied, the stop criterion is no significant improvement in the solution or a maximum number of iterations have been reached.

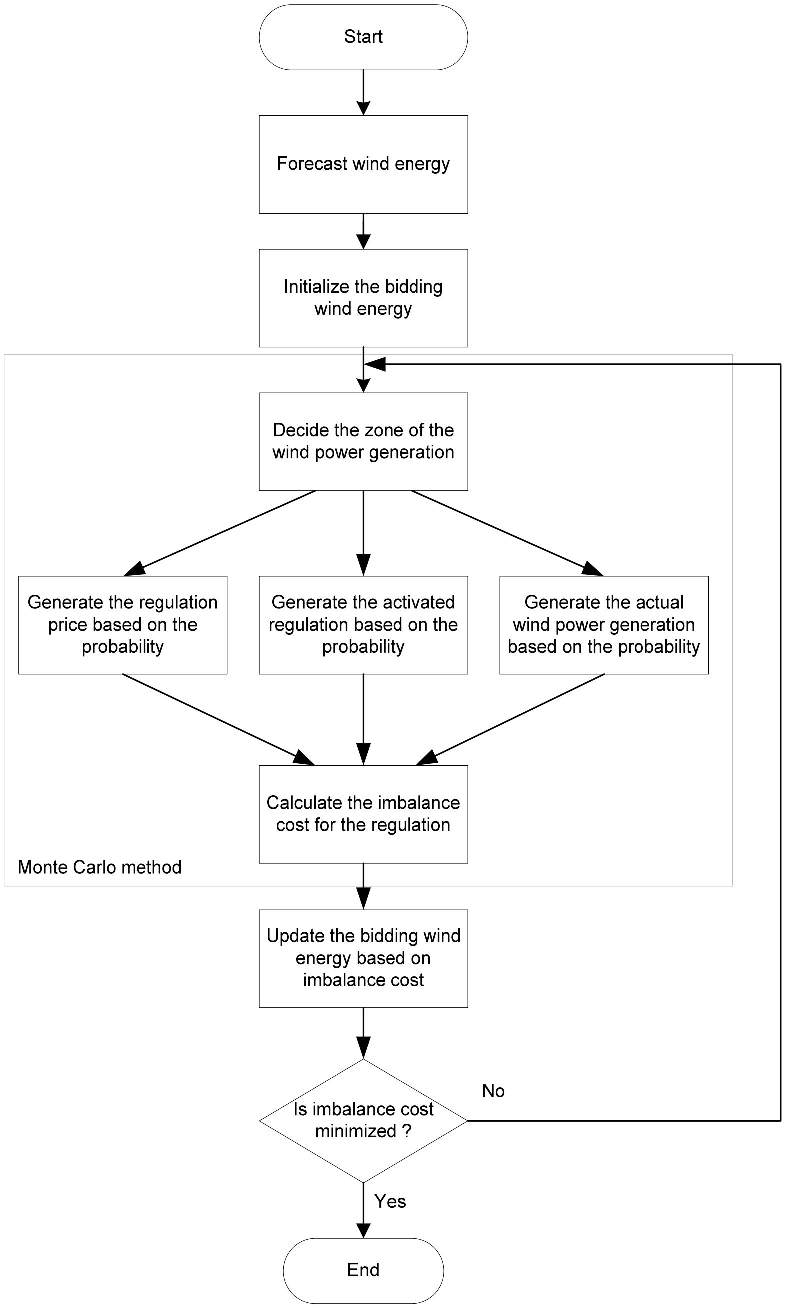


Fig. 2.19. The flow chart of the stochastic optimization algorithm.

2.4.3 Persistence Wind Forecast Method

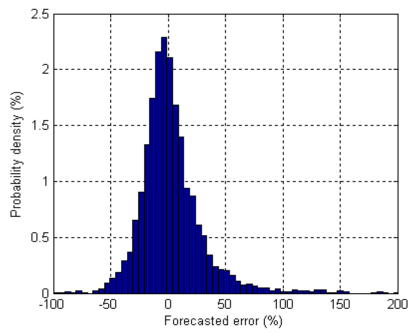
The wind power owners use the advanced wind forecast model based on real time weather information in practice. However, the forecast wind power is normally confidential. Due to the lack of forecast data, the persistence forecast method is here used to obtain a forecasted wind power. The persistence forecast method is one of the most simple wind forecast methods in which the forecasted wind energy for hour t equals to the actual wind energy at hour *(t-1)* [41]. It can be written as

$$E_f(t) = E_a(t-1) \tag{2.12}$$

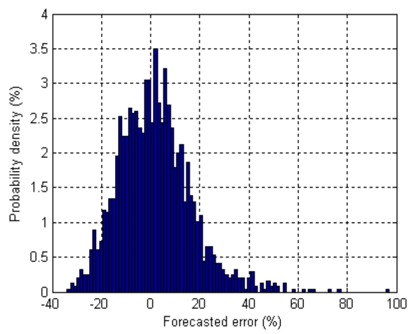
where $E_f(t)$ is the forecasted wind energy for hour t, $E_a(t-1)$ is actual wind energy at hour *(t-1)*. The forecasted error E_{error} of the persistence wind forecast method may be defined as

$$E_{error} = \frac{E_a - E_f}{E_f} \times 100\% \tag{2.13}$$

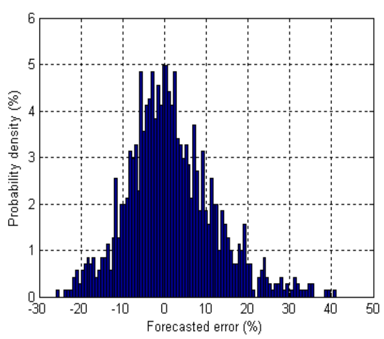
A 20 MW wind farm is investigated in the section and the actual wind power generation in the year 2008 is collected. The forecasted wind energy can be obtained by the persistence wind forecast method and the forecasted error can be calculated using Eq. (2.13). Fig. 2.20 and Table 2.2 illustrate the probability density of the forecasted error for different wind power generation. It can be seen that the average value of the forecasted error is around 0% and the standard deviation of the forecasted error decreases when the wind power generation increases. At low wind power generation periods, the probability of a large forecast error is high and at high wind power generation periods, the probability of a large forecast error is low. The probability density of the forecasted error is used to generate the actual wind energy in the stochastic optimization in order to find the optimal bidding strategy for trading wind power in the Danish short-term electricity market.



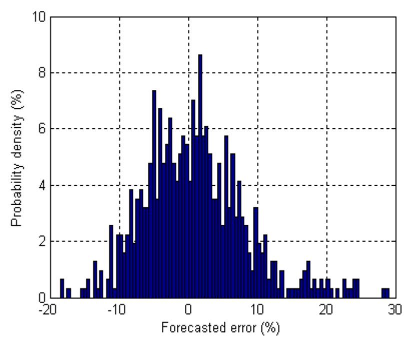
(a) 0%~20%



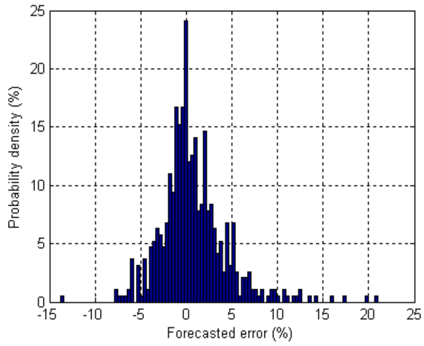
(b) 20%~40%



(c) 40%~60%



(d) 60%~80%



(e) 80%~100%

Fig. 2.20. The probability density of the forecasted error for different wind power generation.

Table 2.2. The mean value and standard deviation of the forecasted error.

Wind power generation	Mean value (%)	Standard deviation (%)
0%~20%	2.6	29.0
20%~40%	1.8	15.0
40%~60%	1.6	10.5
60%~80%	0.9	7.5
80%~100%	0.8	3.7

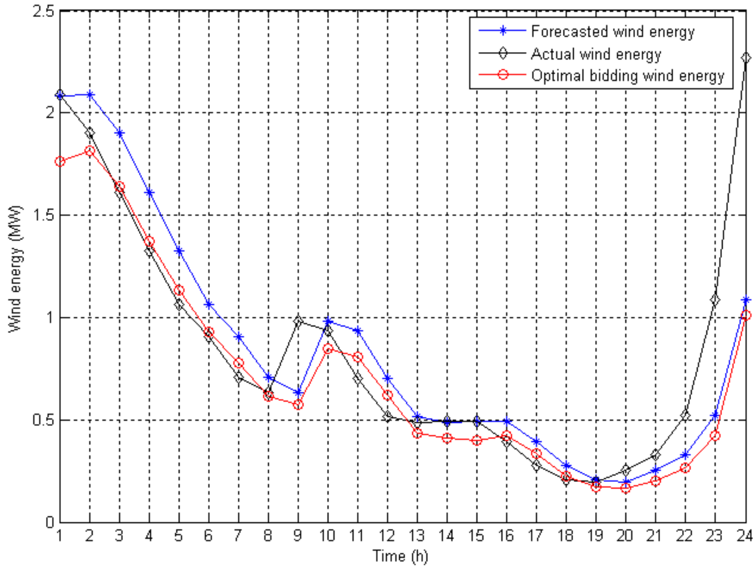
2.4.4 Numerical Results and Discussions

Again the 20 MW wind farm in western Denmark is used as a study case in the section and the actual wind power generation in the year 2008 is collected. The stochastic optimization is performed in order to find the optimal bidding strategy for trading wind power in the short-term electricity market. The imbalance cost for the regulation is calculated when the forecasted wind energy is chosen as the bid wind energy. This case is referred as the original case and the imbalance cost for regulation is referred as the original imbalance cost for comparison purpose. It is assumed that the optimal bid wind energy is in the range of -20% ~ +20% around the forecasted wind energy in the stochastic optimization.

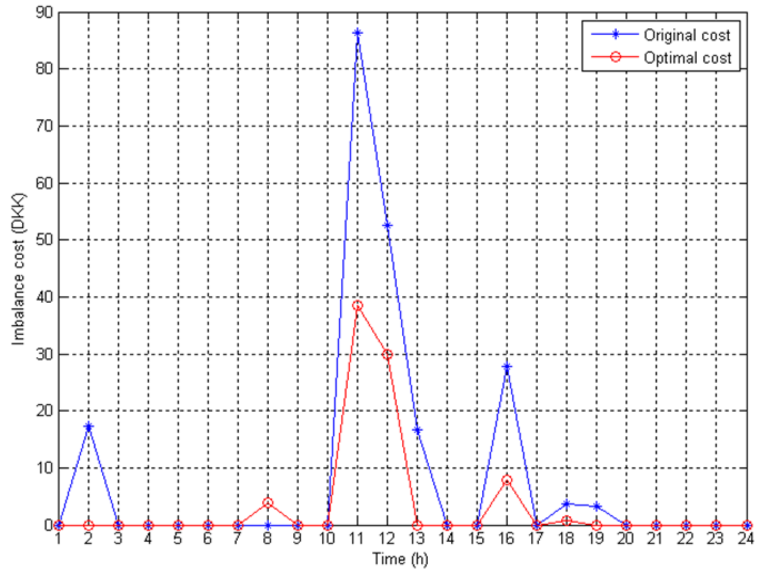
A low wind speed day (1^{st}, July, 2008) is chosen as the first study case. The forecasted wind energy, the actual wind energy, the optimal bid wind energy, the original imbalance cost for the regulation with forecasted bid wind energy and the optimal imbalance cost for the regulation with the optimal bid wind energy are shown in Fig. 2.21. It can be seen that the imbalance cost for the regulation decreases when the optimal bidding strategy is used for trading the wind power in the short-term electricity market. In the low wind speed day, the deviation of the up regulation price Δp_{up} is higher than the deviation of the down regulation price Δp_{down} (see Fig. 2.13) and the probability of the activated up regulation is higher than the probability of the activated down regulation (see Fig. 2.16) in the low wind generation periods. The optimal bid wind energy is lower than the forecasted wind energy in order to avoid to be penalized with a high up regulation price. The total imbalance cost for the regulation in the studied day decreases about 61%. Compared with the case that the wind power owner bids 10% less than the forecasted wind energy (see Fig. 2.18), the total imbalance cost reduction has been increased from 51.4 % to 61%.

Next a high wind speed day (15th, January, 2008) and a medium wind speed day (19th, June, 2008) are chosen as the study cases. Fig. 2.22 and Fig. 2.23 illustrate the forecasted wind energy, the actual wind energy, the optimal bid wind energy, the original imbalance cost for the regulation with forecasted bid wind energy and the optimal imbalance cost for the regulation with the optimal bid wind energy. In the high wind speed day, the optimal bid wind energy is higher than the forecasted wind energy in order to avoid to be penalized with a high down regulation price Δp_{down} due to the high Δp_{down} and the high probability of the activated down regulation in the high wind generation periods. The wind power owners will not pay the imbalance cost for the regulation when the optimal bidding strategy is used in the studied high wind speed day.

However, the imbalance cost for the regulation increases when the optimal bidding strategy is used in the studied medium wind speed day. The deviation of the up regulation price Δp_{up} and the deviation of the down regulation price Δp_{down} are almost the same, and the probability of an activated up regulation and the probability of an activated down regulation are almost the same in the medium wind generation periods. So the stochastic optimization for trading wind power in the Danish short-term electricity market has difficulties to deal with the uncertainty of the regulation price and the activated regulation of the power system in the studied medium wind speed day.

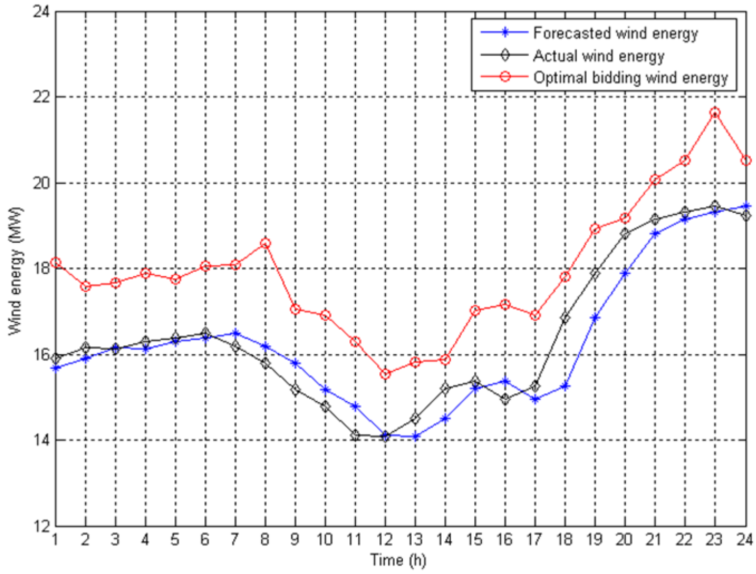


(a)

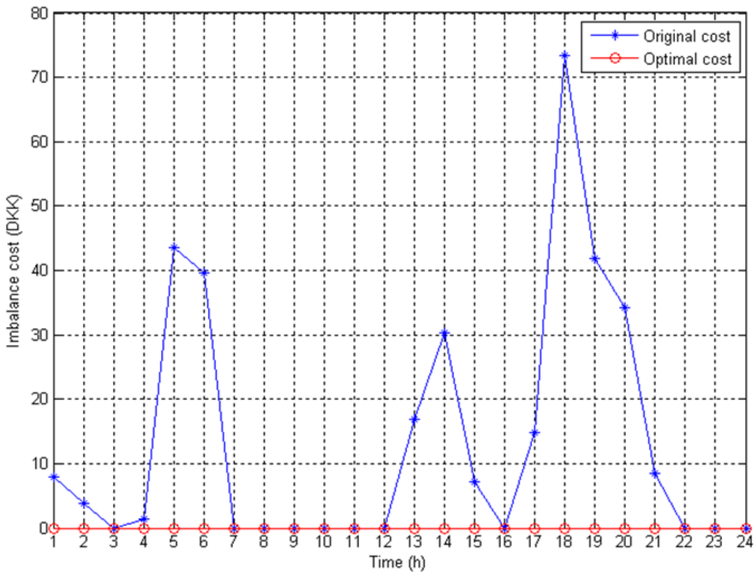


(b)

Fig. 2.21(a). The forecasted wind energy (blue asterisk), the actual wind energy (black diamond) and the optimal bid wind energy (red circle) in a low wind speed day. (b). The original imbalance cost for the regulation (blue asterisk) with forecasted bid wind energy and the optimal imbalance cost for the regulation (red circle) with the optimal bid wind energy in a low wind speed day.

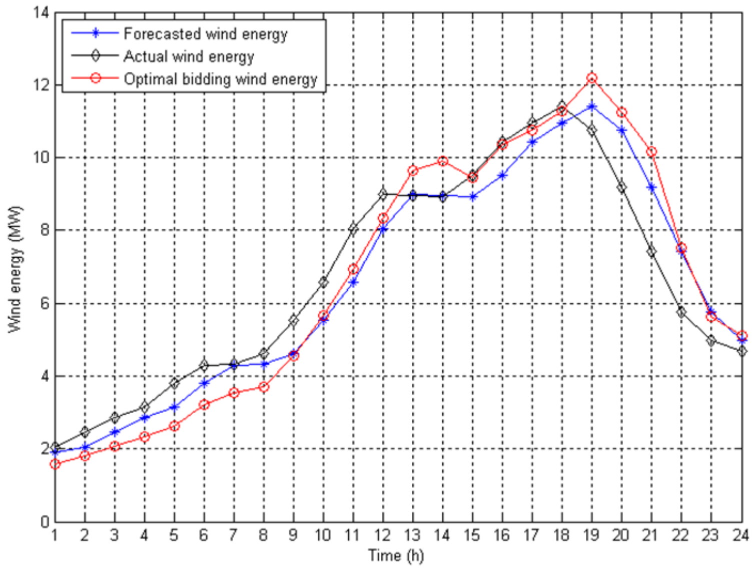


(a)

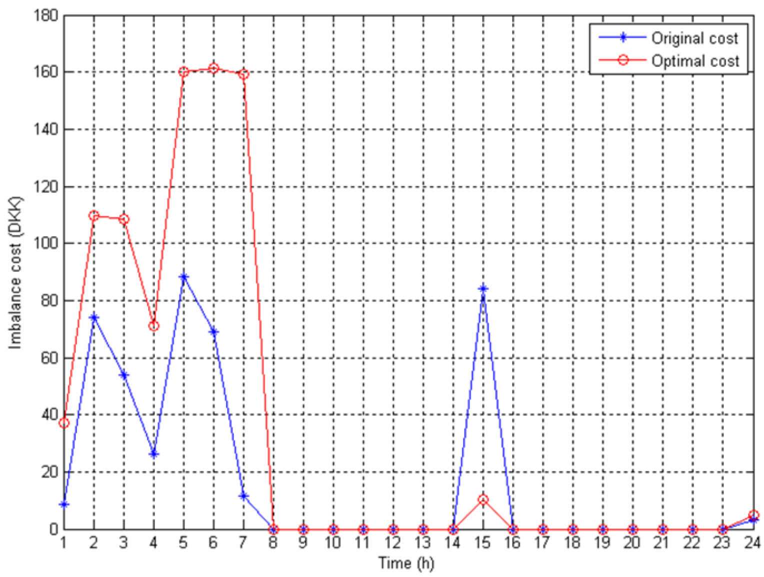


(b)

Fig. 2.22(a). The forecasted wind energy (blue asterisk), the actual wind energy (black diamond) and the optimal bid wind energy (red circle) in a high wind speed day. (b). The original imbalance cost for the regulation (blue asterisk) with forecasted bid wind energy and the optimal imbalance cost for the regulation (red circle) with the optimal bid wind energy in a high wind speed day.



(a)



(b)

Fig. 2.23(a). The forecasted wind energy (blue asterisk), the actual wind energy (black diamond) and the optimal bid wind energy (red circle) in a medium wind speed day. (b). The original imbalance cost for the regulation (blue asterisk) with forecasted bid wind energy and the optimal imbalance cost for the regulation (red circle) with the optimal bid wind energy in a medium wind speed day.

The stochastic optimization for trading wind power in the Danish short-term electricity market can be performed for each day of year 2008. The original imbalance cost for the regulation with forecasted bid wind energy, the optimal imbalance cost for the regulation with the optimal bid wind energy and the saving costs percentage (*SCP*) of each month in the year 2008 are shown in Table 2.3. The saving costs percentage (*SCP*) is defined as

$$SCP = \frac{C_{im}^{org} - C_{im}^{opt}}{C_{im}^{org}} \times 100\% \qquad (2.14)$$

where C_{im}^{org} is the original imbalance cost for the regulation with forecasted bid wind energy and C_{im}^{opt} is the optimal imbalance cost for the regulation with the optimal bid wind energy.

From Table 2.3, it can be seen that the imbalance cost for the regulation is reduced 9.4% in total in year 2008 when the stochastic optimal bidding strategy for trading wind power in the Danish short-term electricity market is used. In some months, the *SCP* is negative, which means the optimal imbalance cost for the regulation with the optimal bid wind energy is higher than the original imbalance cost for the regulation with forecasted bid wind energy. This is as shown in Fig. 2.23 due to a medium wind situation where the stochastic optimization for trading wind power in the Danish short-term electricity market has difficulties to deal with the uncertainty of the regulation price and the activated regulation of the power system. Therefore, the proposed optimal wind power strategy should be skipped in the medium wind situation and the wind power owner should bid using the forecasted wind power instead.

Fig. 2.24 illustrates the saving costs percentage as a function of the wind power generation in the year 2008 (blue line). As it is shown, in both low and high wind power generation periods, the *SCP* is high, which means the imbalance cost for regulation decreases when the stochastic optimal bidding strategy for trading wind power in the Danish short-term electricity market is used. In medium wind power generation periods, the *SCP* is negative, which means the optimal bidding strategy cannot save imbalance costs for regulation. As in the case of medium wind speed day above, this is due to the fact that the deviation of the up regulation price Δp_{up} and the deviation of the down regulation price Δp_{down} are almost the same, and the probability of the activated up regulation and the probability of the activated down regulation are almost the same in the medium wind generation periods.

From the figure, it can be concluded that the stochastic optimal bidding strategy for trading wind power in the Danish short-term electricity market is an effective measure to maximize the revenue of the wind power owners in high or low wind speed periods over the total year. However, since the stochastic optimization has difficulties to deal with the uncertainty of the regulation price and the activated regulation of the power system in the medium wind generation periods, the forecasted wind energy can be chosen as the bid wind energy for medium wind speed days, which means that the stochastic optimization is only adopted in low and high wind speed days. Then the SCP increases from 9.4% (when the stochastic optimal bidding strategy is used in all days) to 13.6% (when the stochastic optimal bidding strategy is only used in both low and high wind speed days) in the year 2008.

Table 2.3. Imbalance costs and *SCP* of each month in the year 2008.

Month	Original Imbalance Cost (DKK)	Optimal Imbalance Cost (DKK)	*SCP*
Jan.	23739	26388	-11.2%
Feb.	13005	13099	-0.7%
Mar.	24518	24816	-1.2%
Apr.	22847	24576	-7.6%
May	14535	8268	43.1%
Jun.	15051	13976	7.1%
Jul.	10130	9629	4.9%
Aug.	5426	4603	15.2%
Sep.	21899	16726	23.6%
Oct.	11750	12144	-3.4%
Nov.	17151	9671	43.6%
Dec.	9263	7598	18.0%
Total	**189310**	**171490**	**9.4%**

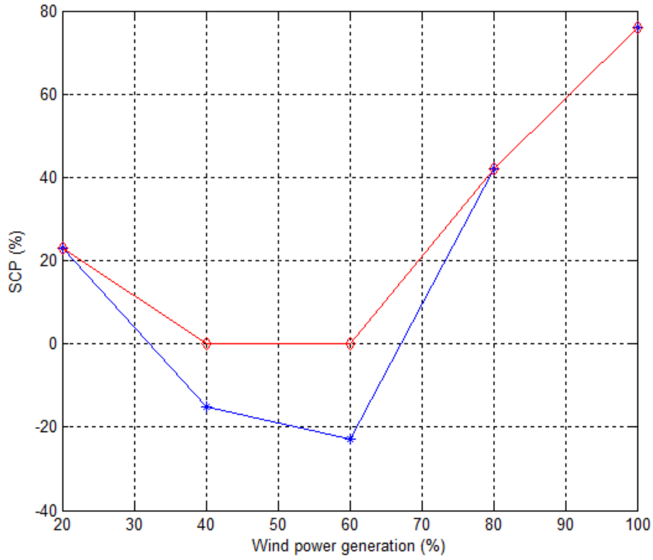


Fig. 2.24. The saving costs percentage (*SCP*) with the wind power generation (blue line: the stochastic optimal bidding strategy is used in all days, red line: the stochastic optimal bidding strategy is only used in both low and high wind speed days).

2.5 Summary

The Danish power system is currently the grid area in the world that has the largest share of wind power in its generation profiles, with around 20% of its annual consumption generated by wind turbines. In this chapter, the Danish power system, which may represent the future of competitive electricity markets in some ways, is chosen as the studied power system. 10 year actual data from the Danish competitive electricity market are collected and analyzed. The relationship among the electricity price (both the spot price and the regulation price), the consumption and the wind power generation in an electricity market is investigated. The spot price and the regulation price generally decrease when the wind power generation in the power system increases or the consumption of the power system decreases. The statistical characteristics of the spot price and the regulation price for different consumption periods and wind power generation are analyzed. These findings are useful for wind power generation companies to make the optimal bidding strategy so that the imbalance cost of trading wind power on the electricity market could be reduced.

The formulation of an imbalance cost minimization problem for trading wind power in the Danish short-term electricity market is then described in the chapter. Because of the uncertainty of the regulation price, the activated regulation of the power system and the forecasted wind power generation, stochastic optimization and a Monte Carlo method are adopted to find an optimal bidding strategy for trading wind power in the Danish short-term electricity market in order to minimize the imbalance costs for regulation. Simulation results show that the stochastic optimal bidding strategy for trading wind power in the Danish short-term electricity market is an effective measure to maximize the revenue of the wind power owners.

The main work of this chapter has also been reported in the author's previous publications [P1-P3].

Chapter 3

Optimal Load Response to Spot Price and Its Impact on Distribution Systems

3.1 Introduction

While the global demand in electrical energy is increasing steadily, the upgrading of national and international power grids is progressing slowly due to the high economic risks of establishing new power stations [16]. In the deregulated and dynamic power markets, there is a strong variability in electricity prices. Load peaks and lacks of generation due to maintenance of generators, power fluctuations from DGs and unexpected outages result in high spot market prices in some periods [20].

Time-of-use (TOU) power price is widely applied in many countries and is considered as one of important approaches of demand side management (DSM) [45]. The conventional approach is to persuade large industrial consumers to shift theirs loads by means of three-section TOU tariffs [46-48]. This kind of tariff provides three different power prices based on the time in a day, which are peak period, flat period and off-peak period. Now many consumers in Denmark, especially small businesses and private households, operate on fixed power price contracts. But the small load peaks could add up very easily to one significant peak that leads to efficiency drawbacks and may cause power system constraints problems, such as over-voltage of buses and over-capacity of branches. Some of these consumers also have the ability to reduce or reschedule their demand in response to a spot market electricity price.

Since the hourly spot market price is available one day ahead in Denmark, if a spot market price could be available for consumers, they may decide to modify the profile of their demand to reduce their electricity costs as much as possible. An optimal load response to a spot market electricity price for demand side management generates different load profiles and has some impacts on power system constraints, such as voltage limits and capacity limits.

In this chapter, a load optimization method to spot market electricity price for demand side management in Denmark is proposed in order to save the energy costs as much as possible. 3 typical different kinds of loads (industrial load, residential load and commercial load) in Denmark are chosen as study cases. The load optimization to spot market price generates different load profiles and reduces the load peaks. These kinds of load patterns have significant effects on power system constraints. The 3 typical different kinds of loads, the optimization methods and the assumptions are presented in Section 3.2. A distribution system where wind power capacity is 126% of maximum loads is chosen as the study case. The impact of the optimal load response on the distribution system is presented in Section 3.3. Section 3.4 summarizes the main conclusions.

3.2 Optimal Load Response to Spot Price

The spot price for electricity is volatile, and this volatility is non-stationary, showing unpredictable variations and spikes due to the changes of the generations and demands in the deregulated and dynamic power markets. The spot price of west Denmark in the year 2007 can be obtained from Energinet.dk [39], which is the transmission system operator of Denmark, and is shown in Fig. 3.1. If the consumers do not have a fixed price contract and could get the spot price one day in advance, they may have some motivations to shift some of their loads from high price periods to low price periods in order to pay minimum energy costs in that day.

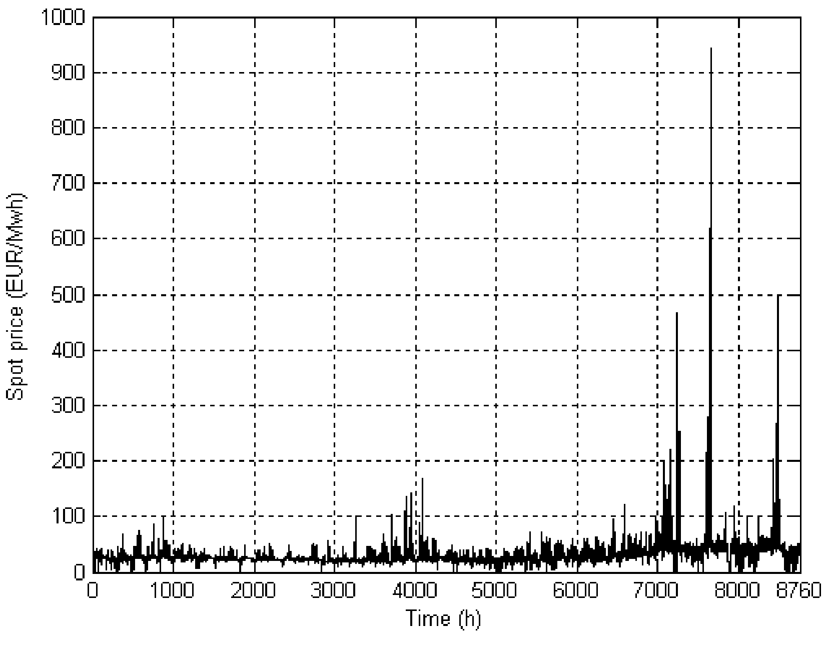


Fig. 3.1. The spot price of west Demark in the year 2007 [39].

Mathematical models are built to analyze how the consumers may shift their loads to achieve minimum energy costs as well as to consider the impacts of optimal load response to the electricity price on power system constraints. The Sequential Quadratic Programming (SQP) method is adopted as the optimization methods. The mathematical model and the needed assumptions are described in the following.

3.2.1 Mathematical Models

The energy costs (EC) paid by the consumers in a day may be calculated with the following equation

$$EC = \sum_{t=1}^{24} sp(t)L(t) \tag{3.1}$$

where *sp(t)* is the spot price at hour *t*, *L(t)* is the load at hour *t*. Since the spot price is available one day ahead, the consumers may reschedule their loads in order to save energy costs. Then the energy cost could be written as

$$EC_x = \sum_{t=1}^{24} sp(t)L_x(t) \tag{3.2}$$

where $L_x(t)$ is the rescheduled load at hour *t*, EC_x is the energy cost of that day under the rescheduled load.

The objective of consumers is to achieve the minimum energy cost by load shifting. The optimization objective function could be chosen as

$$\min(EC_x) = \min(\sum_{t=1}^{24} sp(t)L_x(t)) \tag{3.3}$$

3.2.2 Assumptions

Some necessary assumptions have to be made to this problem.

1) The total consumption in a day is kept the same in the case of original loads and the case of rescheduled loads. The consumers may only change some of their loads from the high price periods to the low price periods. But the total consumption may not be changed due to the similar behaviors in their daily life or production. The assumptions could be written as

$$\sum_{t=1}^{24} L_x(t) = \sum_{t=1}^{24} L(t) \tag{3.4}$$

2) Only some of the loads could be shifted according to the time-of-use power price by the consumers. Some of loads are fixed, that means the customer consumes the power no matter how much the price is. It is here assumed that 20% of the total load is the flexible load and could be shifted according to the time-of-use power price by the consumers.

The 24 hours in a day are divided into three load periods based on the different daily load profiles, shown as the following equation

$$T_p + T_f + T_{op} = 24 \tag{3.5}$$

where T_p is the peak load period, T_f is the flat load period and T_{op} is the off-peak load period. Different category of loads has different load curves and different load periods. The load periods of different loads are decided according to the original daily consumption behaviors of different consumers (see original loads in Fig. 3.3). The specific data of the 3 load periods are shown in Table 3.1.

Table 3.1. The time periods.

	Industrial Load	Residential Load	Commercial Load
Peak Load Period	07:00~16:00	06:00~14:00	09:00~20:00
Flat Load Period	05:00~07:00 16:00~20:00	04:00~06:00 14:00~22:00	05:00~09:00 20:00~23:00
Off-peak Load Period	00:00~05:00 20:00~24:00	00:00~04:00 22:00~24:00	00:00~05:00 23:00~24:00

It is assumed that the allowed shifting load ranges are (-20%~0%), (-10%~10%) and (0%~20%) in the peak load period, flat load period and off-peak load period, respectively.

3) Because the power consumption of Denmark is relatively small in the Nord Pool power market and the load variations are small, the spot prices are not changed after the load response to time-of-use power prices.

3.2.3 Optimization Methods

The consumers may try to find the minimum value of the objective function (see Eq. (3.3)) under the assumptions mentioned. This kind of problem is an optimization problem under constraints, mathematically.

The sequential quadratic programming method represents the state of the art in nonlinear programming methods [42]. This method makes a lot of iterations in order to find the optimization results under the constraints. At each major iteration an approximation is made of the Hessian matrix using a Quasi-Newton updating method [43]. This is then used to generate a quadratic programming sub-problem whose solution is used to form a search direction for a line search procedure [44]. The optimization method is implemented using Matlab optimization toolbox.

3.2.4 Simulation Results

A winter weekday of year 2007 is chosen as the study case. The spot prices and the 3 typical loads of west Denmark are collected for the study. Fig. 3.2 illustrates the spot price of that day. There are two price peaks at about 09:00 and 18:00, respectively. The consumer may reduce the consumption near the price peaks in order to reduce the energy costs.

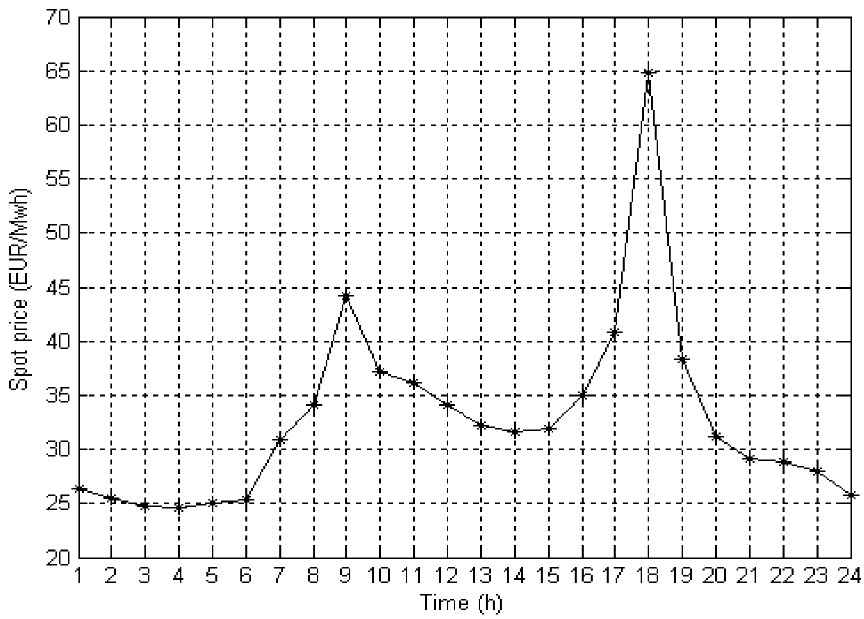


Fig. 3.2. The spot price of west Denmark in a winter weekday [39].

Optimal load responses of typical loads in west Denmark to time-of-use power price for demand side management are shown in Fig. 3.3. The consumers shift some of the loads from the high price periods to the low price periods in order to achieve the minimum energy costs in the day. All loads is reduced about 20% at the price peak 1 (about 09:00) and only the commercial load can be reduced about 20% at the price peak 2 (about 18:00), because only the commercial load is in the peak load period at the price peak 2, as shown in table 3.1.

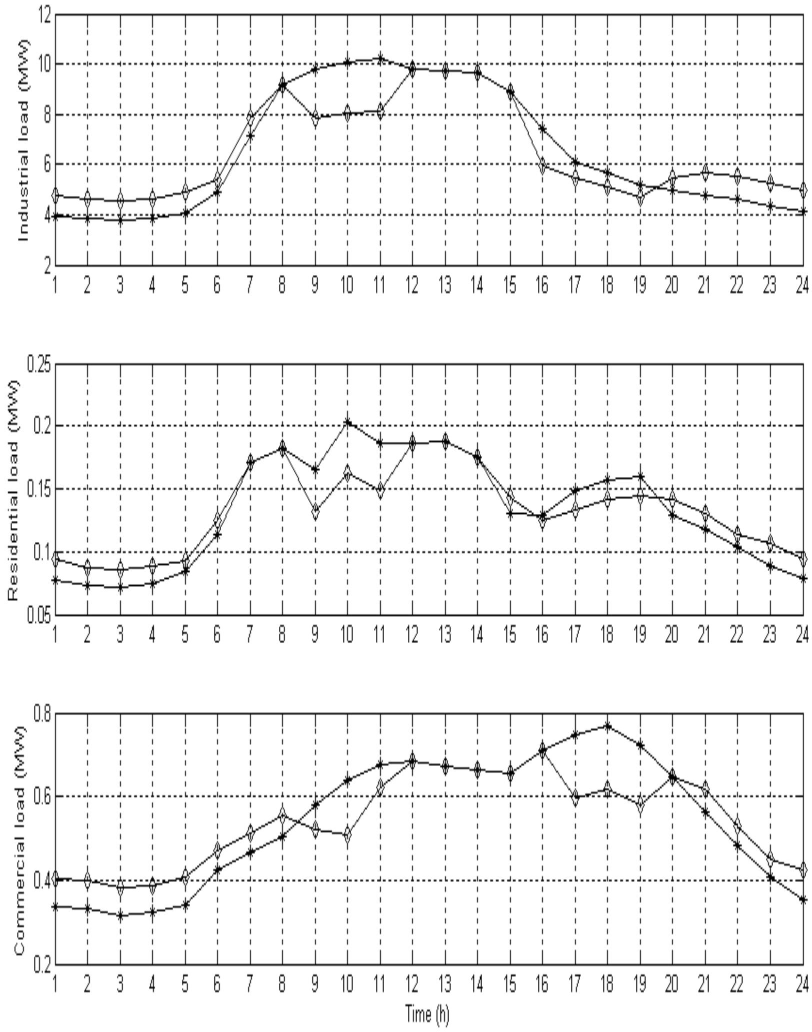


Fig. 3.3. Original load (asterisk) and optimal load (diamond) of typical Dainsh loads in a winter weekday.

The energy costs of typical consumers in this day are shown in table 3.2. The saving costs percentage (*SCP*) is defined as

$$SCP = \frac{EC - EC_x}{EC} \tag{3.6}$$

Table 3.2. The energy costs.

	Industrial Load	Residential Load	Commercial Load
EC (EUR)	5291.6	109.5	448.6
EC_x (EUR)	5172.2	107.2	436.4
Saving Costs Percentage (*SCP*)	2.3%	2.1%	2.7%

The method could be adopted at each day of year 2007. The *SCP* of different loads at January, 2007 is shown in Fig. 3.4. The energy costs decrease up to 9.6% due to optimal load responses to time-of-use power price for industrial load. The industrial consumers are more likely to shift their loads than the residential and commercial consumers due to the more energy costs saving by shifting loads. When more loads are flexible loads and could be shifted according to the time-of-use power price by the consumers, the more energy costs saving could be achieved.

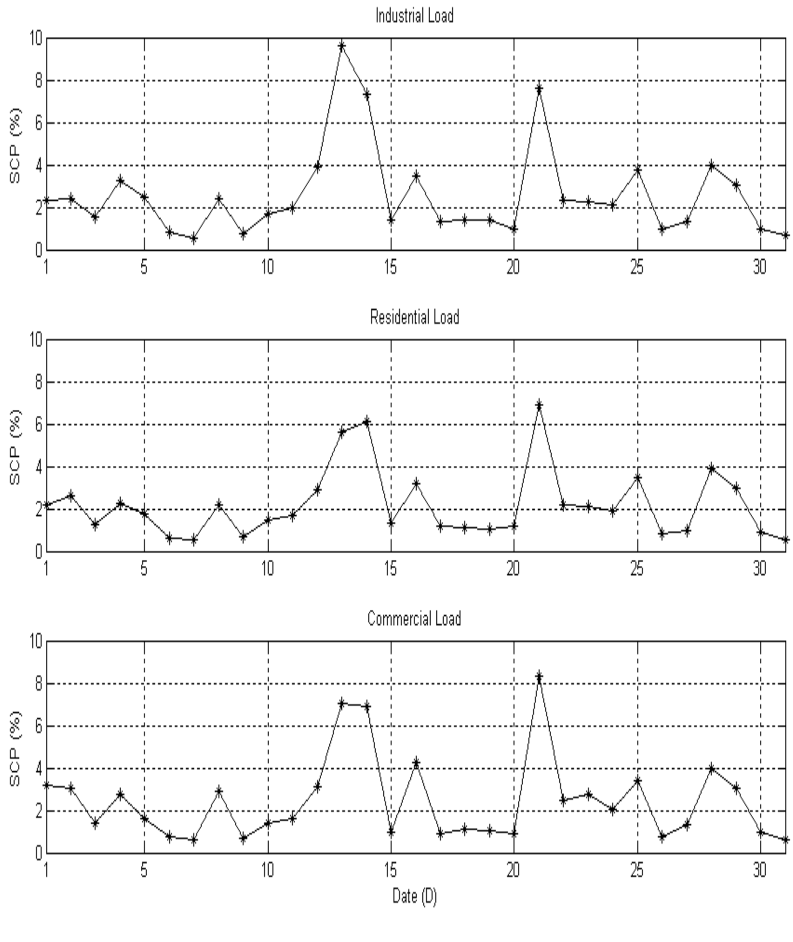


Fig. 3.4. The *SCP* of different loads at January, 2007.

The optimal load response to time-of-use power price for demand side management generates different load profiles of each day in year 2007. The original load duration curve and the optimal load duration curve of residential load in year 2007 are shown in Fig. 3.5. It is indicated that the peak electricity consumption is reduced and the off-peak electricity consumption is increased significantly. This kind of load patterns may also have significant effects on the power system normal operation.

The actual price paid by the private costumers consists of spot price, tax and other fees. In this chapter, only the spot price is taken into consideration. It is likely that the future price for the private costumers could be proportional to the spot price to give an incitement for shifting their consumption.

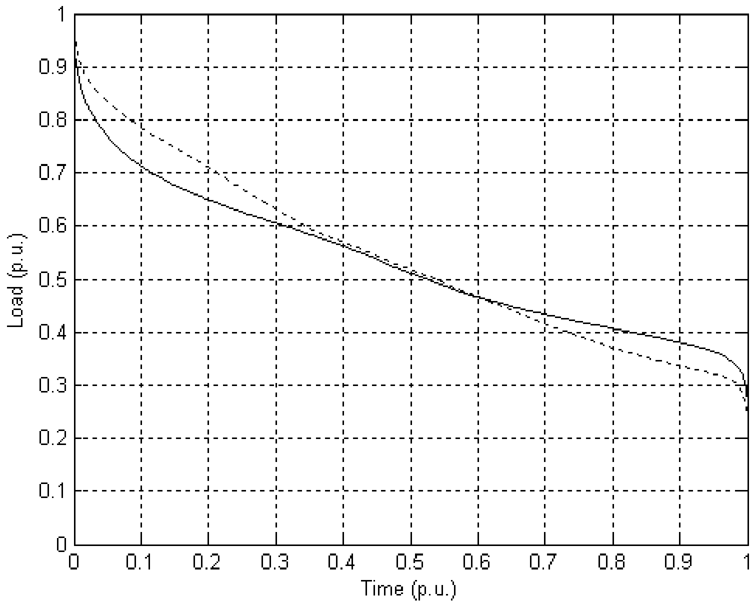


Fig. 3.5. The original load duration curve (dot line) and the optimal load duration curve (solid line) of residential load in year 2007.

3.3 Impact on Power System Constraints

As discussed in the previous section, the optimal load response to the spot market price generates different load profiles and reduces the load peaks. These kinds of load patterns have significant effects on power system constraints.

In order to investigate the impact of optimal load response to the electricity price on power system constraints, power flow calculation is adopted. The two basic equations that govern the flow of power in power system networks are written as follows [49]

$$P_i - L_i = \sum_j |V_i||V_j| Y_{i,j} \cos(\theta_{i,j} + \delta_j - \delta_i) \tag{3.7}$$

$$Q_i - QL_i = -\sum_j |V_i||V_j| Y_{i,j} \sin(\theta_{i,j} + \delta_j - \delta_i) \tag{3.8}$$

where V_i and δ_i are the voltage magnitude and angle at bus i, respectively, $Y_{i,j}$ and $\theta_{i,j}$ are the bus admittance matrix element and its associated angle, respectively, P_i and L_i are active power generation and demand at bus i, respectively, and Q_i and QL_i are reactive power generation and demand at bus i, respectively.

An 18-bus distribution system configuration as shown in Fig. 3.6 is used as a study case and the network parameters are given in Table 3.3. It is a simplified and modified network configuration based on the 20 kV Størvring distribution system in Denmark, which is operated by Himmerlands Elforsyning. The modified distribution system includes eight 2 MW modern variable speed wind turbines and the three typical kinds of loads. The wind power data and different kinds of load data are obtained from Danish Energy Association. Variable speed operation of the wind turbine can be realized by appropriate adjustment of the rotor speed and pitch angle [50]. The reactive power of the wind turbine is controlled to zero to ensure unity power factor operation and reduce currents of the power electronic converters. An industrial load is assumed at bus 5, commercial loads are assumed at bus 11 and bus 13, a residential load is assumed at bus 14, which are the typical loads in the distribution system. The generation and load data of the distribution system are in Table 3.4. The studied distribution system is with high wind power penetrations, where the wind power capacity is 126% of maximum loads. Wind generation is variable in nature due to the variability of the incident wind speed at the wind turbine site. The wind power of each wind turbine and the typical loads of the distribution system in the year 2007 are shown in Fig. 3.7.

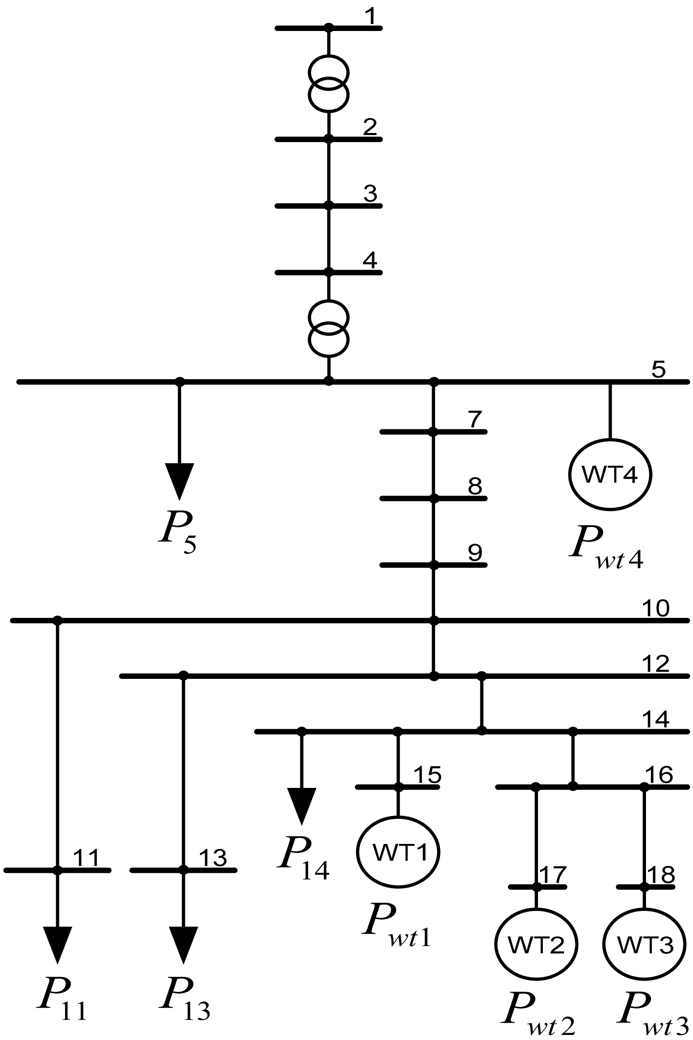
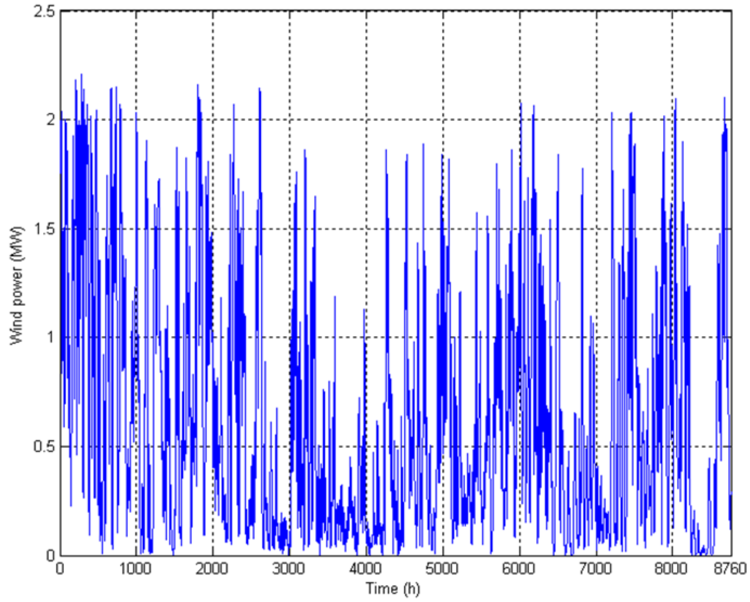
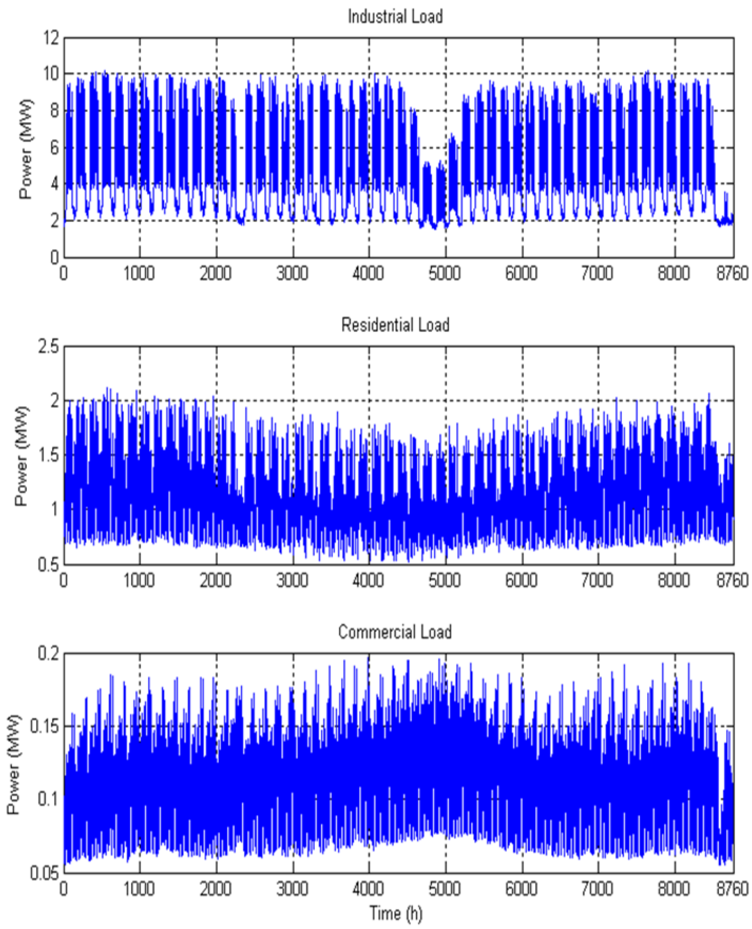


Fig. 3.6. Distribution system configuration under investigation.



(a)



(b)

Fig. 3.7. (a) The wind power of each wind turbine in the year 2007. (b) The 3 typical loads of the distribution system in the year 2007.

Table 3.3. The network parameters.

Buses	Resistance (p.u.)	Reactance (p.u.)	Line charging (p.u.)
1-2	0.01250	0.12437	0
2-3	0.01187	0.01826	0.01301
3-4	0.07661	0.10637	0.00121
4-5	0.02530	0.44730	0
5-7	0.00336	0.00158	0
7-8	0.04784	0.02242	0.000085
8-9	0.12184	0.05711	0.00022
9-10	0.03365	0.02264	0
10-11	10.05036	39.79559	0
10-12	0.18194	0.13912	0
12-13	10.00038	39.96833	0
12-14	0.08182	0.02043	0.000115
14-15	0.10000	0.57741	0
14-16	0.01810	0.00453	0
16-17	0.10000	0.57741	0
16-18	0.10183	0.57786	0

Table 3.4. The generation and load data.

Bus	P_{lmax} (MW)	P_{lmin} (MW)	$\cos\varphi_l$	P_{wtmax} (MW)	P_{wtmin} (MW)	$\cos\varphi_{wt}$
5	10.2	1.5	0.9	10	0.5	1
11	0.2	0.05	0.8	NA	NA	NA
13	0.2	0.05	0.8	NA	NA	NA
14	2.1	0.5	0.85	NA	NA	NA
15	NA	NA	NA	2	0.1	1
17	NA	NA	NA	2	0.1	1
18	NA	NA	NA	2	0.1	1

where P_{lmax} and P_{lmin} are the maximum and minimum active power of the load, respectively, $\cos\varphi_l$ is the power factor of the load, P_{wtmax} and P_{wtmin} are the maximum and minimum active power of the wind turbine, respectively, $\cos\varphi_{wt}$ is the power factor of the wind turbine.

In order to investigate the impact of optimal load response to spot market electricity price on power system constraints in the distribution system, power flow calculation based on eq. (3.7) and eq. (3.8) is used for each hour of year 2007 in the simulation. Fig. 3.8 illustrates the apparent power of the transformer between bus 1 and bus 2 based on the original load and the optimal load. The probability density and cumulative probability of the apparent power of the transformer are shown in Fig. 3.9. It can be seen that the relatively high parts of apparent power is reduced due to the optimal load response to the electricity price. Table 3.5 shows the average value and the standard deviation of the apparent power based on the original load and the optimal load. The average value of the apparent power is almost the same with the original load and the optimal load due to the assumption that the total consumption in a day is kept the same in the case of original loads and the case of optimal loads. The standard deviation of the apparent power is decreased with the optimal load response to the electricity price. The transformer capacity is 12 MVA in this case. Because the relatively high parts of the apparent power is reduced due to the optimal load response to the electricity price, the overloading percentage of the transformer decreases from 3.23% to 1.69%. The overloading percentage is defined as the transformer overloading hours over the total hours in a year. The total power loss in the distribution system of year 2007 is also reduced with the optimal load response.

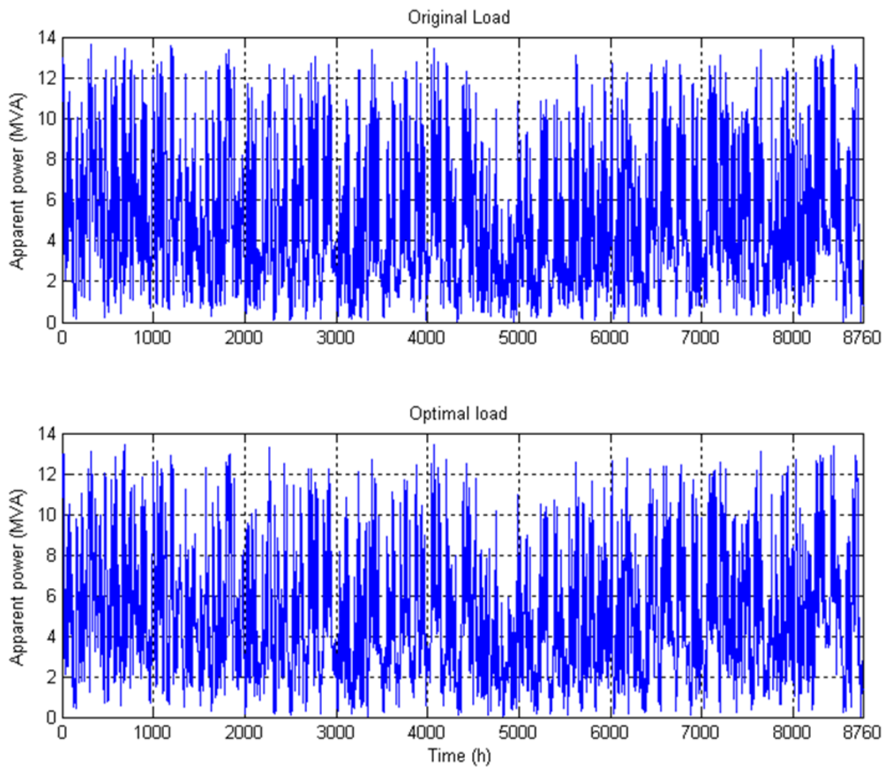
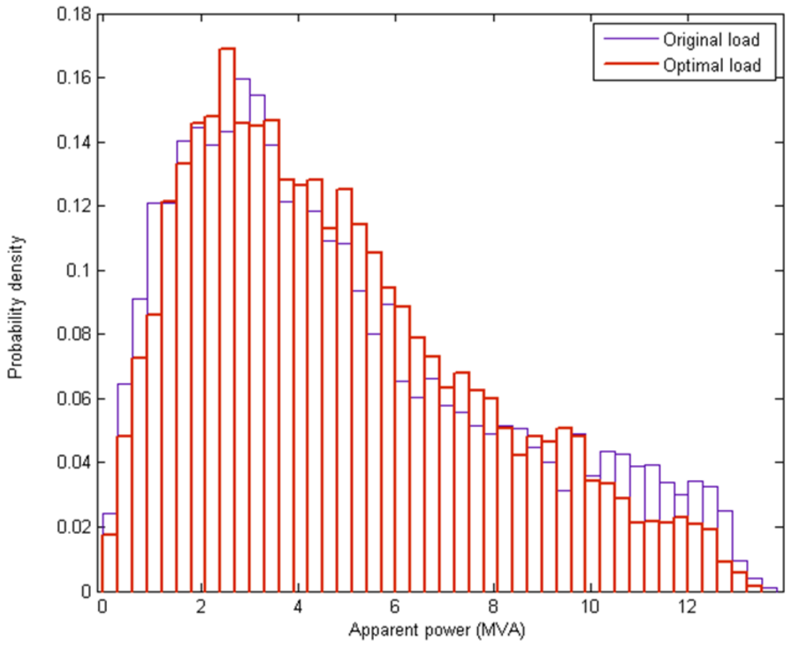
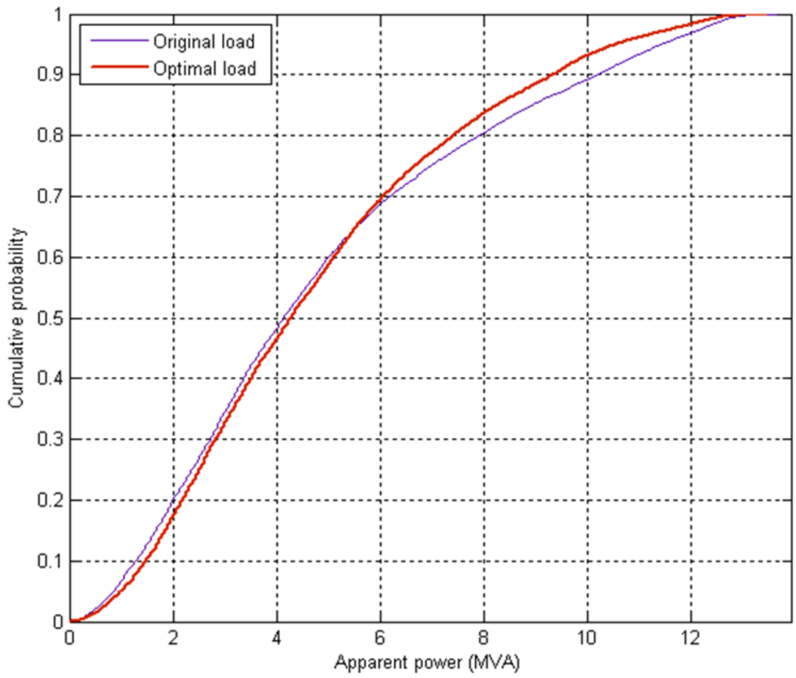


Fig. 3.8. The apparent power of the transformer between bus 1 and bus 2 based on the original load (upper one) and the optimal load (bottom one).



(a)



(b)

Fig. 3.9. (a) The probability density of the apparent power of the transformer between bus 1 and bus 2 based on the original load (blue) and the optimal load (red). (b) The cumulative probability of the apparent power of the transformer between bus 1 and bus 2 based on the original load (blue) and the optimal load (red).

Table 3.5. The apparent power of the transformer.

	Original Load	Optimal Load
Average value (MWA)	4.93	4.84
Standard deviation (MVA)	3.25	2.94
Overloading percentage	3.23%	1.69%
Total power loss (MW)	672.4	635.7

3.4 Summary

The hourly spot market price is available one day ahead in Denmark. Consumers may shift their loads from high price periods to the low price periods during a day in order to save their energy costs. This chapter presents a load optimization method to the spot price in order to save the consumers' energy costs as much as possible. Optimal load responses of 3 typical loads (industrial load, residential load and commercial load) in Denmark are studied. A distribution system where wind power capacity is 126% of maximum loads is chosen as the study case. The optimal load response to the spot price generates different load profiles. Simulation results show that these kinds of load patterns have good impacts on the power system constrains in the distribution system with high wind power penetrations. The overloading percentage of the transformer in the distribution system decreases from 3.23% to 1.69% with the optimal load response to the spot price.

The main work of this chapter has also been reported in the author's previous publications [P4, P5].

Chapter 4

Power Loss Minimization Using Demand Side Management

4.1 Introduction

The liberalization of the electricity markets has led to replacement of daily tariffs to hourly or half-hourly changing prices at least for industry and decentralized power generation in many parts of the world [17]. Economists argue that time-of-use electricity prices are a powerful way to encourage consumers to behave in an economically optimal way [17], [18]. Consumers may have some motivations to shift their loads from high price periods to low price periods in order to save their energy costs, if an hourly electricity price is available one day ahead.

The use of demand response in power systems has attracted a great deal of attention to the smart grid due to its feasibility and quick action [51]. Significant progress has been made in the research on and implementation of demand response programs during the past decade [52-55]. Two demand response programs (a participating load program and a demand relief program) have been implemented by the California ISO [52]. In Pennsylvania, a voluntary emergency load response and a mandatory interruptible load are used for reliability programs [53]. Recently, an event-driven demand response scheme is proposed to enhance the power system security [54]. Another important benefit of demand response is to avoid construction of expensive power plants to serve the peaks that occur for just a few hours per year [55].

The optimal load response to an hourly electricity price for demand side management generates new load profiles and provides also an opportunity to achieve power loss minimization in distribution systems. Power loss minimization in distribution systems could be achieved by deciding an optimal hourly electricity price. This issue can be formulated as a nonlinear optimization problem.

The particle swarm optimization (PSO) method is recently described in the literature [56]-[60] and the applications of PSO in power systems are very wide. Reference [61] focuses on problems of fuel cost minimization, voltage profile improvement and voltage stability enhancement. PSO is also employed to calculate the amount of shunt reactive power compensation in power loss minimization problems [62]. Fuzzy adaptive particle swarm optimization (FAPSO) has a better dynamic balance between global and local search abilities due to a nonlinear and a dynamic change in the inertia weight in the fuzzy evaluation during the iterations [63]. FAPSO is also employed for bidding strategy optimization in uniform price spot markets [64].

In this chapter, a new method of achieving power loss minimization in distribution systems by using price signal to guide the demand side management is proposed. The FAPSO algorithm is used as the optimization tool to solve the power loss minimization problem. The chapter is organized as follows. Section 4.2 and Section 4.3 provides modeling of the power loss minimization procedure for distribution systems, such as load optimization to electricity prices and power loss minimization with optimal electricity prices. The FAPSO algorithm for power loss minimization in distribution systems is presented in Section 4.4. The power loss minimization in the distribution system is realized by deciding appropriate electricity prices. Simulation results and discussions are presented in Section 4.5. Section 4.6 summarizes the main conclusions of the chapter.

4.2 Load Optimization to Electricity Price

Conventionally, many consumers in distribution systems, especially small industries and private households, operate on fixed electricity price contracts no matter when they consume the electricity. If different electricity prices for different times are available for consumers, they may have some motivations to shift their loads from high price periods to low price periods in order to achieve minimal electricity costs.

The demand for most commodities decreases when the price of the commodity increases. Fig. 4.1 illustrates the demand curve Fig. 4.1 [22]. It is defined that the price elasticity coefficient of demand is the relative slope of this demand curve [22]:

$$\varepsilon = \frac{\Delta l / l_0}{\Delta p / p_0} \tag{4.1}$$

where Δp, Δl are the deviations of the electricity price and electricity demand, respectively, p_0, l_0 are the original equilibrium point of the electricity price and electricity demand, respectively. An increase in the price of the commodity will reduce the demand of the commodity. The elasticity coefficient is negative for most commodities.

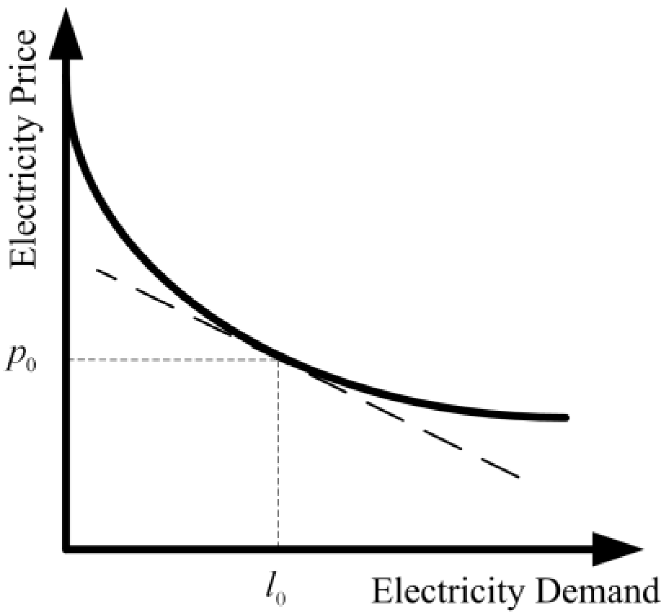


Fig. 4.1. Typical demand curve.

The deviation of the electricity price and the deviation of the electricity demand at hour t are given by:

$$\Delta p_t = p_t^* - p_{fixed} \tag{4.2}$$

$$\Delta l_t = l_t^* - l_t \tag{4.3}$$

where p_{fixed} is the original fixed electricity price, p_t^* is the new electricity price, Δp_t is the deviation of the electricity price at hour t, l_t is the original electricity demand, l_t^* is the new electricity demand, Δl_t is the deviation of the electricity demand at hour t. Since the consumers operate on fixed electricity price contracts conventionally, the original electricity prices p_{fixed} are equal for all hours.

With the definition of equation (4.1), (4.3) can be rewritten as:

$$l_t^* = l_t + \varepsilon_t l_t \frac{\Delta p_t}{p_{fixed}} \tag{4.4}$$

where ε_t is the elasticity coefficient at hour t. As shown in (4.4), when a larger deviation of the electricity price is given to consumers at one hour, the deviation of the electricity demand at the same hour is larger.

As mentioned earlier, if different electricity prices for different times are available, they might shift their loads from high price periods to low price periods in order to achieve minimal electricity costs. In the following a mathematical model and basic assumptions are set up to analyze how the consumers may shift their loads to achieve minimal electricity costs. The sequential quadratic programming (SQP) method is adopted as optimization method [42].

4.2.1 Mathematical Models

The electricity cost paid by a consumer in a day can be calculated using the following equation

$$EC = p_{fixed}\sum_{t=1}^{24} l_t \tag{4.5}$$

where p_{fixed} is the fixed electricity price, l_t is the load at hour t, EC is the electricity cost paid by the consumer in a day. When different electricity prices p_t^* for different times are available, the consumers may reschedule their loads as l_t^* in order to save electricity costs. The new electricity cost EC^* under the rescheduled load can be written as

$$EC^* = \sum_{t=1}^{24} p_t^* l_t^* \tag{4.6}$$

The objective of consumers is to achieve minimum electricity cost by load shifting. The optimization objective function could be chosen as

$$\min(EC^*) = \min(\sum_{t=1}^{24} p_t^* l_t^*) \tag{4.7}$$

The result is that the consumers shift some of the loads from high price periods to low price periods in order to achieve the minimum electricity costs in the day.

4.2.2 Assumptions and Constraints

Some necessary assumptions and constraints have to be made related to this problem.

1) The total consumption of the rescheduled load in a day is kept the same as described in the previous chapter. This assumption can be written as

$$\sum_{t=1}^{24} l_t^* = \sum_{t=1}^{24} l_t \tag{4.8}$$

2) Only some of the loads can be shifted by the consumers according to the hourly electricity price. Some loads are fixed, that means the customer consumes the power no matter the price. The amount of shifted load is decided by the demand-price elasticity curve, which is shown in Fig. 4.1. It is here assumed that the consumers are able to shift their loads in a range of (-10%~10%) around l_t^* in equation (4.4). It is also assumed that the power factors of the loads keep the same after the shifting.

4.2.3 Optimization Methods

The consumers may try to find the minimum value of the objective function (see Eq. (4.7)) under the set up assumptions. This kind of problem is, mathematically, an optimization problem under constraints.

A number of methods can be used for the above optimization problem, for instance, dynamic programming [66], sequential quadratic programming [42], genetic algorithm [67] or particle swarm optimization [56]-[58]. The sequential quadratic programming method is chosen as the optimization method for this problem, because it is faster than the population-based methods, such as genetic algorithm and particle swarm optimization. This method can provide the reasonable accurate results and it is also easy to implement in MATLAB [43-44].

4.3 Power Loss Minimization with Optimal Price

The optimal load response to an hourly electricity price for demand side management generates new load profiles and provides at the same time an opportunity to achieve power loss minimization in distribution systems by choosing an optimal hourly electricity price.

The total power loss minimization problem in a distribution system in a day can be written as:

$$\min(P_{loss}) = \min(\sum_{t=1}^{24} \sum_{b=1}^{N_r} I_{b,t}^2 R_b) \tag{4.9}$$

where P_{loss} is the total loss of the distribution system in a day, R_b is the resistance of branch b, $I_{b,t}$ is the current of branch b at hour t, N_r is the number of total branches.

The two basic equations (Eq. (3.7) and Eq. (3.8)) that govern the power flow in power system networks are used to calculate the power flow of the system for a particular hour. The total power loss function is minimized subject to the following constraints:

Voltage limits are introduced to the formulation to ensure that the voltages at each bus are within acceptable level. These limits are formulated as follows

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{4.10}$$

where V_i^{min} and V_i^{max} are the minimum and the maximum voltage limits at bus i, which are set to -5% ~ +5% in this study.

Current limits are also introduced to the formulation to ensure that the currents through each branch are within acceptable levels. These limits are formulated as follows

$$I_b \le I_b^{\max} \tag{4.11}$$

where I_b^{max} is the maximum current limits of branch b.

Different sets of electricity prices may generate different loads and different loads may generate different power losses in the distribution system. As a consequence, the power loss minimization could be realized by choosing an appropriate set of electricity prices. Fig. 4.2 illustrates an overview of the optimization model. The power loss minimization problem is modeled in two layers. In the outer layer the total power loss in the distribution system is minimized by deciding an electricity price. In the inner layer the electricity cost is minimized by deciding the actual load based on the electricity price generated in the outer layer. The optimization model will be discussed in detail in the next section.

Choosing the optimal hourly electricity price to achieve power loss minimization in a distribution system is formulated as a nonlinear optimization problem. FAPSO is here proposed as the tool for the power loss minimization study for distribution systems.

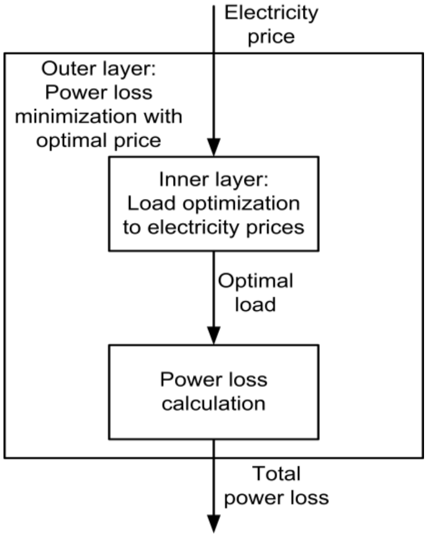


Fig. 4.2. The overview of the optimization model.

4.4 Fuzzy Adaptive Particle Swarm Optimization Algorithm

A modern population-based algorithm, known as FAPSO, has been adopted in this chapter to choose an optimal electricity price in order to achieve power loss minimization. The PSO approach introduced by Kennedy and Eberhart [68] is a self-educating stochastic optimization algorithm that can be applied to any nonlinear optimization problem. In PSO, each potential solution, which is called a particle, flies in the dimensional problem space with a velocity, which is dynamically adjusted according to the flying experiences of its own and its colleagues. The following equations are used to update the particles [56], [68]:

$$v_i^{k+1} = \omega * v_i^k + a_1 * rand_1 * (pbest_i^k - x_i^k) + a_2 * rand_2 * (gbest^k - x_i^k) \quad (4.12)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (4.13)$$

where k is the number of iterations, i is the number of particles, v_i^k and v_i^{k+1} are the velocities of particle i at iteration k and $k+1$, respectively, x_i^k and x_i^{k+1} are the positions of particle i at iteration k and $k+1$, respectively, $pbest_i^k$ is the best previous position of particle i at iteration k, $gbest^k$ is the best previous position of all particles at iteration k, ω is the inertia weight, a_1 and a_2 are learning factors, $rand_1$ and $rand_2$ are stochastic numbers. They are randomly generated from a standard uniform distribution function within the range [0, 1]. The position of particle i at iteration k, x_i^k, is set to the vector of the new electricity price p_t^* in the day.

$$x_i^k = [p_1^*,\ p_2^*,\ p_3^*,\ \ldots,\ p_{24}^*]_i^k \tag{4.14}$$

The velocity of each particle is calculated based on the velocity update equation (4.12), which has 3 terms. The first term $\omega * v_i^k$ is the momentum part which is based on its previous velocity. The second term $a_1 * rand_1 * (pbest_i^k - x_i^k)$ only takes into account the particle's own experiences. The third term $a_2 * rand_2 * (gbest^k - x_i^k)$ represents the interaction between all the particles. Then the new velocity is added to the current position of the particle to obtain its next position according to (4.13). The value of each dimension of every velocity v_i^k is clamped to the range [$-v_{max}$, v_{max}] to reduce the likelihood of the particle leaving the search space. The value of v_{max} is usually chosen to be

$$v_{\max} = m \times (x_{\max} - x_{\min}) \tag{4.15}$$

where x_{max}, x_{min} are the maximal and minimal tolerable limits of the electricity price, respectively, m is a coefficient in [0, 1].

In PSO, the inertia weight ω is used to balance the global and the local searching abilities. A large inertia weight facilitates a global search while a small inertia weight facilitates a local search. The inertia weight should be nonlinearly, dynamically changed to achieve better balance between global and local search abilities in order to achieve better performance [59]. The PSO searching process is a nonlinear and complicated process, and a constant or linear decreasing inertia weight approach does not truly reflect the actual searching process required to find the optimal solutions [69]. The fuzzy system, which has nonlinear and dynamic evaluation performances, is a good candidate for deciding the inertia weight to solve the power loss minimization problem in distribution systems.

The fuzzy system maps sets of input variables into fuzzy sets using membership functions. The output is assigned based on these fuzzy input sets according to the predefined logic [70]. As in [64] and [71], the variables selected as input to the fuzzy system are the normalized total power loss and current inertia weight, whereas the output variable is the deviation of the inertia weight. The normalized total power loss is used as an input variable in the range of [0, 1], and is defined as

$$P_{norm} = \frac{P_{loss} - P_{\min}}{P_{\max} - P_{\min}} \tag{4.16}$$

where P_{loss} is the total power loss in each iteration calculated by (4.9), P_{max} is a large value which is greater than or equal to any feasible power loss, P_{min} is a small value which is less than any feasible power loss. The inertia weight value is normally chosen between 0.5 and

1.0. The deviation of the inertia weight is chosen in the range of [-0.1, 0.1]. Three fuzzy sets for input fuzzy variables are S (small), M (medium) and L (large). The associated membership functions are shown in Fig. 4.3(a) and 4.3(b), respectively. Three fuzzy sets for output variables are NE (negative), ZE (zero) and PE (positive). The associated membership functions are shown in Fig. 4.3(c). $\mu_{P_{norm}}$, μ_{ω} and $\mu_{\Delta\omega}$ are the truth values of the normalized total power loss, the inertia weight and the deviation of the inertia weight, respectively.

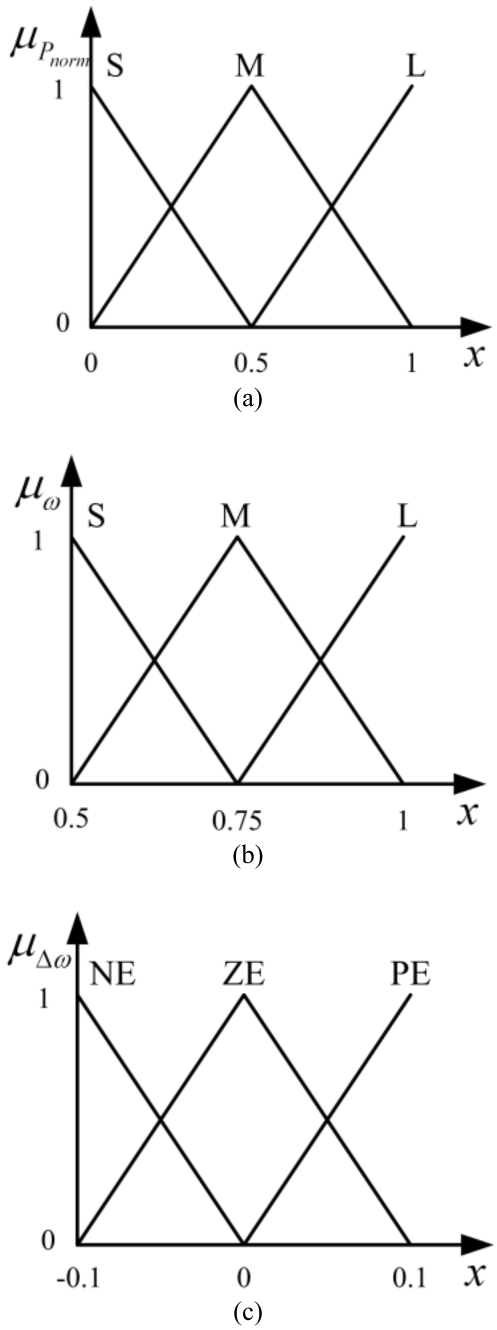


Fig. 4.3. (a) The membership of the normalized total power loss in the fuzzy system. (b) The membership of the inertia weight in the fuzzy system. (c) The membership of the deviation of the inertia weight in the fuzzy system.

The degrees of membership of normalized total power loss P_{norm} and inertia weight are calculated using their membership functions, respectively. Input linguistic variables are connected using the "AND" operator in the fuzzy rules. Simple IF/THEN rules are shown in Table 4.1, because it is good enough to change the inertia weight in the PSO algorithm. It has 9 possible rules for the 2 input variables and 3 linguistic values of each variable. The Larsen product has been used as the fuzzy implication operator for the individual rules [64]. The overall fuzzy output is being obtained by combining all the clipped fuzzy sets. The aggregated fuzzy output is converted into a single value using centroid defuzzification method [64].

Table 4.1. The fuzzy rules for the deviation of the inertia weight.

Rule No.	Antecedent		Consequent
	P_{norm}	ω	$\Delta\omega$
1	S	S	ZE
2	S	M	NE
3	S	L	NE
4	M	S	PE
5	M	M	ZE
6	M	L	NE
7	L	S	PE
8	L	M	ZE
9	L	L	NE

Once the deviation of the inertia weight is calculated based on the fuzzy system, the inertia weight of the next iteration can be updated as follows:

$$\omega^{k+1} = \omega^k + \Delta\omega^k \tag{4.17}$$

The flow chart of the proposed FAPSO algorithm for the power loss minimization in distribution systems is shown in Fig. 4.4. The parameters of the FAPSO, such as the velocity and position of each particle, are initialized in the first step. Then consumers shift their loads according to the position of each particle (electricity price) in order to achieve the minimum electricity costs in the day as discussed in Section 4.2, which is the inner layer in this figure.

The inner layer tries to minimize the electricity cost by deciding the load based on the electricity price generated in the outer layer. The inner layer iterates many times in each iteration of the outer layer. When the inner layer converges, the new loads are generated. Then the total power loss of each particle in the distribution system in the day can be calculated according to (4.9). The velocity and the position of each particle are updated according to (4.12) and (4.13). Finally, the inertia weight of the PSO will be updated using the fuzzy system. The outer layer tries to minimize the total power loss in the distribution system by deciding the electricity price, with respect to the shifted load computed in the inner layer. The FAPSO algorithm makes a lot of iterations in order to find the best solution until the stopping criterion is satisfied. The stopping criterion is that no significant improvement in the solution is made anymore or that the maximum number of iterations is reached.

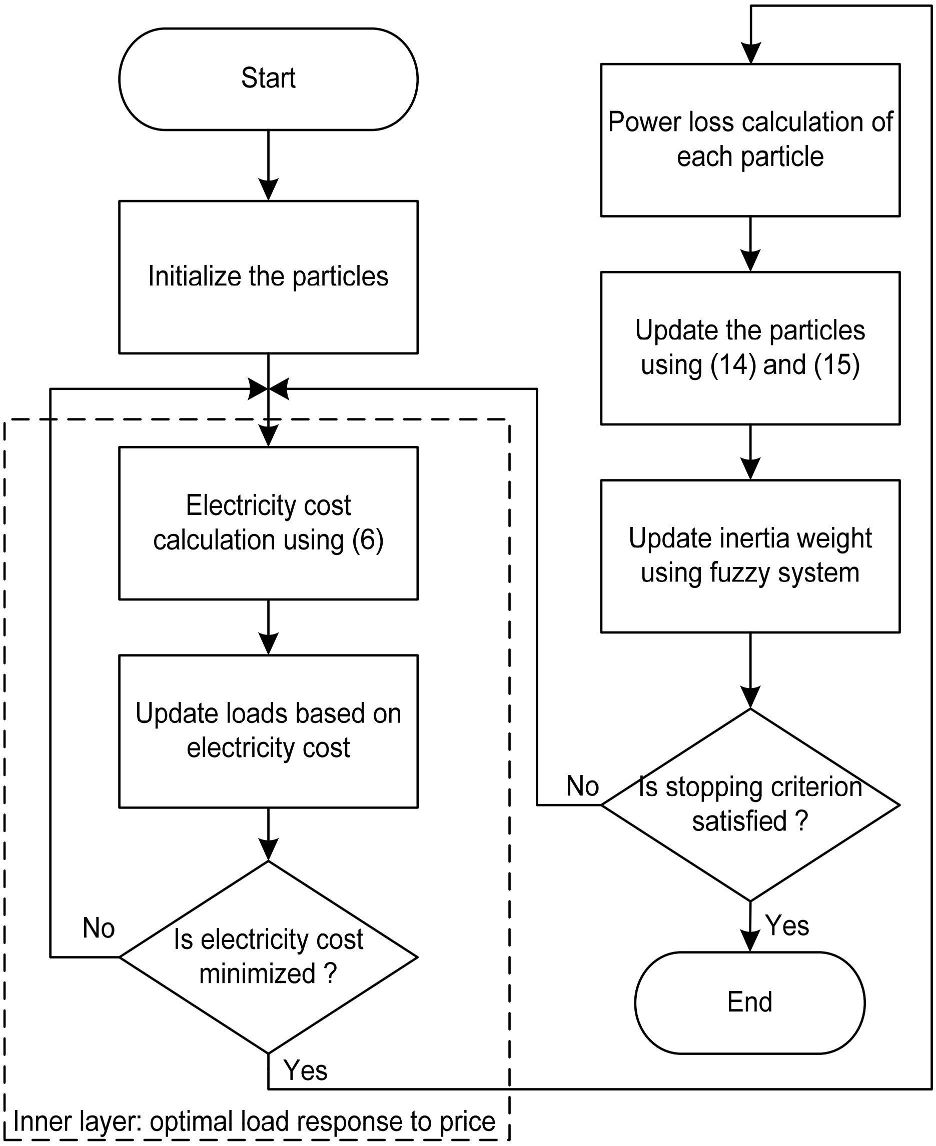


Fig. 4.4. The flow chart of FAPSO algorithm.

4.5 Simulation Results and Discussions

A modified 18-bus distribution system configuration as shown in Fig. 4.5 is used as a study case and the network parameters are the same as the networks in the previous chapter, which has been given in Table 3.3. The distribution system includes three 2 MW modern variable speed wind turbines and three typical kinds of loads. Variable speed operation of the wind turbines can be realized by appropriate adjustment of the rotor speed and pitch angle [50]. Different types of loads, such as industrial load, residential load and commercial load, which are the typical loads in the distribution system, are assumed at the buses of the studied system. The load data of the distribution system is in Table 4.2. Wind generation is variable in nature due to the variability of the incident wind speed at the wind turbine site. A medium wind speed day is chosen as the first study case. The wind power of each wind turbine in the distribution system is shown in Fig. 4.6. It is assumed that all wind turbines in the system are subject to the same wind speed.

Table 4.2. The load data.

Bus	P_{lmax} (MW)	P_{lmin} (MW)	*IL* (%)	*RI* (%)	*CL1* (%)	*CL2* (%)
5	7.86	2.98	62.5	25.0	6.3	6.2
7	1.19	0.45	41.7	41.7	0	16.6
8	0.37	0.15	0	50	50	0
9	0.48	0.21	0	0	40	60
10	0.76	0.31	62.5	0	37.5	0
11	0.20	0.08	0	0	100	0
12	0.47	0.19	0	60	40	0
13	0.20	0.08	0	0	0	100
14	1.61	0.65	0	58.8	29.4	11.8
16	0.20	0.07	0	100	0	0

where *IL* is industrial load, *RL* is residential load, *CL1* is commercial load type 1 and *CL2* is commercial load type 2. P_{lmax} and P_{lmin} are the maximum and minimum active power of the load, respectively.

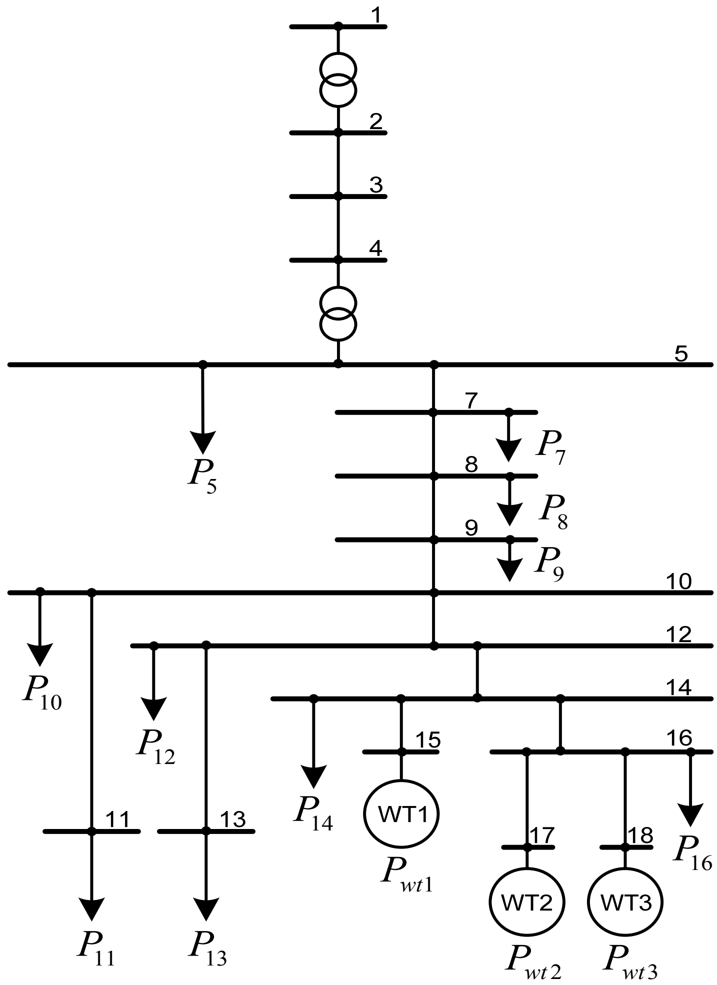


Fig. 4.5. Distribution system configuration under investigation.

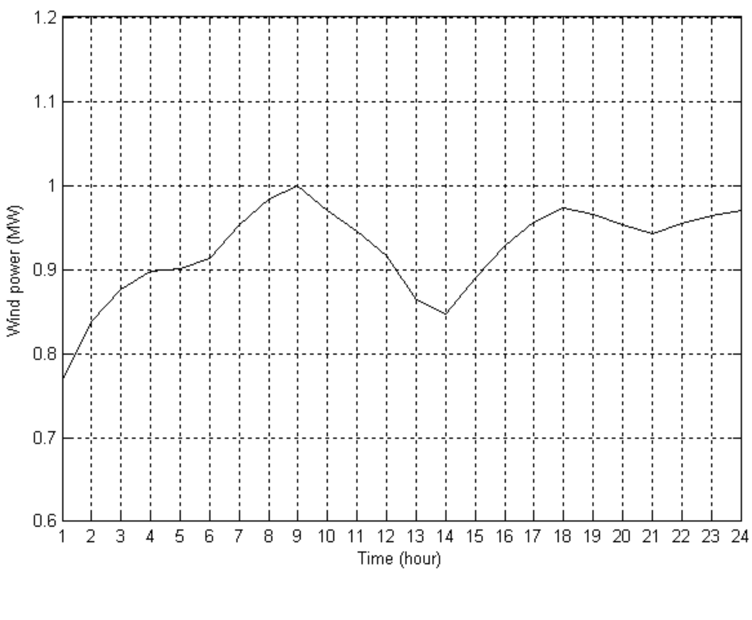


Fig. 4.6. The wind power of each wind turbine at different hours.

The price elasticity coefficient ε of the loads is set to -0.5 in this case, which means that a 10% increase in electricity price compared to the original fixed electricity price result in a 5% decrease of the loads. As electricity price for verifying the method spot market prices from the Nordic system is used, and the average value of the spot market price in a day (32.75 EUR/MWh) is chosen as the original fixed electricity price in the study. The electricity price is to be set within tolerable limits [x_{min}, x_{max}], which are set to -20% ~ +20% in this study, in order to minimize the total power loss in the distribution system. It is also assumed that the power factor of each load is the same after the load response. The other simulation parameters used in the FAPSO algorithm are shown in Table 4.3.

Table 4.3. The parameters used in the FAPSO algorithm.

Parameter	Value
Initial inertia weight (ω)	0.8
Learning factor (a_1)	2
Learning factor (a_2)	2
Particle number	40
Maximum iteration number	500

Figs. 4.7-4.9 illustrate the optimal electricity price and the original fixed electricity price, the optimal response of the loads under the new electricity price and the original loads under the fixed electricity price, and finally the total power losses in the distribution system under the new electricity price and the fixed electricity price. When different electricity prices for different hours are given to consumers, they shift their loads from the high price periods to low price periods in order to achieve minimal electricity costs. The curve of optimal response for the load at bus 5 under the new electricity price, which is the dominant load in the distribution system, becomes flatter compared to the curve of the original load at bus 5 under the fixed electricity price. As a consequence, the curve of the power loss in the distribution system under the new electricity price is also flatter. The total daily power loss in the distribution system decreases from 1957.7 kWh (under the original fixed electricity price) to 1728.5 kWh (under the new optimal electricity price), which means around 12% power loss reduction in the distribution system. It can be also observed that the peak load of the distribution system is reduced which is good for the distribution company.

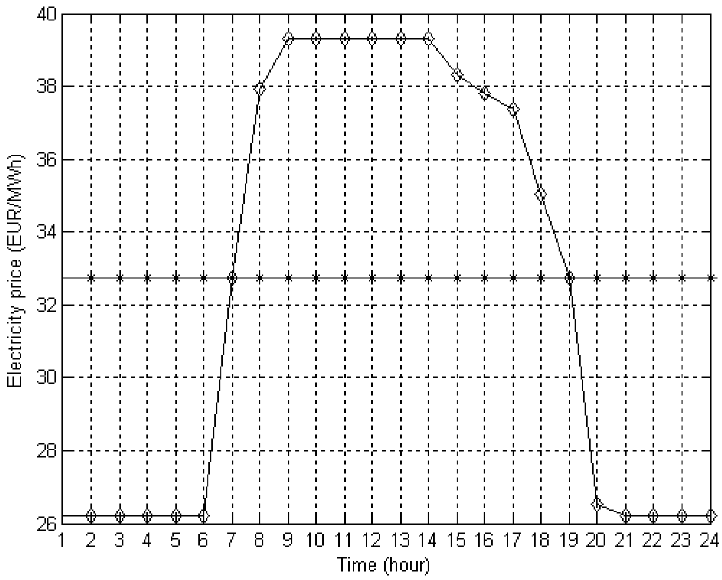
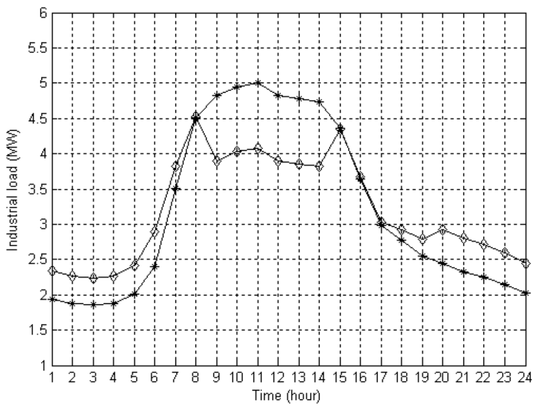
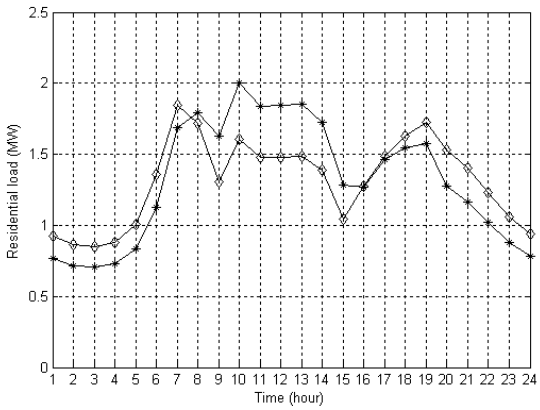


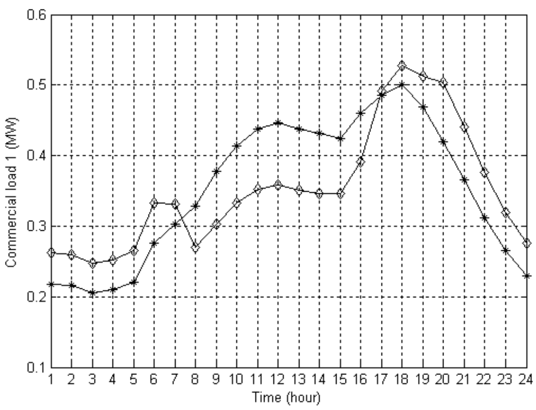
Fig. 4.7. The original fixed electricity price (asterisk) and the optimal electricity price (diamond).



(a)



(b)



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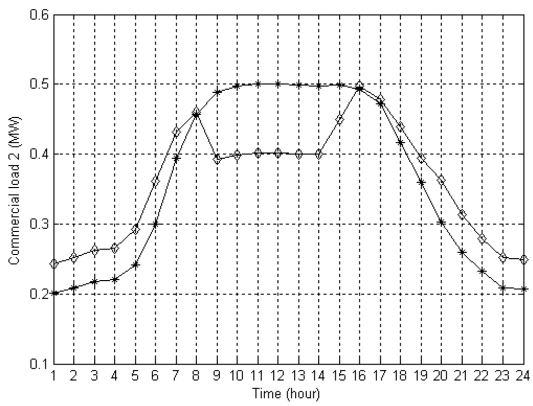
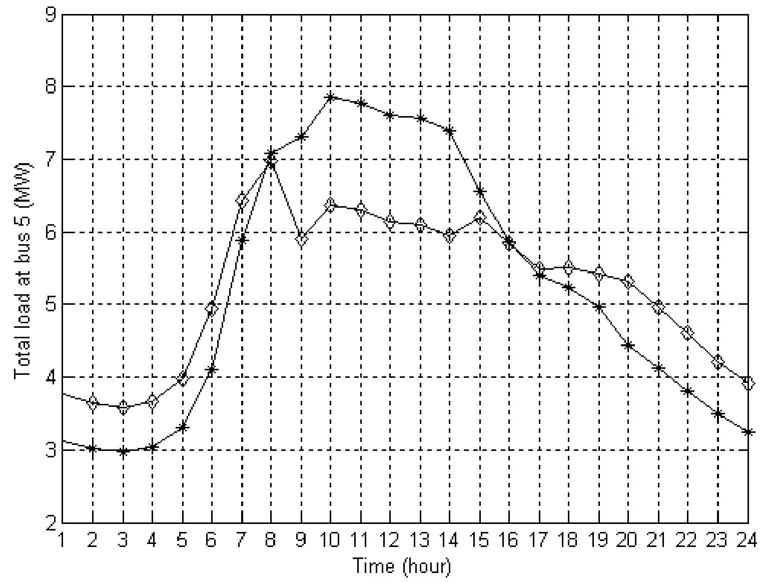


(d)



(e)

Fig. 4.8. (a) The original industrial load at bus 5 under the fixed electricity price (asterisk) and the optimal response load under the new electricity price (diamond). (b) The original residential load at bus 5 under the fixed electricity price (asterisk) and the optimal response load under the new electricity price (diamond). (c) The original commercial load 1 at bus 5 under the fixed electricity price (asterisk) and the optimal response load under the new electricity price (diamond). (d) The original commercial load 2 at bus 5 under the fixed electricity price (asterisk) and the optimal response loads under the new electricity price (diamond). (e) The original total load at bus 5 under the fixed electricity price (asterisk) and the optimal response loads under the new electricity price (diamond).

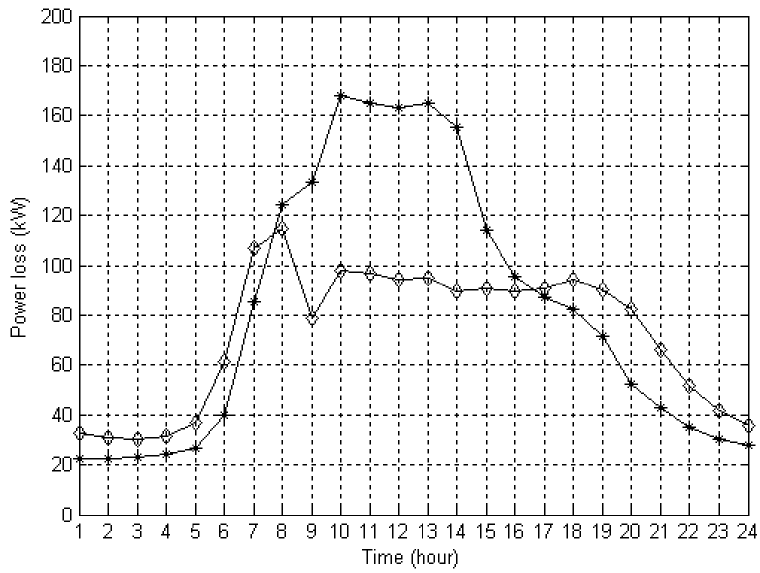


Fig. 4.9. The total power loss under the fixed electricity price (asterisk) and the total power loss under the new electricity price (diamond) in the distribution system.

Power loss minimization in the distribution system by choosing optimal electricity prices using the FAPSO algorithm are tested in many cases. Fig. 4.10 illustrates the variation of power loss reduction with the price elasticity coefficient of the loads under the optimal electricity price, normalized based on the original power loss in the distribution system. The power loss reduction increases as the elasticity coefficient increases, which means more loads may be shifted according to the same electricity price. From the figure, it can be concluded that the power loss reduction in the distribution system are higher, when the loads in the distribution system are more flexible. Fig. 4.11 demonstrates the variation of power loss reduction with the tolerable limits [x_{min}, x_{max}] of the electricity price under the optimal electricity price, normalized based on the original power loss in the distribution system. From the figure, it can be seen that the power loss reduction in the distribution system increases, when the tolerable limits of the electricity price increases, which means the optimal electricity price may be chosen in a wide range.

Power loss minimization in the distribution system by choosing optimal electricity prices using the FAPSO algorithm is also tested in many cases of different wind power penetrations. The wind power of each wind turbine is calculated by the following formula:

$$P_{wt}^{*} = P_{wt} \times SF \tag{4.18}$$

where P_{wt} is the wind power of the basic case (see Fig. 4.6), SF is the scaling factor of the wind power, P^{*}_{wt} is the new wind power for different cases. The relative power loss reduction RP_{loss} in the distribution system may be defined as:

$$RP_{loss} = \frac{P_{loss} - P_{loss}^{*}}{P_{loss}} \tag{4.19}$$

where P_{loss} is the power loss in the distribution system under the fixed electricity price, P^{*}_{loss} is the power loss in the distribution system under the optimal electricity price.

Fig. 4.12 illustrates the variation of the relative power loss reduction in the distribution system with the scaling factor of the wind power. As it is shown, in medium wind power cases, where the local load at bus 14 and bus 16 may be supplied by the nearest wind turbines, the relative power loss reduction RP_{loss} is high because the total power loss P_{loss} is low in this case. In the low and high wind power cases, the sub-distribution system (distribution system at bus 14) may consume or generate power from/to the outside of the sub-distribution system, which causes additional power loss in the distribution system. From the figure, it can be concluded that the optimal choosing of electricity prices using the FAPSO algorithm is an effective measure to minimize the power loss in a distribution system.

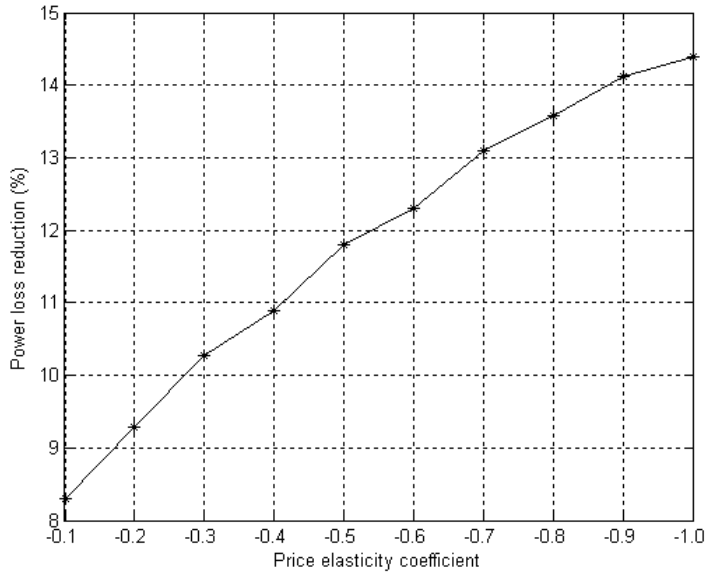


Fig. 4.10. The variation of power loss reduction with the price elasticity coefficient of loads under optimal electricity price.

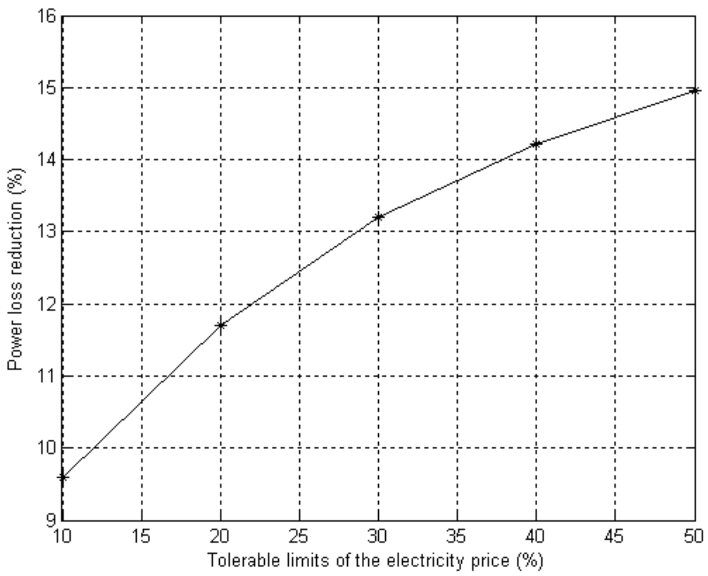


Fig. 4.11. The variation of power loss reduction with the tolerable limits of the electricity price under optimal electricity price.

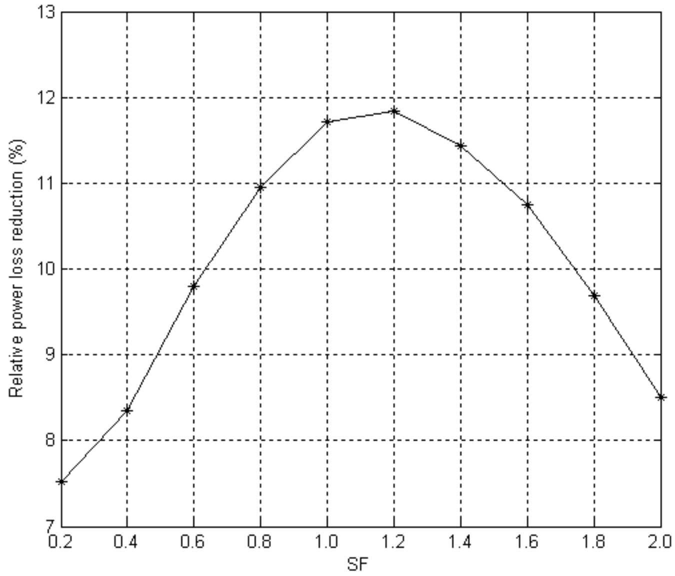


Fig. 4.12. The variation of relative power loss reduction in the distribution system with the scaling factor of the wind power.

Due to privacy issues, it is not allowed to give individual consumer data to third parties. The data used in the chapter are the aggregation of data from several Danish consumers in the same category. So it is hard to consider individual consumers geographically located at different locations in the feeder. However, the basic idea and algorithm may be equally used in the system with individual consumer data.

If the deviation in the electricity price Δp_t or the deviation in the electricity demand Δl_t is large, use of the linearized demand curve will give a large error. However, the electricity price was set within tolerable limits -20% ~ +20% in this chapter, which may not give very large errors in equation (4.4). If there is a large deviation in the electricity price Δp_t, detailed information about the demand response behavior is needed, either as a function or as a table.

The combination of reactive power control and the proposed optimal load response to electricity price may give a lower total daily power loss. However, the focus of this chapter is to show the effectiveness of power loss minimization using optimal load response to electricity price and keep it as simple as possible. Therefore, the extra reactive power compensation devices and the reactive power control of wind turbines are not considered in the chapter.

The effectiveness of the FAPSO approach is demonstrated through comparison of simulation results with the PSO approach. Owing to the randomness in these two approaches, the algorithms were executed 10 times when applied to the test system. The average value of total daily power loss is 1728.5 kWh for the FAPSO approach and 1737.1 kWh for the PSO approach. The average computational time for the test system is 17 minutes for the FAPSO approach and 25 minutes for the PSO approach, which indicates the computational efficiency increases around 32%. The configuration of the computer is Intel T9400 2.6GHz CPU, 4GB RAM, MATLAB 2011a version. Therefore, it can be concluded that the PSO is not as efficient as the FAPSO, though similar results have been obtained.

The proposed algorithm may be equally used in a much larger distribution system. However, the computational time becomes long, when the system is very large, because the power flow is calculated at each iteration of the optimization. When the system is very large and probably the information regarding all the loads is not available, some simplifications are needed in order to model the aggregated load at each feeder. For example, in a 20 kV distribution system, the 400 V network could be simplified with an aggregated load and the loss associated with the low voltage network at 20/0.4 kV transformers. In the future, on-line measurement and calculation will be implemented in the smart grid. All loads and load variations can be easily included in the proposed method.

The inaccurate forecast of the electricity price will cause economic losses, which can be considered as a risk for the distribution company [72-74]. The risk management for the distribution company is quite complicated and not considered in the chapter.

4.6 Summary

Power loss minimization in a distribution system may be realized by shifting some of the loads from the peak load periods to the off-peak load periods. This chapter describes an idea of power loss minimization in a distribution system by choosing an optimal hourly electricity price. The power loss minimization problem in distribution systems is modeled into two layers: load optimization to electricity prices (the inner layer) and power loss minimization with optimal electricity prices (the outer layer). The objective functions and the necessary assumptions of each optimization layer are described in this chapter. On the basis of the developed 2 layers model of the optimization problem, a fuzzy adaptive particle swarm optimization algorithm is presented as a tool for power loss minimization in distribution systems. Around 12% power loss reduction in studied distribution system can be achieved when the proposed idea and algorithm are employed. It can be concluded from the simulation results that optimal choosing of electricity prices using the FAPSO algorithm is an effective measure to minimize the power loss in the distribution system.

The main work of this chapter has also been reported in the author's previous publications [P6].

Chapter 5

Power System Operation Improvement Using Demand Side Management

5.1 Introduction

The demand side management has been used to respond to the deficiency of operation reserves or some major emergencies in power systems due to its feasibility and quick action [75]. When the power system operates near its physical boundaries, a different electricity price for different hours may be given to consumers in order to motivate them to reduce or reschedule their demands. In this way, the power flow may be changed and the power systems will be operated in a good condition consequently, when an appropriate electricity price is given to consumers. Although, the load response is normally considered in distribution systems, the new aggregated load profiles in distribution systems will also have some impacts on the transmission system operation. The transmission system operator may use this kind of load characteristics to improve the operation of transmission systems.

In this chapter, three different cases are studied to solve power system constraints, improve power system small signal stability and power system transient stability using demand side management, respectively. The chapter is organized as follows. Section 5.2 presents case one including the method and simulation results of solving power system constraints in distribution systems with high wind power penetrations by deciding an appropriate electricity price. Then two different cases of improving power system small signal stability and power system transient stability in transmission systems with high wind power penetrations using demand side management are discussed in Section 5.3 and Section 5.4, respectively. Section 5.5 summarizes the main conclusions of the chapter.

5.2 Solving Power System Constraints

5.2.1 Problem Formulation and Algorithms

The consumers may have some motivations to modify the profile of their demand from high price periods to low price periods, when different electricity prices for different hours are available for them. The consumer behavior may provide an opportunity to solve power system constraints such as transformer loadings, voltage drops/fluctuations, max current through lines etc. in distribution systems with high wind power penetrations. Here a procedure for setting up an appropriate electricity price, for a distribution network grid connected to a higher voltage network via a transformer, is calculated based on the transformer loading.

Fig. 5.1 illustrates a flow chart of the proposed algorithm. The parameters of the algorithm, such as network parameters, wind generation data and load data are initialized in the first step. A standard Newton-Raphason power flow algorithm is used to calculate the apparent power of the transformer between the distribution network and the transmission grid. When the transformer is overloaded, the electricity price is updated according to the power flow direction through the transformer, and the difference ΔS between the apparent power S through the transformer and the maximum capacity of the transformer S_{max}. The sensitivity factor dp/dS is calculated in each iteration. Then a price signal is generated based on the sensitivity factor. Finally, the optimal load response program based on the electricity price signal is executed as described in Chapter 3. The algorithm makes many iterations in order to find the appropriate electricity prices for different hours until the stopping criterion is satisfied. The stopping criterion is that the transformer is no longer overloaded or the maximum number of iterations is reached.

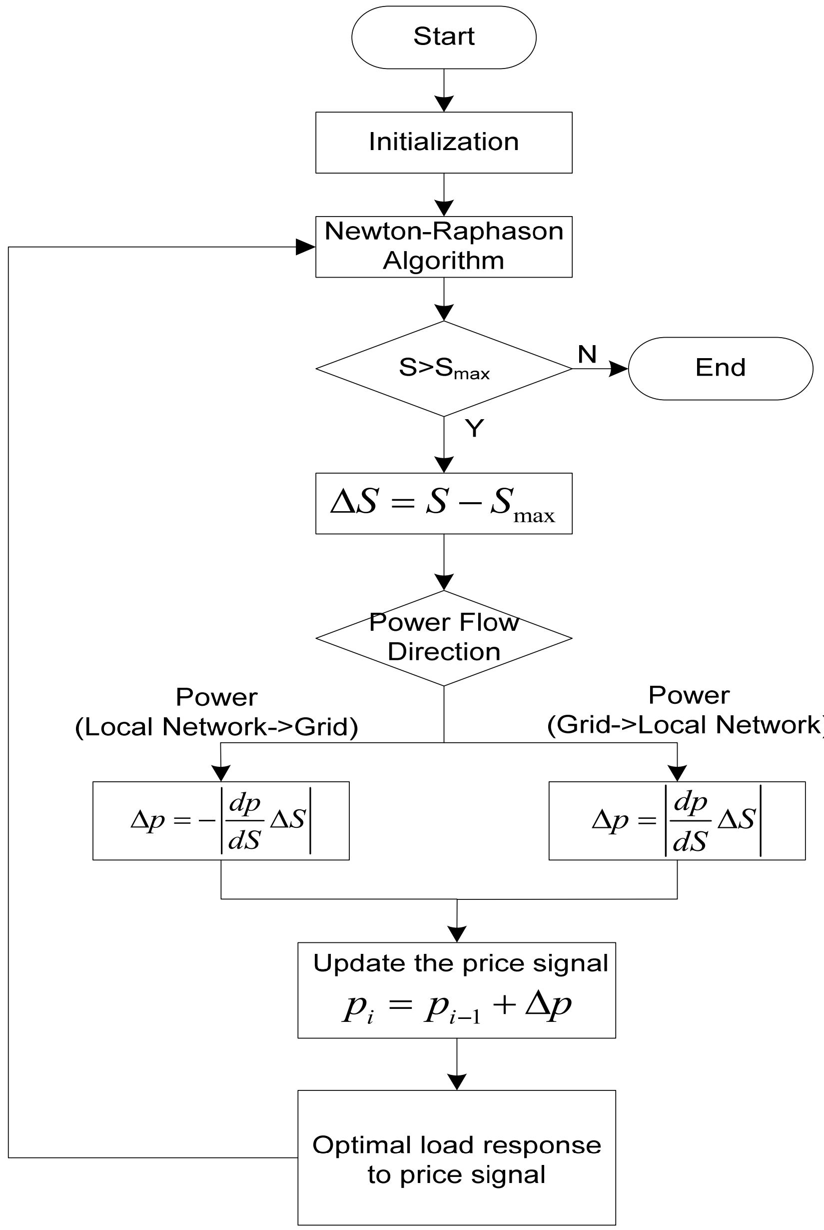


Fig. 5.1. Flow chart of proposed algorithm to counteract transformer overloading.

5.2.2 Case Study of Counteracting Transformer Overloading

The 18-bus distribution system with high wind power penetrations, which is the same as the system in Chapter 3 (see Fig. 3.6), is used as a study case for verification of the proposed algorithm. The load and wind power generation data are also the same. The price elasticity coefficient of the loads is set to -1.0 in this case, which means that a 10% increase in electricity price compared to the original fixed electricity price result in a 10% decrease of the loads. The average value of the spot market price in a day (32.4 EUR/MWh) is chosen as the original fixed electricity price in the study. The electricity price is to be set within tolerable limits, which are set to -20% ~ +20% in this study. The transformer capacity is 12 MVA in this case.

A winter week is chosen as the first study case. Figs. 5.2-5.5 illustrate the original fixed electricity price and the new electricity price, the load responses to the new electricity price and the original loads, the wind power generation, the apparent power of the transformer between bus 1 and bus 2 based on the original fixed electricity price and the new electricity price in the distribution system, respectively. When different electricity prices for different hours are given to consumers, they shift their loads from the high price periods to the low price periods in order to achieve lower electricity costs. When the wind power generations are very low and the loads are relatively high (Thursday in this case), a higher electricity price is given to consumers in order to encourage them to reduce their load in some periods. When the wind power generations are very high and the loads are relatively low (Sunday in this case), a lower electricity price is given to consumers in order to encourage them to increase their load in some periods. From Fig. 5.5, it can be seen that the apparent power of the transformer between bus 1 and bus 2 can be limited to less than the transformer capacity using the new electricity price in order not to overload the transformer.

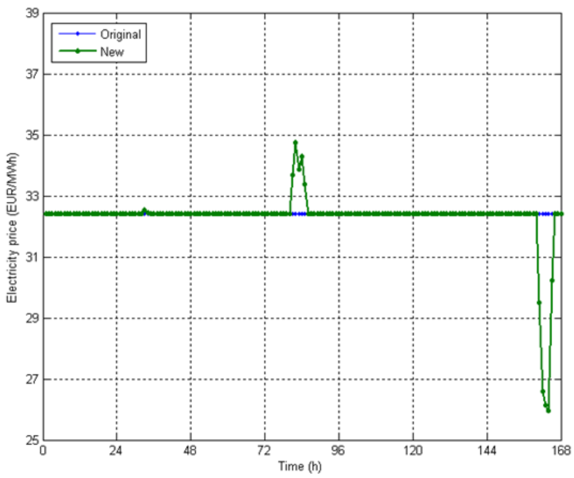
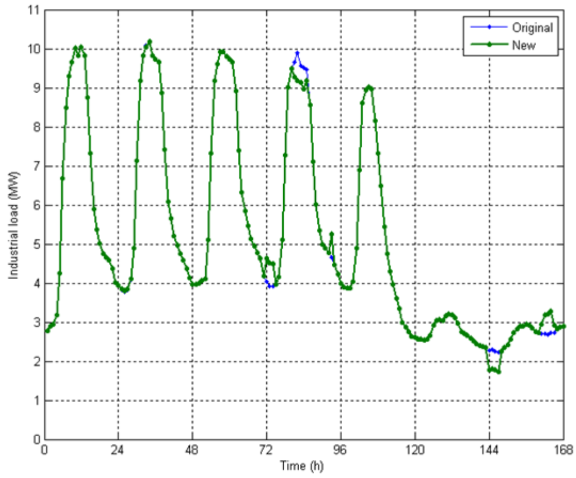
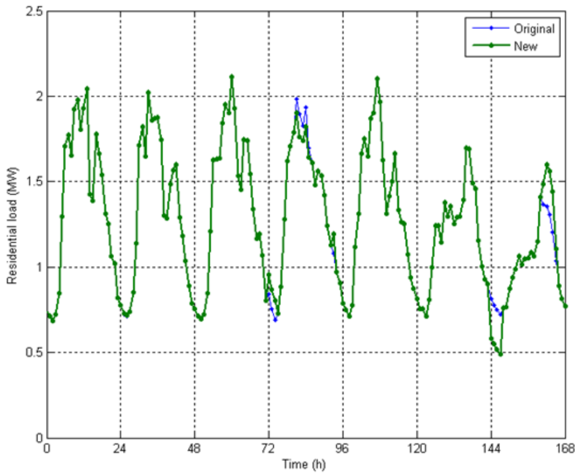


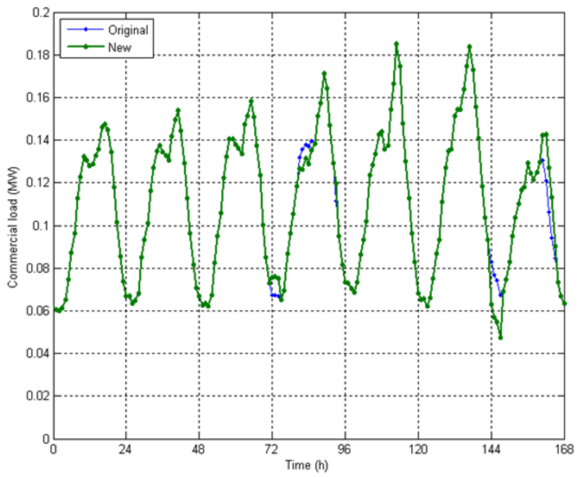
Fig. 5.2. The decided electricity prices.



(a) The original and new industrial load.



(b) The original and new residential load.



(c) The original and new commercial load.

Fig. 5.3. The original and new loads in the distribution system.

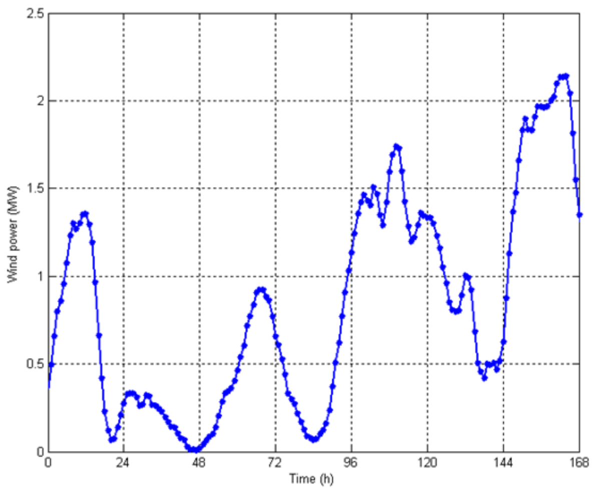


Fig. 5.4. The wind power generation.

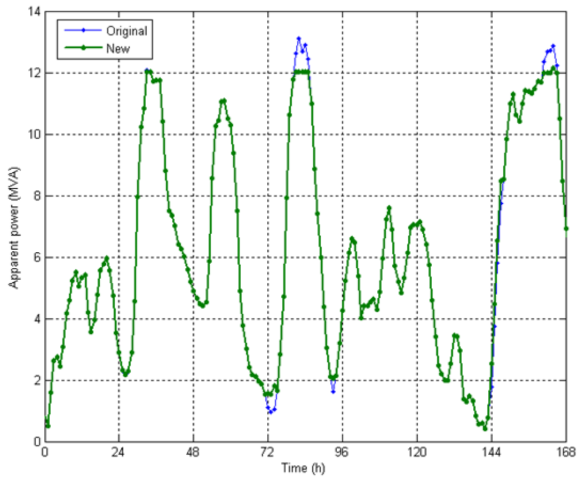


Fig. 5.5. The apparent power through the transformer.

The proposed algorithm is also used at each day of the whole year. Fig. 5.6 shows the apparent power through the transformer based on the original fixed electricity price and the new electricity price. The probability density of the apparent power of the transformer is illustrated in Fig. 5.7. It can be seen that the relatively high parts of apparent power is reduced due to the load response to the electricity price. Most of the time, the transformer is not operated overloaded with the new electricity price. Table 5.1 shows the average value and the standard deviation of the apparent power. The average value of the apparent power is almost the same due to the assumption that the total consumption in a day is kept the same in the cases of the original electricity price and the new electricity price. Because the high parts of the apparent power is reduced due to the load response to the new electricity price, the overloading percentage of the transformer decreases from 3.23% to 0.25%.

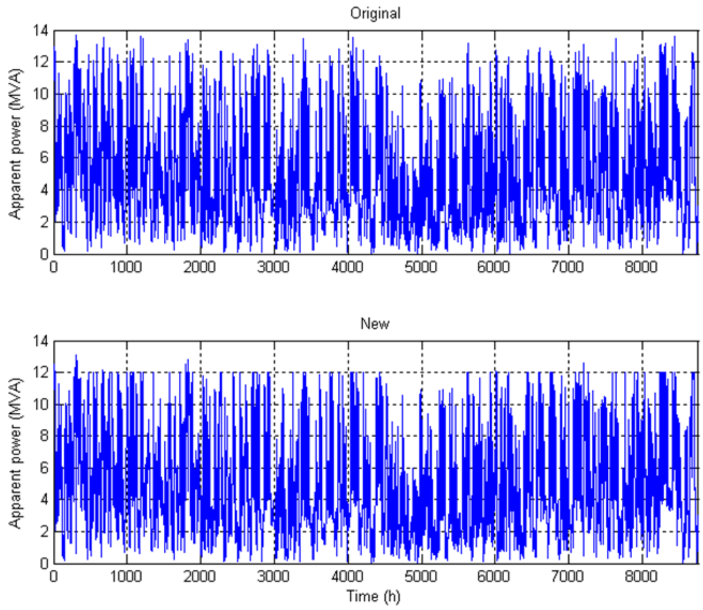


Fig. 5.6. The apparent power through the transformer for the original fixed electricity price (upper one) and the new electricity price (bottom one).

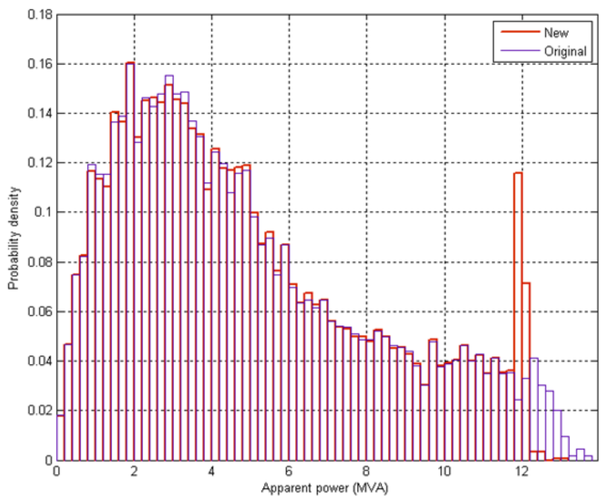


Fig. 5.7. The probability density of the apparent power through the transformer.

Table 5.1. The apparent power through the transformer.

	Original electricity price	New electricity price
Average value (MVA)	4.940	4.937
Standard deviation (MVA)	3.273	3.231
Overloading percentage	3.23%	0.25%

The overloading percentage of the transformer in the studied power system will be further reduced when the proposed algorithm and the optimal load response according to the spot market (see Figs. 3.8 and 3.9), which has been discussed in Chapter 3, are combined together.

5.3 Small Signal Stability Improvement

As discussed in Section 5.2, optimal load response to electricity prices for demand side management will generate different load profiles in distribution systems. However, the new aggregated load profiles in distribution systems will also have some impacts on the transmission system operation. The transmission system operator may use this kind of load characteristics to improve the operation of transmission systems. Section 5.3 and Section 5.4 provide two examples of improving small signal stability and transient stability of transmission power systems using the optimal load response to electricity prices for demand side management.

5.3.1 Small Signal Stability

Small signal stability relates to the ability of a power system to maintain synchronism among generators under small disturbances. It characterizes the nature of a power system at a certain operating point [76].

A state equation in the form of Eq. (5.1) can be used to describe a power system [76].

$$\frac{dX}{dt} = f\left(X\right) \tag{5.1}$$

where X is the state vector of the power system, t is the time and f is normally a set of nonlinear functions.

Taylor's series expansion is used to linearize the state equation at this operating point in order to analyze the small signal stability of the power system at an operating point. The linearized state equation is shown as Eq. (5.2) [76].

$$\frac{d\Delta X}{dt} = A \cdot \Delta X \tag{5.2}$$

In Eq. (5.2), the prefix Δ is a small deviation and A is the state matrix. The small signal stability is given by the eigenvalues of matrix A. Eigenvalues are shown as Eq. (5.3) [76].

$$\lambda = \sigma \pm j \cdot \omega \tag{5.3}$$

Each eigenvalue represents an oscillation mode of the power system at the given operating point. The real component σ represents the damping and the imaginary component ω gives the frequency of the corresponding mode.

The decay rate of the oscillation can also be drawn from eigenvalues by calculating the damping ratio which is defined as Eq. (5.4) [76].

$$\zeta = \frac{-\sigma}{\sqrt{\sigma^2 + \omega^2}} \tag{5.4}$$

The damping ratio ζ is a common index for small signal stability analysis. The larger ζ means that the power system has wider stability margin.

A participation factor is used to measure the participation of one state variable in one oscillation mode. The participation factor is defined as Eq. (5.5) [76].

$$p_{ik} = \frac{\partial \lambda_i}{\partial a_{kk}} \tag{5.5}$$

In Eq. (5.5), p_{ik} is the participation factor of the *kth* state variable in the *ith* mode and a_{kk} is the element in the *kth* line and *kth* column of matrix *A*.

5.3.2 Problem Formulation and Algorithms

Improving the power system small signal stability may be achieved by deciding an appropriate electricity price for different hours for the costumers.

The objective of the power system small signal stability improvement is that the damping ratio of the power system should be larger than a setting value to ensure that the power system has enough stability margins. This objective can be written as

$$\zeta_t \geq \zeta_{setting} \tag{5.6}$$

where $\zeta_{setting}$ is the setting damping ratio value, which is set to 10% in this study to make sure that the power system has enough stability margins. ζ_t is the minimum damping ratio for all the oscillation modes in the power system at hour *t*. ζ_t can be written as

$$\zeta_t = \min(\zeta_{1,t}, \zeta_{2,t}, \ldots, \zeta_{i,t}) \tag{5.7}$$

where $\zeta_{1,t}$, $\zeta_{2,t}$ and $\zeta_{i,t}$ are the damping ratio of the corresponding oscillation modes with the oscillation frequency range between 0.1 Hz and 2.0 Hz. It is because oscillation modes within this frequency range are considered most harmful for the power system operation [77].

All eigenvalues of the corresponding oscillation modes for the power system must have negative real parts in order to make sure that the power system is stable as described in Section 5.3.1. It can be expressed as

$$\mathrm{Real}\left(\lambda_{j,t}\right) < 0 \tag{5.8}$$

where $\lambda_{j,t}$ is the real part of *jth* eigenvalue at hour *t*.

Voltage and current limits are also needed in the formulation to make sure that the voltages at each bus and the currents through each branch are within acceptable level. These limits can be formulated as follows

$$V_n^{\min} \le V_n \le V_n^{\max} \tag{5.9}$$

$$I_b \le I_b^{\max} \tag{5.10}$$

where V_n^{min} and V_n^{max} are the minimum and the maximum voltage limits at bus *n*, I_b^{max} is the maximum current limits of branch *b*.

Fig. 5.8 illustrates the flow chart of the proposed algorithm for power system small signal stability improvement by choosing the electricity price for different hours in power systems with high wind power penetrations. The parameters used in the algorithm, such as the network parameters, the wind generation data and the load data are initialized in the first step. The damping ratio of the power system is then calculated using the DIgSILENT PowerFactory software. If the damping ratio of the power system is smaller than the setting value, the electricity price is calculated based on the sign of $\Delta\zeta$ and Δp. If both $\Delta\zeta$ and Δp are positive or negative in the previous iteration, the electricity price should be increased in order to achieve a higher damping ratio. On the other hand, if $\Delta\zeta$ is positive and Δp is negative, or $\Delta\zeta$ is negative and Δp is positive in the previous iteration, the electricity price should be decreased in order to achieve a higher damping ratio. Consumers may then shift their loads from the high price period to the low price period in order to achieve minimum electricity costs in the day as discussed in Chapter 3, which is shown in the dashed box in this figure. The algorithm makes a lot of iterations in order to find the appropriate electricity price until the stopping criterion is satisfied. The stopping criterion in the algorithm is that the damping ratio is larger than the setting value or the maximum number of iterations is reached.

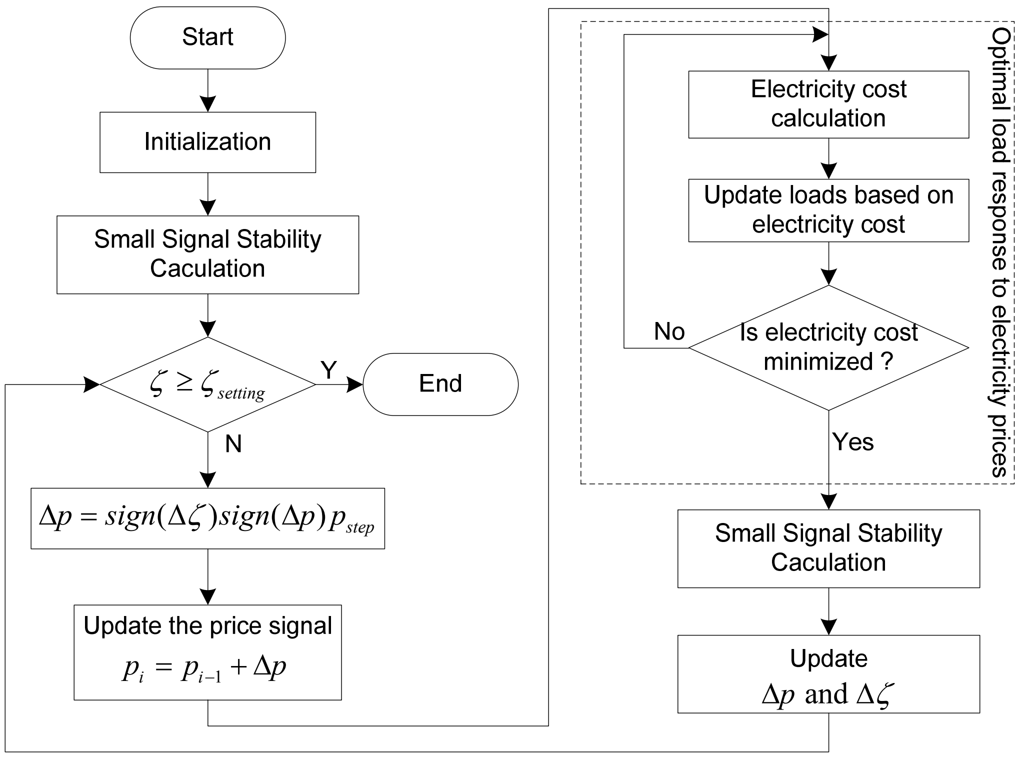


Fig. 5.8. The flow chart of the algorithm to achieve small signal stability.

5.3.3 Case Study of Achieving Small Signal Stability

A 17-bus transmission power system configuration with high wind power penetration is chosen as a study case. Fig. 5.9 illustrates the configuration of the system. This model resembles a simplified model of the Eastern Danish power system. It has the same generation capacity, load capacity and wind power integration level to the Eastern Danish power system [78]. There are four central power plants (modeled as synchronous generators), load centers, wind power, decentralized combined heat and power plants (DCHP), interconnections to other power grids, reactors and reactive power compensators in the studied power system.

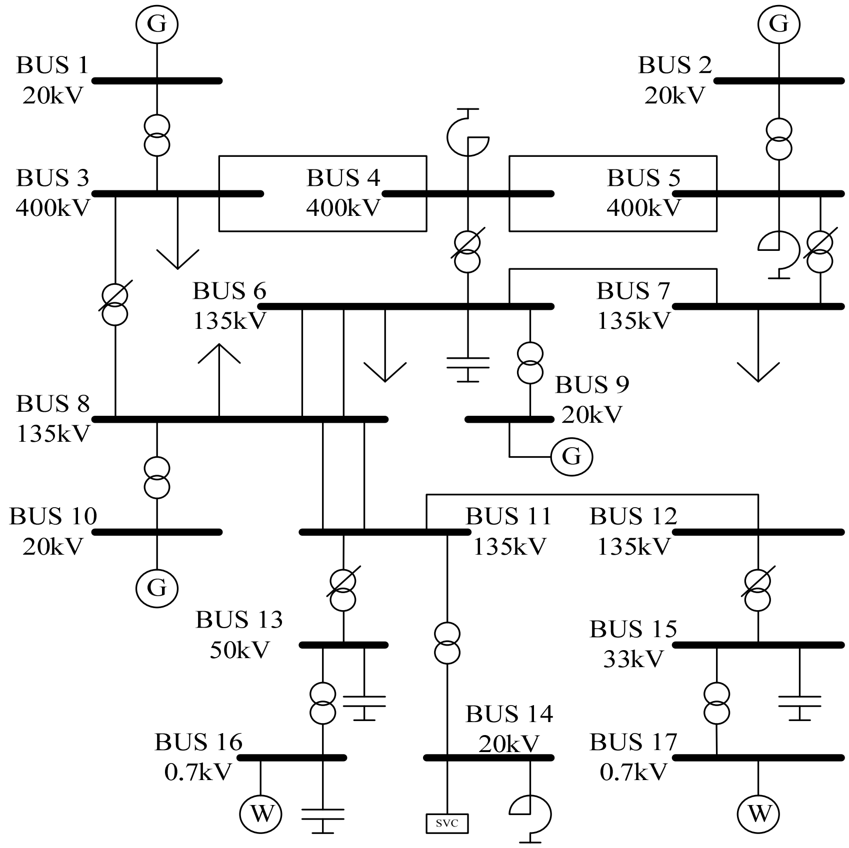


Fig. 5.9. The studied power system configuration.

The price elasticity coefficient of the loads in the power system is set to -0.5 in this case, which means that a 10% increase in electricity price will result in a 5% decrease of the loads. A winter weekday is chosen as the first study case. The average value of the spot market price in this day (32.75 EUR/MWh) is chosen as the original fixed electricity price in the study. The new chosen electricity price and the original fixed electricity price are shown in Fig. 5.10. The optimal load response under the new electricity price and the original load under the original fixed electricity price, the damping ratio of the power system under the new electricity price and the original fixed electricity price are shown in Fig. 5.11 and Fig. 5.12, respectively. From Fig. 5.12, it can be seen that the damping ratio of the power system under the original fixed electricity price is less than the setting value (10%) in the hour 18:00 and 19:00. So the proposed algorithm is executed to choose a new electricity price in order to increase the damping ratio of the power system during the two hours.

From these figures, it can be seen that the electricity price is shifted during the two hours. Consequently, the consumers shift some of their loads from the high price periods (hour 18:00 and hour 19:00) to the low price periods (other hours) in order to reduce their electricity costs. It can be also seen from Fig. 5.12 that the damping ratio of the power system is larger than the setting value by using the different electricity prices for different hours. In this way the power system signal stability is improved.

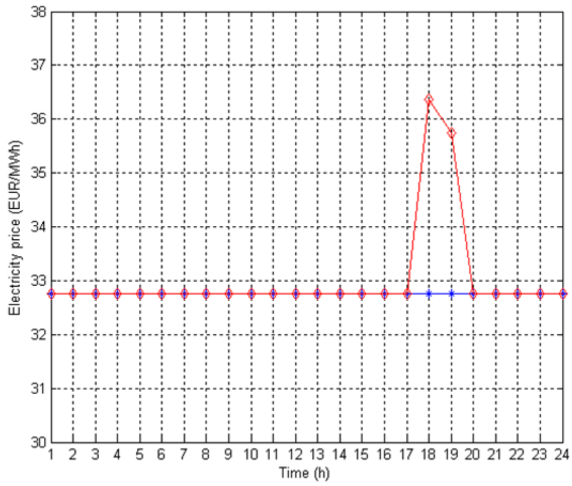


Fig. 5.10. The new chosen electricity price (red diamond line) and the original fixed electricity price (blue asterisk line).

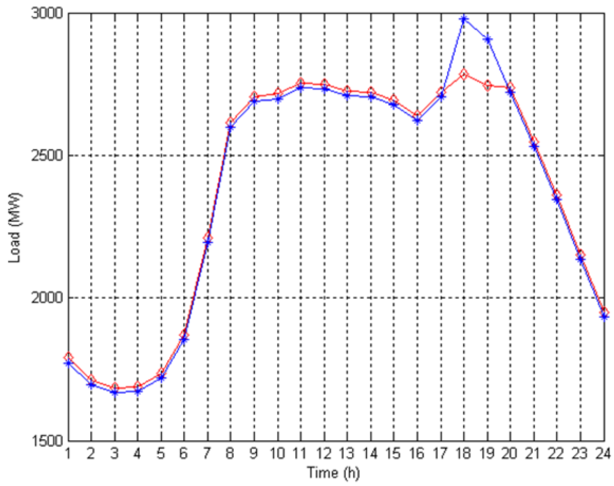


Fig. 5.11. The optimal response load under the new electricity price (red diamond line) and the original load under the original fixed electricity price (blue asterisk line).

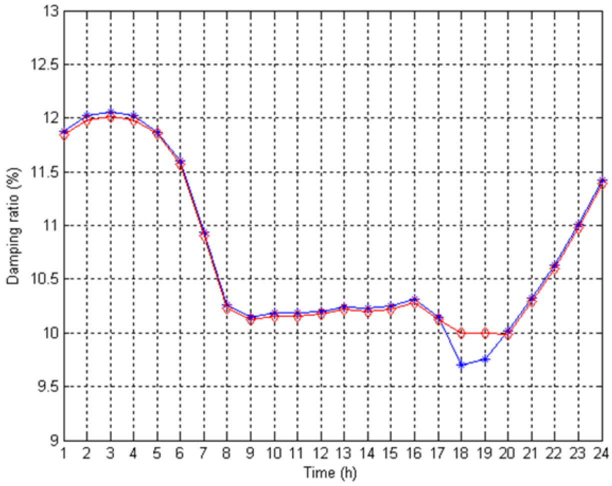


Fig. 5.12. The damping ratio of the power system under the new electricity price (red diamond line) and the original fixed electricity price (blue asterisk line).

A time domain simulation with a 3 phase fault at bus 8 is then conducted using the DIgSILENT PowerFactory software under the original fixed electricity price and the new electricity price at hour 18:00 in this day. The generator speed of the generator at bus 10 is shown in Fig. 5.13. It shows that the maximum oscillation magnitude of the rotation speed decreases about 7.5% when the new electricity price is used in the power system. It indicates that the power system small signal stability has been improved by deciding the appropriate electricity prices for different hours.

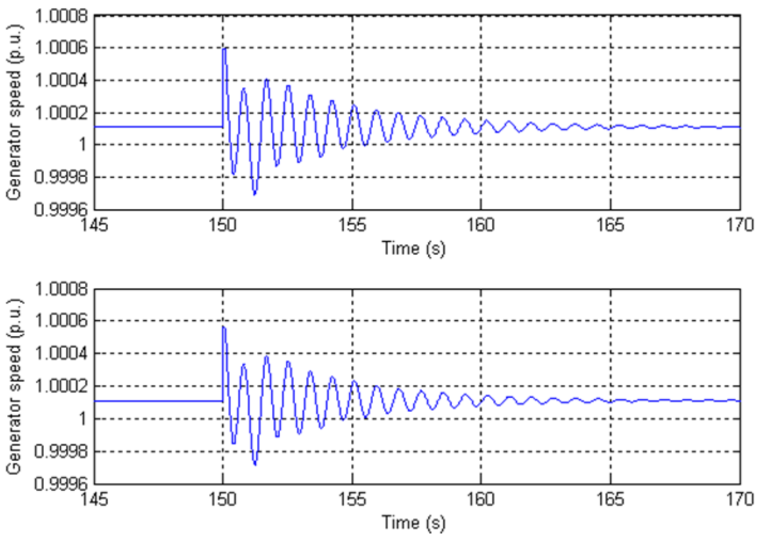


Fig. 5.13. The generator speed of the generator at bus 10 under the original fixed electricity price (the upper figure) and the new electricity price (the bottom figure).

Finally, the algorithm is adopted on each day of the year 2007. Fig. 5.14 illustrates the damping ratio of the power system under the original fixed electricity price and the new electricity price in the year 2007. It can be observed that the damping ratio of the power system is larger than 10% by using the appropriate electricity prices. It can be concluded that the proposed idea and algorithm is an effective measure to improve the small signal stability of power systems with high wind power penetrations.

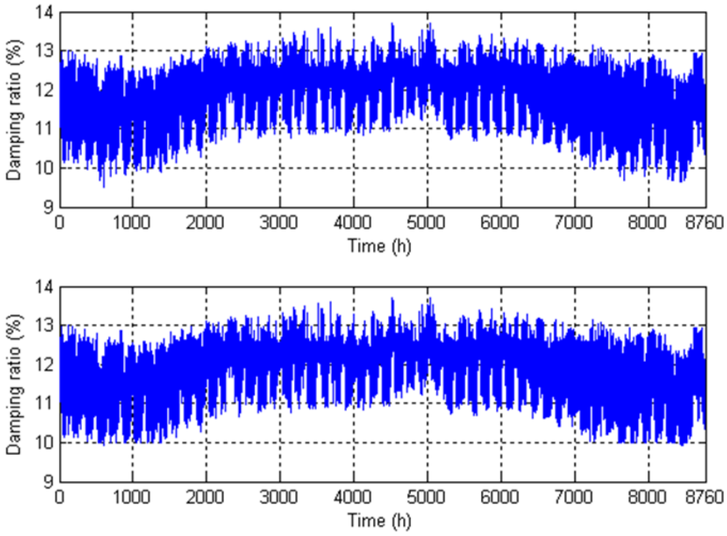


Fig. 5.14. The damping ratio of the power system under the original fixed electricity price (the upper figure) and the new electricity price (the bottom figure) in the year 2007.

5.4 Transient Stability Improvement

As discussed in previous sections, the optimal load response to electricity prices may be used to solve power system constraints and improve the small signal stability of power systems. In this section, a similar idea and algorithm are proposed in order to improve the power system transient stability under some large disturbances.

5.4.1 Power System Transient Stability

Power system transient stability is defined as the ability of the power system to re-establish the initial steady state or come into a new steady state after large disturbances, such as a fault on transmission facilities, loss of generation, or loss of a large load [76]. The system response to such disturbances involves large excursions of generator rotor angles, power flows, bus voltage, and other system variables. If the resulting angular separation between the machines in the system remains within certain bounds, the system maintains synchronism [76].

At the time being, the most practical available method of transient stability analysis is time-domain simulation in which the nonlinear differential equations are solved by using step-by-step numerical integration techniques [76]. Critical Clearing Time (CCT) is normally considered as a principal criterion for transient stability assessment. CCT is defined as maximal fault duration from which the system can return to steady state [76]. The longer CCT means that the power system is more stable. The power system should at least have CCT longer than the operational time of relay protection in power systems. CCT depends on system conditions, such as operating points, grid topologies, system parameters and system demands.

Fig. 5.15 illustrates a 102-bus power system configuration with high wind power penetration. This configuration resembles a simplified model of the Western Danish power system and is chosen as the studied power system. It has the same generation capacity, load capacity, wind power integration level and also interconnection capacity compared with the Western Danish power system. There are eight central power plants (modeled as synchronous generators), load centers, wind power, decentralized combined heat and power plants (DCHP), interconnections to other power grids, reactors and reactive power compensators in the studied power system. The power system is modeled and built using the DIgSILENT PowerFactory software. The load and wind power of the power system in a studied winter weekday of the year 2008 are shown in Fig. 5.16. It can be observed that the load is high in the morning between 09:00 and 12:00, and in the evening between 18:00 and 19:00.

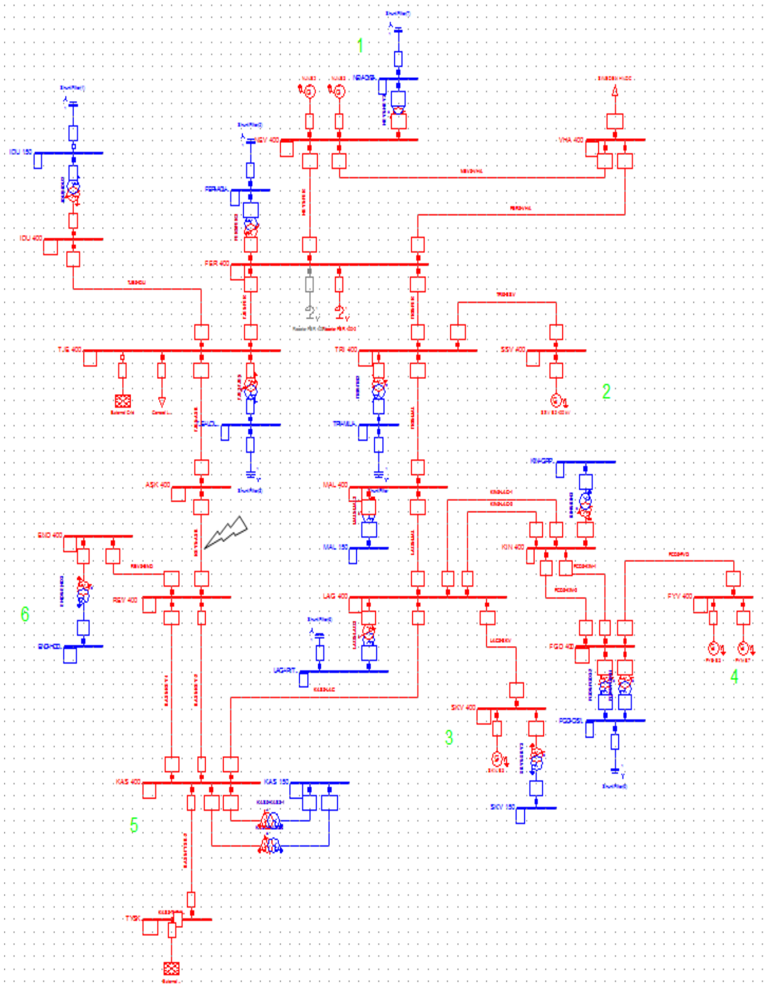


Fig. 5.15. The studied power system configuration.

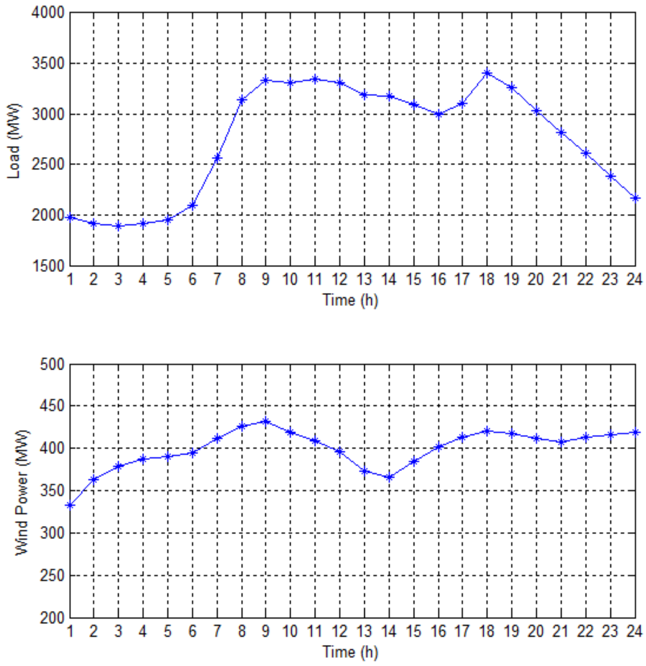


Fig. 5.16. The load and wind power of the power system in a studied winter weekday of the year 2008.

A time domain simulation with a 3 phase fault at the main transmission line (see Fig. 5.15) is conducted in order to evaluate the transient stability of this power system at hour 18:00 in the studied day. It is assumed that the power system protection devices work properly and the fault can be cleared after 120 ms in the first study case. The voltage of the transmission system and the maximum differences of synchronous generator rotor angle in the studied system after the fault are shown in Fig. 5.17 and Fig. 5.18, respectively. It can be observed from these figures that the studied power system is stable after the 3 phase fault at the main transmission line.

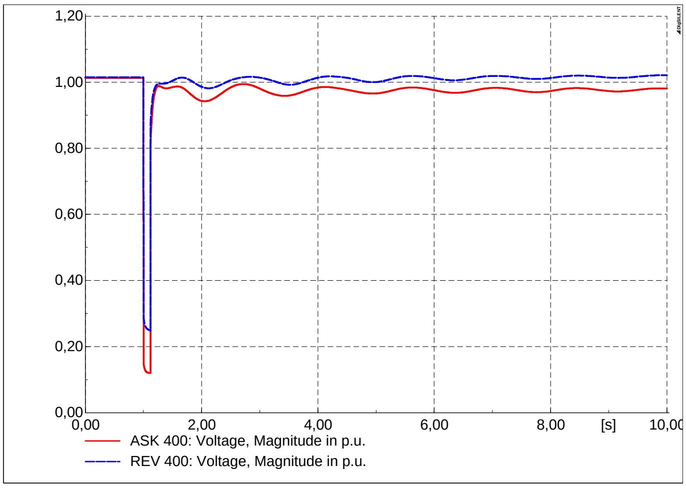


Fig. 5.17. The dynamic voltage response of 2 buses in the system.

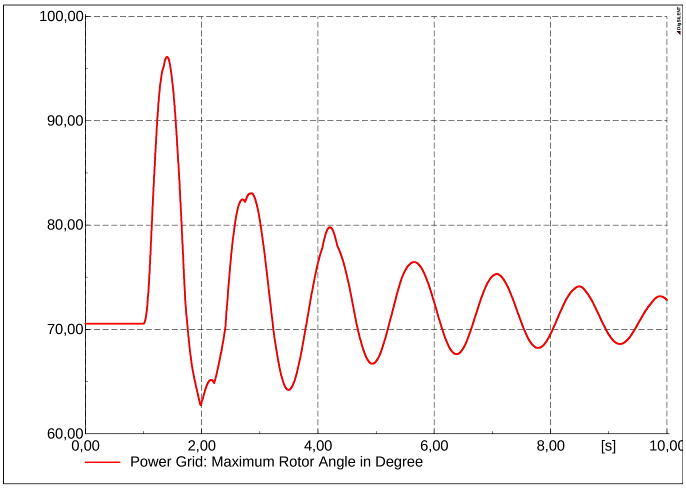


Fig. 5.18. The maximum differences of synchronous generator rotor angle in the system.

However, the system may become unstable if the protection system fails to clear the fault after some time. Two cases are conducted with the different fault clearing time. The fault clearing time is 400 ms for one case and 410 ms for another case. Fig. 5.19 illustrates the comparison of the maximum differences of the synchronous generator rotor angle in the system for the 2 different cases. It indicates the maximum differences of synchronous generator rotor angle excesses 180 degrees when the fault is cleared after 410 ms, which suggests that the system is unstable in the case. Therefore, the CCT value is 400 ms in this case, which is maximal fault duration from which the system can return to steady state.

The same procedures can be repeated in order to calculate the CCT of different hours in the studied day using the same 3 phase fault. The CCT value of different hours in the day is shown in Fig. 5.20. It can be observed that the CCT is lower, which suggests the power system is less stable, when the system demand is lower in the studied transmission system. If the Transmission System Operator (TSO) is not satisfied with CCT value in the day, the optimal load response to an electricity price for demand side management may be then adopted to improve the transient stability.

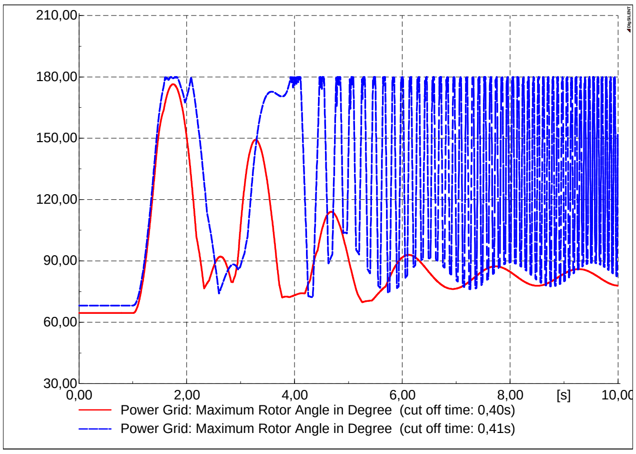


Fig. 5.19. The maximum differences of synchronous generator rotor angle for the different cases.

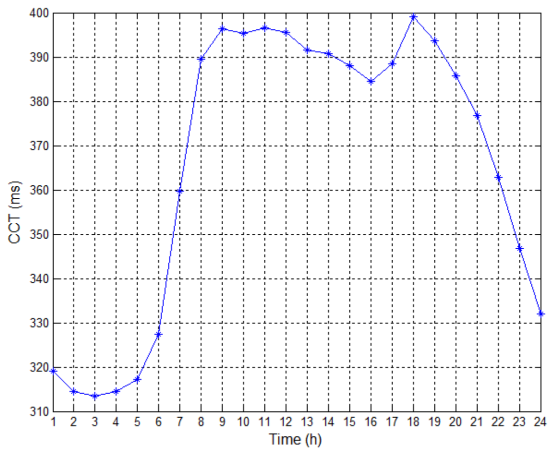


Fig. 5.20. The CCT value of different hours in the studied day.

5.4.2 Problem Formulation and Algorithms

Improving the power system transient stability could also be achieved by deciding appropriate electricity prices for different hours in a day. For example, if the CCT is lower than an accepted value in a specific hour, an appropriate electricity price will be given in the hour. Then the consumers may optimally respond to the electricity price in order to save their energy costs. This behavior will generate a new load for the specific hour. Consequently, the CCT may be improved by this optimal load response behavior. The flow chart of the proposed algorithm for power system transient stability improvement by choosing the electricity prices for different hours in power systems is shown in Fig. 5.21.

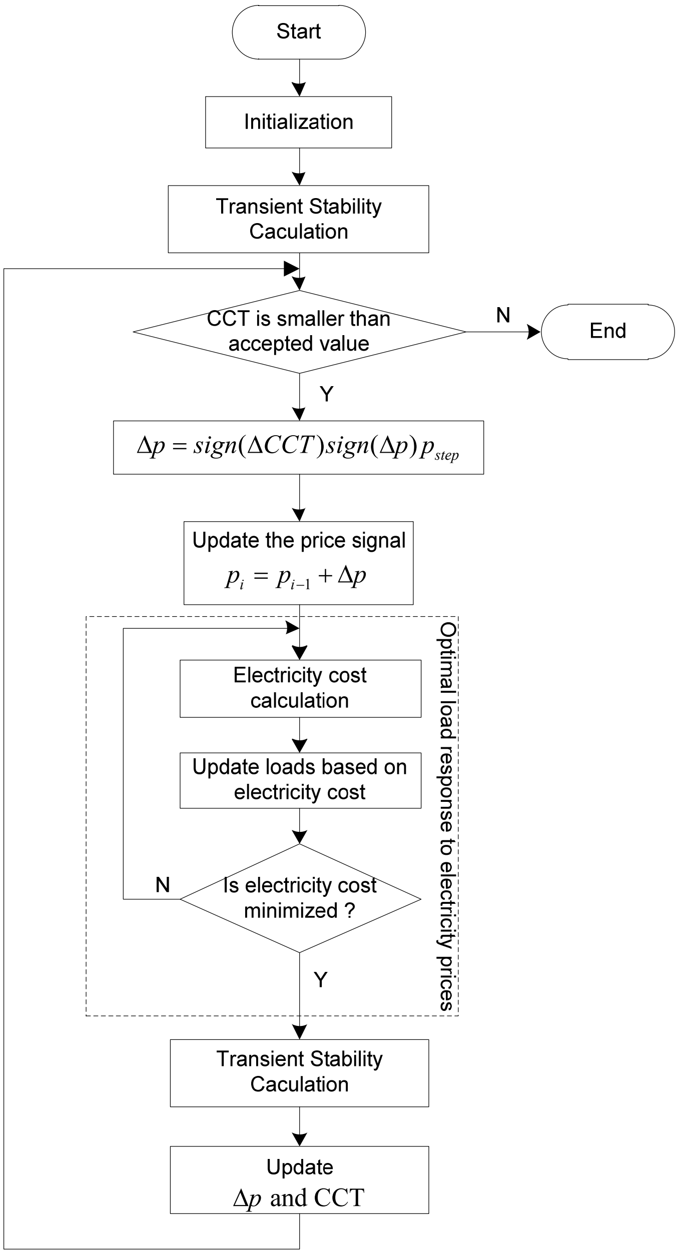


Fig. 5.21. The flow chart of the algorithm for optimizing CCT using elastic prices.

The parameters of the algorithm, such as the network parameters, the generation data and the load data are initialized in the first step. The time domain simulation with a 3 phase fault at the main transmission line is conducted in order to calculate the CCT value using the DIgSILENT PowerFactory software. If the CCT is smaller than the accepted value, which is assumed and set as 330 ms in this paper, the electricity price is calculated based on the sign of the ΔCCT and the Δp. The principle is similar to the small signal stability improvement, which has been discussed in the previous section. If both ΔCCT and Δp are positive or negative in the previous iteration, the electricity price should be increased in order to achieve a bigger CCT value. On the other hand, if ΔCCT is positive and Δp is negative, or ΔCCT is negative and Δp is positive in the previous iteration, the electricity price should be decreased in order to achieve a bigger CCT value. Consumers then shift their loads based on the electricity prices for different hours in order to save their energy costs as discussed in Chapter 3, which is shown in the dashed box in this figure. The algorithm makes a lot of iterations in order to find the appropriate electricity prices until the stopping criterion is satisfied. The stopping criterion is that the CCT is larger than the accepted value or the maximum number of iterations is reached.

5.4.3 Case Study For Optimizing CCT

The average value of the spot market price in the studied day (32.75 EUR/MWh) is chosen as the original fixed electricity price in the study. The new electricity price and the original fixed electricity price, the optimal load response under the 2 different cases are shown in Fig. 5.22 and Fig. 5.23, respectively. The CCT values of the power system under the 2 different cases are shown in Fig. 5.24. It can be seen from Fig. 5.22 that the electricity price is shifted during the hours in the early morning, because the CCT is less than the accepted value (330 ms) in these time periods. The customers then reschedule some of their loads from the high price periods to the low price periods in order to save their energy costs. Fig. 5.24 indicates that CCT value increases by using optimal load response according to the electricity prices for different hours, which suggests that the transient stability of the power system is improved.

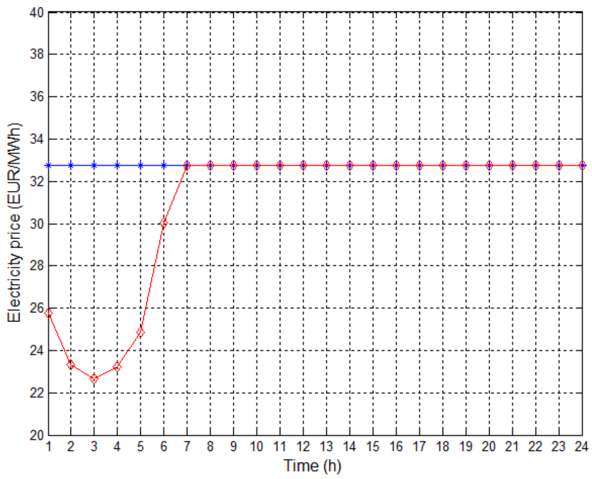


Fig. 5.22. The new electricity price (red diamond line) and the original fixed electricity price (blue asterisk line).

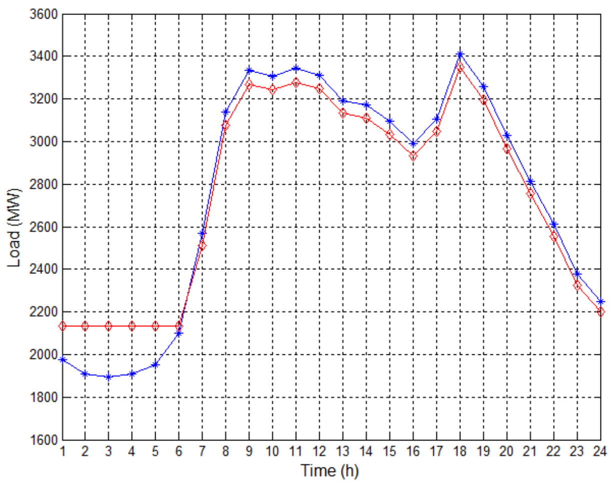


Fig. 5.23. The optimal response load under the new electricity price (red diamond line) and the original load under the original fixed electricity price (blue asterisk line).

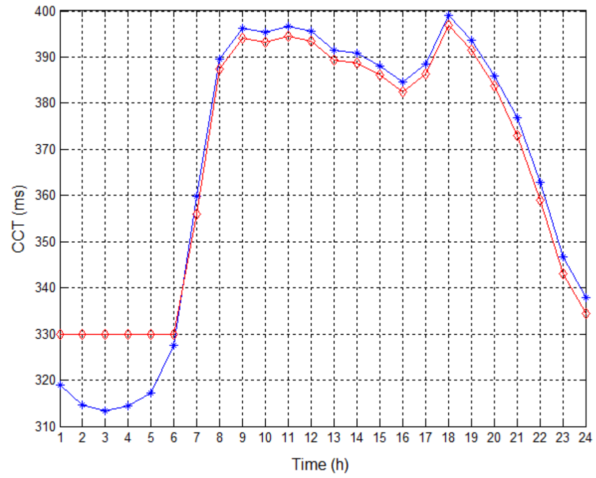


Fig. 5.24. The CCT value of the power system under the new electricity price (red diamond line) and the original fixed electricity price (blue asterisk line).

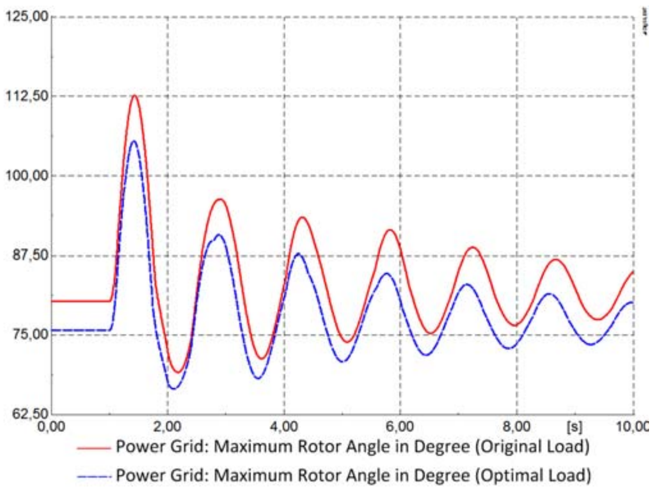


Fig. 5.25. The comparison of the maximum differences of synchronous generator rotor angle in the system for the case of original load (red) and optimal load (blue), when the fault is cleared after 120 ms.

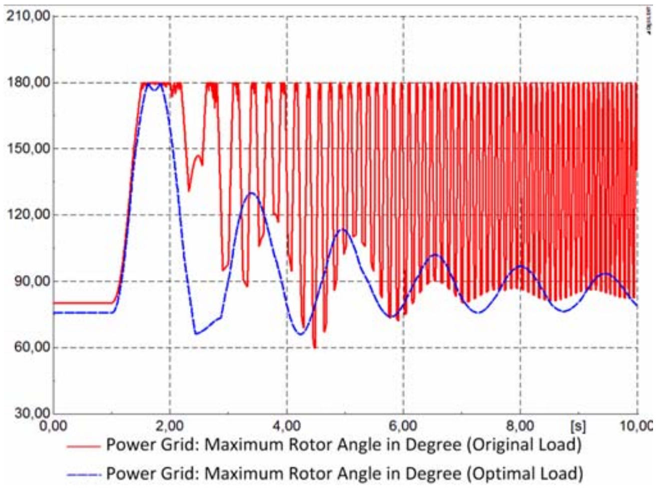


Fig. 5.26. The comparison of the maximum differences of synchronous generator rotor angle in the system for the case of original load (red) and optimal load (blue), when the fault is cleared after 320 ms.

When the CCT value is very low, which indicates that the power system may operate near its physical stability boundaries, the TSO may choose the proposed algorithm to improve the power system transient stability. The system costs will of course not be minimized from the electricity market point of view in this way. But it will eventually save a huge amount of money by preventing the power system collapse and blackout.

5.5 Summary

As discussed in the previous chapters, the optimal load response to electricity prices for different hours for demand side management may generate different load profiles. When the power system operates near its physical boundaries, a different electricity price for different hours may be given to consumers in order to motivate them to reschedule their demands. Consequently, the power flow may be changed and the power systems will be operated in a good condition, when appropriate electricity prices are given to consumers. This chapter describes the ideas and algorithms of power system operation improvement using demand side management. In this chapter, three different cases are studied to solve power system constraints, improve power system small signal stability and power system transient stability by deciding appropriate electricity prices for different hours. Three different power systems with high wind power penetrations are chosen as study cases in this chapter. It can be concluded from the simulation results that optimal choosing of electricity prices is an effective measure to improve operation conditions of power systems with high wind power penetrations.

However, there may be some conflicts when the previous three cases are taken into consideration at the same time. The system operators may only care the most serious problem at this situation or a multi-objective optimization is required to combine the previous three cases together.

The main work of this chapter has also been reported in the author's previous publications [P7-P9].

Chapter 6

Optimal Operation Strategies for Battery Energy Storage Systems

6.1 Introduction

EU's energy policy addresses the transportation sector, requiring a mandatory limit of 120 grams of CO_2/km for new cars by 2012 to reduce the greenhouse gas emissions [21], [22]. Recent developments and advances in battery energy storage systems and power electronics technologies are making Plug-In Electric Vehicles (PEV) a possible solution in the future. PEVs have attracted more attentions all over the world. Germany plans to have 1 million PEVs deployed by 2020 [79]. Japan plans to have 50% market share of next generation PEVs by 2020 [80]. The battery storage of electric vehicles is one of the emerging concepts, which can act as a controllable load or as a generator in the distribution power system. It may allow the power system to be operated in a more flexible, controllable manner [23-30].

Conventionally, PEVs start charging immediately after plugging in and keep charging until their batteries are full. A new peak in electricity demand during the late afternoon may be caused due to this. This way of charging is normally referred to as dumb charging PEVs. Tariffs by hourly prices have been adapted in many parts of the world due to the liberalization of the electricity markets. The hourly spot market price is available one day ahead in Denmark and the consumers may make some optimal charge and discharge schedules for their PEVs in order to minimize their energy costs [81].

The battery of a PEV can act as a source of stored energy to provide a number of ancillary services [82-86]. The possible ancillary services for PEV are supply of primary and secondary control, and voltage regulation. Reference [82] proposed a primary control method for PEVs and verified that the proposed method can reduce the frequency deviation significantly. PEVs could also provide secondary control in order to balance the demand and generation in power systems [83, 84]. The voltage regulation ability may be embedded in the charger of PEVs. The charger can control the charge/discharge power automatically according to the voltage of the connecting point. The chargers may be able provide some reactive power to support the voltage, when advanced power electronic converters are employed in the chargers [85, 86]. The secondary control possibility of PEVs is very important to some countries like Denmark with high wind power penetration.

In this chapter, different cases are studied to investigate the technical and economic benefits for both the power system operators and the battery energy storage system (BESS) owners when such energy storage system is installed in the power system. The chapter is organized as follows. An optimal operation strategy for two kinds of BESS, based on polysulfide-bromine (PSB) and vanadium redox (VRB) battery technologies, is proposed in Section 6.2 in order to achieve maximum profits of the BESS. Section 6.3 presents an optimal operation strategy for PEVs in relation to the hourly electricity price in order to achieve minimum energy costs of the PEV. Furthermore, the application of battery storage based aggregated PEV is analyzed as a regulation services provider in Section 6.4. The economic benefits of PEVs in both spot market and regulation market are estimated in this section. Finally, Section 6.5 summarizes the main conclusions.

6.2 Optimal Operation of Battery in Spot Market

6.2.1 Problem Formulation and Algorithms

The mathematical models are built to analyze how to optimally operate the battery energy storage system to achieve maximum profits in the spot market. The sequential quadratic programming (SQP) method, which has been discussed in Chapter 3, is adopted as the optimization methods.

The power output of the BESS is chosen as state variable in the problem formulation and the energy stored in the BESS can be calculated from the sum of the power output of the BESS [87]. Energy stored in the BESS is expressed as follows.

When the BESS is charging at hour t ($P_t > 0$),

$$E_{t+1} = E_t + \eta P_t \times (1 \text{ hour}) \tag{6.1}$$

and when the BESS is discharging at hour t ($P_t < 0$),

$$E_{t+1} = E_t + P_t \times (1 \text{ hour}) \tag{6.2}$$

where E_t, E_{t+1} are the energy stored in the BESS at hour t and hour $t+1$, respectively, P_t is the power output of the BESS at hour t, η is the efficiency of the BESS.

Since the hourly spot market price is available one day ahead, the decision variable vector of operation for this optimization problem is chosen as 24 values of the power output P_t of the BESS.

The BESS capital cost must be considered in order to establish an economic analysis. The BESS capital cost is a function of the storage device power and energy capacities and their specific costs depending on the chosen technology. The BESS capital cost is defined as a function of two main parts. One is related to the storable energy and the other depends on the peak power that the storage can deliver. Therefore, the BESS capital cost will be expressed as [24], [88].

$$C_{capital} = C_P P_{\max} + C_W E_{\max} \tag{6.3}$$

where $C_{capital}$ is the BESS capital cost, $P_{\max}$, $E_{\max}$ are BESS power and energy capacities, respectively, C_P is the power cost coefficient, C_W is the energy cost coefficient.

Energy storage technologies presented in this chapter are redox-flow batteries. The discharge time is from minutes to hours and charge/discharge power rating is several MW [89], [90]. The present work uses the following technologies: polysulfide-bromine (PSB) and vanadium redox (VRB) battery technologies [89], [90]. Technical and economic characteristics of the BESS considered in this study are presented in Table 6.1 [24], [89].

Table 6.1. Technical and Economic Data of the BESS.

Technologies	PSB	VRB
C_P (USD/kW)	150	426
C_W (USD/kWh)	65	100
Efficiency (%)	65	70
Lifespan (years)	15	15

Since the spot price is available one day ahead, the owners of the BESS may decide the charge/discharge schedule in order to achieve maximum profits. The revenue of the BESS in a day can be written as

$$R = \sum_{t=1}^{24} P_t \times SP_t \tag{6.4}$$

where R is the revenue of the BESS, P_t is the charge/discharge power at hour t, SP_t is the spot price at hour t.

The objective of owners of the BESS is to achieve the maximum revenue by deciding the charge/discharge power. The optimization objective function can be expressed as

$$\max(R) = \max(\sum_{t=1}^{24} P_t \times SP_t) \tag{6.5}$$

Some necessary limitations and assumptions have to be made to this problem.

1) The charge/discharge power of the BESS and the energy stored in the BESS should be less than the BESS power and energy capacities in order not to overload the system. This limitation can be expressed as

$$-P_{\max} \leq P_t \leq P_{\max} \tag{6.6}$$

$$0 \leq E_t \leq E_{\max} \tag{6.7}$$

2) Since the spot price is only available one day ahead, it is assumed that all the energy stored in the BESS is discharged in the same day. Because the optimization is starting at mid-night and normally the electricity price is low at the early morning, it could be assumed that the energy stored in the BESS is zero at 00:00 hour. There may be few days when the price is lower before the mid-night than after the mid-night. However, the BESS is assumed not charging before the mid-night in order to simplify the problem.

3) Because the power consumption of Denmark is relatively small in the Nordic power market and the charge/discharge power of the BESS are small, it is assumed that the spot prices are not changed by the operation of the BESS.

The consumers may try to find the maximum value of objective function under the assumptions mentioned. The sequential quadratic programming method, which was discussed in Chapter 3, is used as the optimization method for this problem.

6.2.2 Case Study of BESS Optimal Operation

A winter weekday of year 2007 is chosen as the first study case. Fig. 6.1 illustrates the spot price of west Denmark in the studied day. The owners of the BESS may decide to discharge the BESS near the price peaks in order to achieve the maximum profits. It is assumed that the BESS power capacity $P_{\max}$ is 1 MW and the BESS energy capacity $E_{\max}$ is 5 MWh in the basic study case.

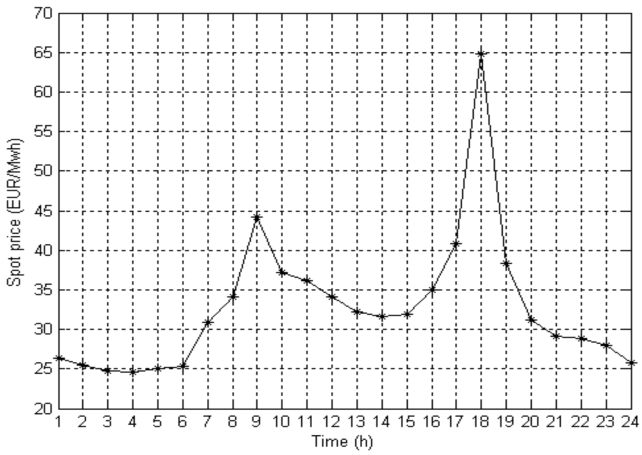


Fig. 6.1. The spot price of west Denmark in a winter weekday.

The optimal charge/discharge power of the BESS and the stored energy in the BESS in the winter weekday are shown in Fig. 6.2 and Fig. 6.3. The BESS is charged when the electricity price is low in the early morning and discharged near the two price peaks at about 09:00 and 18:00. Although the charge/discharge curves are almost the same for both batteries, the energy stored in the VRB battery is higher than the PSB battery due to higher efficiency of the VRB battery. The revenue of the BESS in the winter weekday is 34.2 EUR for the PSB battery and 43 EUR for the VRB battery.

A special summer weekday of year 2007 when the spot price variations are small is chosen as another study case. Fig. 6.4 shows the spot price of that day. The variation of the electricity price in the summer weekday is smaller than the variation of the electricity price in the winter weekday. The optimal charge/discharge power of the BESS and the stored energy in the BESS in the summer weekday are shown in Fig. 6.5 and Fig. 6.6. It can be seen that the PSB battery cannot make any profits in the summer weekday, but the VRB battery can still make some profits in the same day due to higher efficiency of the VRB battery.

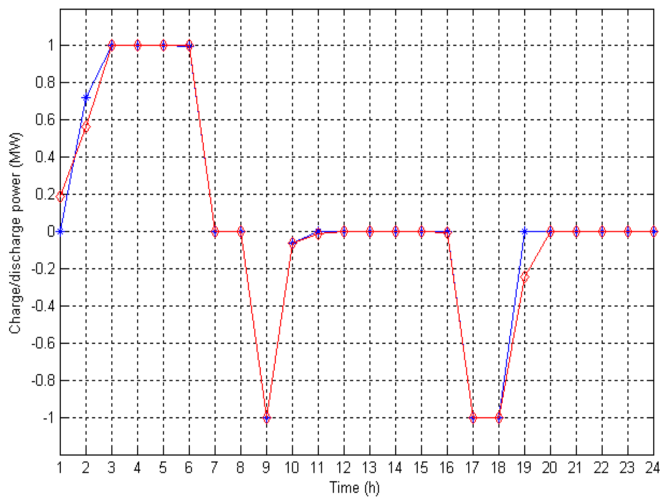


Fig. 6.2. The optimal charge/discharge power of the BESS in a winter weekday (blue asterisk line: PSB battery technology, red diamond line: VRB battery technology).

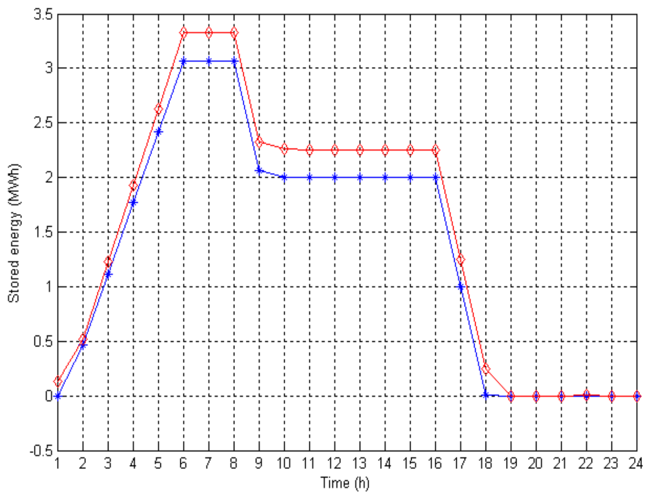


Fig. 6.3. The stored energy in the BESS in a winter weekday (blue asterisk line: PSB battery technology, red diamond line: VRB battery technology).

The BESS can make more profits when the variation of the electricity price is higher. It could be easily concluded that the BESS can make some profits only when the following inequality is satisfied.

$$\eta SP_{\max} > SP_{\min} \tag{6.8}$$

where $SP_{\max}$ and $SP_{\min}$ are the maximum and minimum electricity price in a day, respectively.

The method could be adopted at each day of year 2007. The revenue of the BESS at January and October, 2007 is illustrated in Fig. 6.7. It can be observed that the revenue of the VRB battery is always higher than the revenue of the PSB battery due to higher efficiency of the VRB battery. The revenue of the BESS at each month in the year 2007 is shown in Table 6.2. It is indicated that the revenue of both batteries is higher in October, November and December due to the bigger variations of the electricity price in these months.

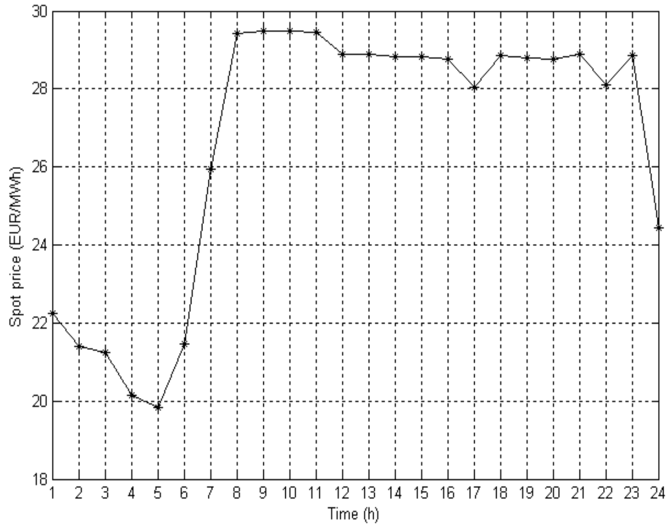


Fig. 6.4. The spot price of west Denmark in a summer weekday.

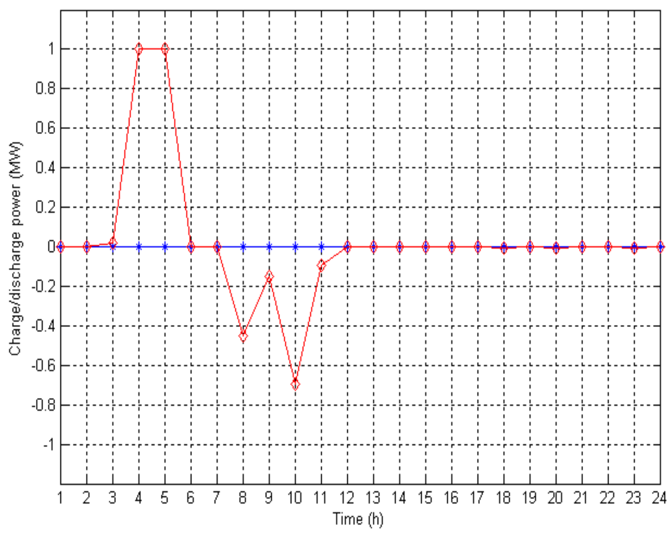


Fig. 6.5. The optimal charge/discharge power of the BESS in a summer weekday (blue asterisk line: PSB battery technology, red diamond line: VRB battery technology).

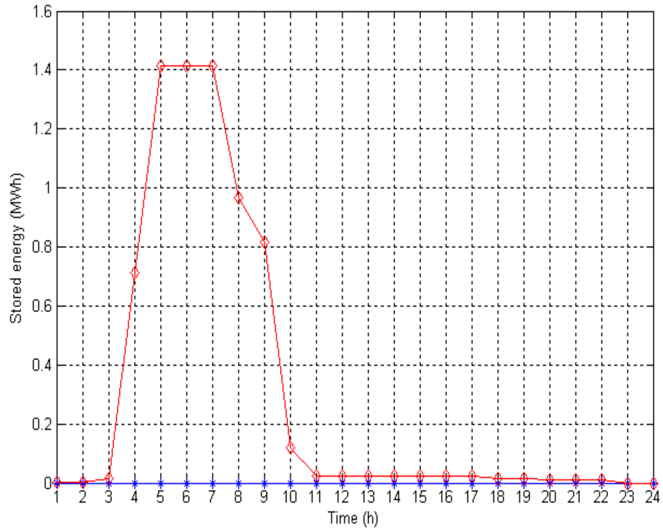
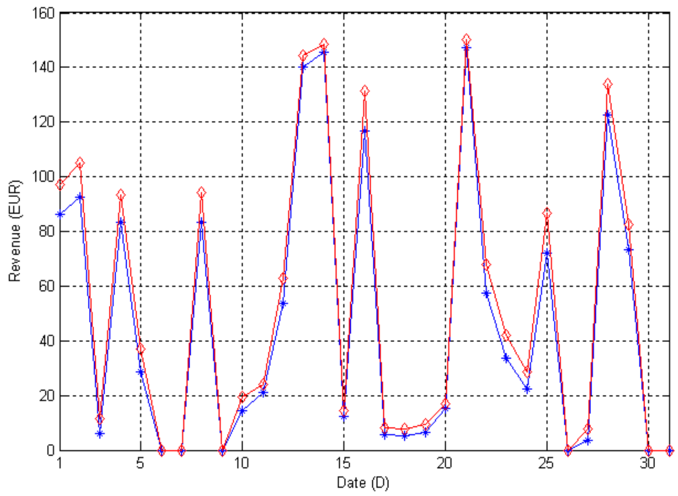
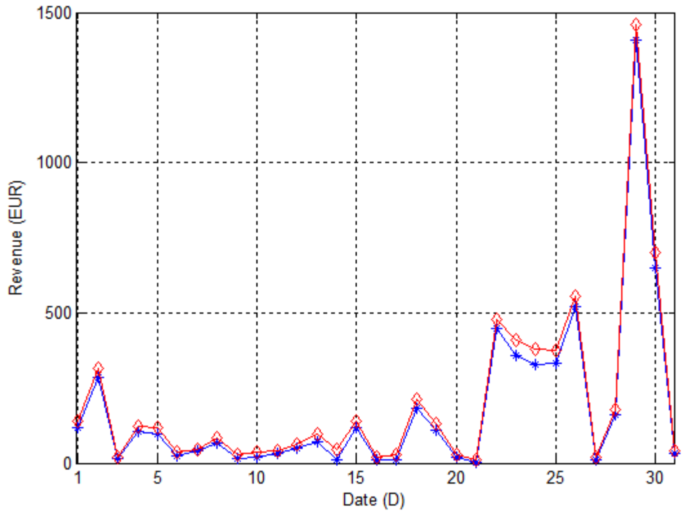


Fig. 6.6. The stored energy in the BESS in a summer weekday (blue asterisk line: PSB battery technology, red diamond line: VRB battery technology).



(a)



(b)

Fig. 6.7. (a) The revenue of the BESS at January, 2007. (b) The revenue of the BESS at October, 2007 (blue asterisk line: PSB battery technology, red diamond line: VRB battery technology).

Table 6.2. The Revenue of the BESS in the Year 2007.

Month	Revenue of PSB(EUR)	Revenue of VRB(EUR)
Jan.	1448	1625
Feb.	751	1064
Mar.	372	513
Apr.	374	494
May	969	1169
Jun.	2562	2920
Jul.	1132	1368
Aug.	1848	2199
Sep.	1761	2160
Oct.	5654	6332
Nov.	4615	5081
Dec.	4512	5027
Total	**25996**	**29953**

Payback period is an important guideline in the economic analysis. It is the period of time required for the return on an investment to re-pay the sum of the original investment. It can be expressed as the following equation, if operational and maintenance costs are neglected.

$$\sum_{n=1}^{PP} \frac{R_{annual}}{(1+r)^n} \geq C_{capital} \tag{6.9}$$

where PP is the payback period, which is the minimum value that satisfies the inequality, R_{annual} is the annual revenue of the BESS, $C_{capital}$ is the BESS capital cost, r is the annual bank interest rate. It means that after the payback period, the total revenue is more than the BESS capital cost with the consideration of the annual bank interest rate, which is assumed 4% in the study.

The annual revenue, capital cost and payback period of the BESS are shown in Table 6.3. Although the annual revenue of the VRB battery is higher than the annual revenue of the PSB battery, it will take longer time to return the original investment of the VRB battery. So the PSB battery is the better investment choice for the time being.

Table 6.3. The Annual Revenue, Capital Cost and Payback Period of the BESS.

Technologies	PSB	VRB
R_{annual} (EUR)	25996	29953
$C_{capital}$ (USD)	475000	926000
PP (years)	18	45

Since the PSB battery is the better investment choice for the time being, the further studies only focus on the PSB battery. When the PSB battery is invested for the power system, another question is to decide the power capacity $P_{\max}$ and the energy capacity $E_{\max}$ of the PSB. Table 6.4 illustrates the annual revenue, capital cost and payback period of the PSB, when the power capacity $P_{\max}$ is 1 MW and the energy capacity $E_{\max}$ of the PSB changes from 1 MWh to 10 MWh. It can be seen that the annual revenue of the PSB increases with the energy capacity of the PSB and the payback period first decreases with the energy capacity and then increases with the energy capacity.

Table 6.4. The Annual Revenue, Capital Cost and Payback Period of the PSB.

W_{max} (MWh)	*Rannual* (EUR)	$C_{capital}$ (USD)	*PP* (years)
1	10919	215000	19
2	18063	280000	14
3	22390	345000	14
4	25072	410000	15
5	25996	475000	18
6	26181	540000	21
7	26220	605000	25
8	26249	670000	29
9	26296	735000	36
10	26334	800000	43

The variations of the annual revenue, the capital cost and the payback period of the PSB battery with the energy capacity are shown in Figs. 6.8-6.10. It can be seen that the annual revenue of the PSB battery increases quickly at the lower energy capacity and becomes flat at the higher energy capacity. The capital cost of the PSB battery increases as a linear relationship with the energy capacity of the PSB battery. At the lower energy capacity, the payback period of the PSB battery decreases with the energy capacity because the increase in the speed of the annual revenue is higher than the increase in the speed of the capital cost of the BESS. At the higher energy capacity, the payback period of the PSB battery increases with the energy capacity because the increase in the speed of the annual revenue is lower than the increase in the speed of the capital cost of the BESS.

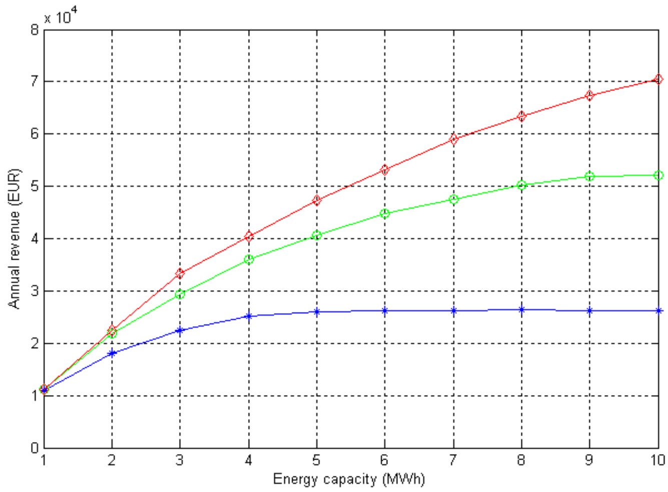


Fig. 6.8. The variations of the annual revenue of the PSB battery with the energy capacity (blue asterisk line: P_{max} = 1 MW, green circle line: P_{max} = 2 MW, red diamond line: asterisk P_{max} = 3 MW).

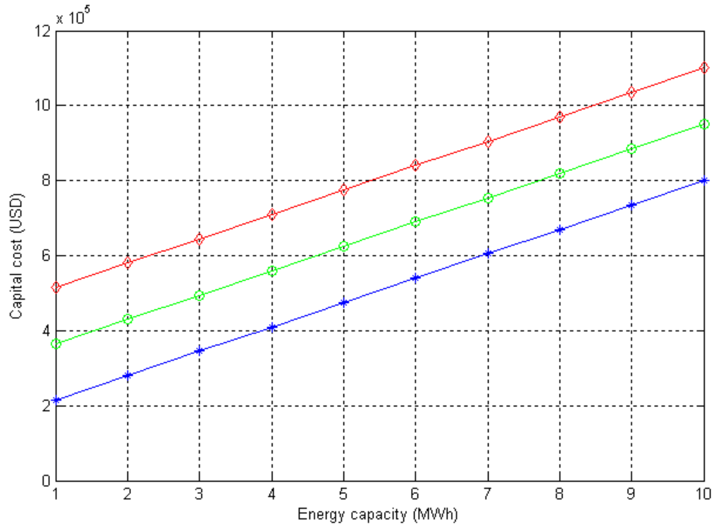


Fig. 6.9. The variations of the capital cost of the PSB battery with the energy capacity (blue asterisk line: P_{max} = 1 MW, green circle line: P_{max} = 2 MW, red diamond line: P_{max} = 3 MW).

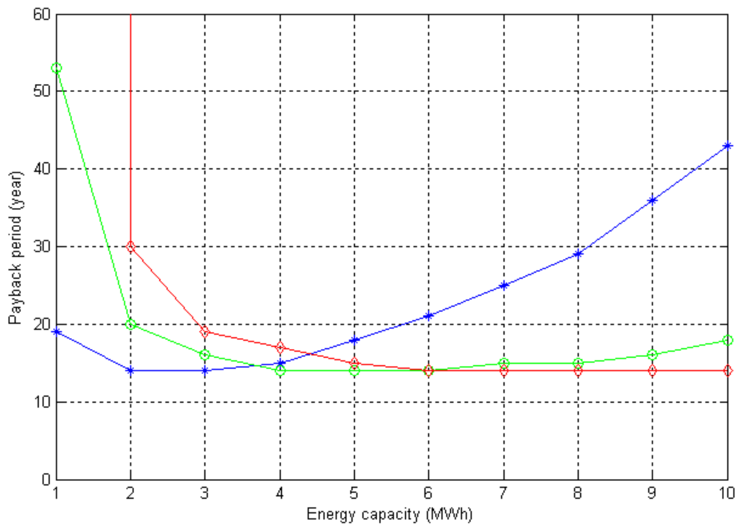


Fig. 6.10. The variations of the payback period of the PSB battery with the energy capacity (blue asterisk line: P_{max} = 1 MW, green circle line: P_{max} = 2 MW, red diamond line: P_{max} = 3 MW).

It can be seen from Fig. 6.10 that the payback period of the PSB battery is around 14 years if the power capacity and energy capacity of the PSB battery are chosen appropriately. However, since the lifetime of the battery is only 15 years, so both the PSB battery and the VRB battery are not good solutions in the spot market today. Therefore, the performance of the plug-in electric vehicle will be investigated in the next section.

6.3 Optimal Operation of Plug-in Electric Vehicles in Spot Market

6.3.1 Problem Formulation and Algorithms

Since the hourly spot market price is available one day ahead, the plug-in electric vehicle (PEV) owners may make some optimal charge and discharge schedules for their PEVs in order to minimize their energy costs. The problem formulation of PEV optimal operation in the spot market is similar with the normal BESS optimal operation, which has been discussed in Section 6.2. When the PEV is charging at hour t ($P_t > 0$),

$$E_{t+1} = E_t + \eta_c P_t \times (1 \text{ hour}) \tag{6.10}$$

when the PEV is discharging at hour t ($P_t < 0$),

$$E_{t+1} = E_t + \frac{P_t}{\eta_d} \times (1 \text{ hour}) \tag{6.11}$$

and when the PEV is being driven at hour t,

$$E_{t+1} = E_t - C \times D_t \tag{6.12}$$

where E_t, E_{t+1} are the energy stored in the battery of the PEV at hour t and hour $t+1$, respectively, P_t is the charge/discharge power of the PEV at hour t, η_c, η_d is the charging/discharging efficiency of the PEV, C is the driving energy consumption per kilometer, D_t is the driving distance at hour t.

Since the spot market price is an hourly price and available one day ahead, the optimization variable is defined as the hourly values of the power output P_t of the PEV. Electric characteristics of the PEV are needed in order to establish an economic analysis. The electric characteristics are based on the existing and operating electric vehicle Toyata RAV4 EV shown in Table 6.5 [91], [92].

Since the spot price is available one day ahead, the owners of the PEV may decide the charge/discharge schedule in order to achieve minimum energy costs. The energy costs of the PEV can be written as

$$EC = \sum_{t=t_a}^{t_b} P_t \times SP_t \tag{6.13}$$

where EC is the energy costs of the PEV, P_t is the charge/discharge power at hour t, SP_t is the spot price at hour t, t_a is the starting hour of the charge/discharge for the PEV, t_b is the ending hour of the charge/discharge for the PEV.

Table 6.5. The Electric Characteristics of Toyata RAV4 EV

Description	Value
Battery Capacity (kWh)	27
Battery Weight (kg)	551
System Voltage (V)	288
Maximum Range (km)	190
Driving Energy Consumption (kWh/km)	0.139
Charging Efficiency (%)	90
Discharging Efficiency (%)	90
Maximum Charging Power (kW)	10

The objective of owners of the PEV is to achieve the minimum energy costs by deciding the charge/discharge power P_t, while the PEV still can satisfy the owner's daily usage. The optimization objective function can be chosen as

$$\min(EC) = \min(\sum_{t=t_a}^{t_b} P_t \times SP_t) \tag{6.14}$$

Some necessary limitations and assumptions have to be made as follows.

1) The charge/discharge power of the PEV should be less than the power capacity of the PEV in order not to overload the system. This limitation can be written as

$$-P_{\max} \le P_t \le P_{\max} \tag{6.15}$$

where P_{max} is the maximum charge/discharge power. It is assumed that the energy stored in the battery of the PEV is within the range 20%~80% of maximum energy in order to leave some energy for PEV to provide regulation service, except the hour when PEV is just about to be driven.

$$0.2E_{\max} \le E_t \le 0.8E_{\max} \tag{6.16}$$

where E_{max} is the maximum energy stored in the PEV. This equation is only valid for making the optimal charge/discharge schedule in the spot market. It is also assumed that the battery of the PEV is fully charged before the use of the PEV in order to ensure the best performance of the PEV. The assumption can be written as

$$E_{t_c} = E_{\max} \tag{6.17}$$

where t_c is the time before the driving of PEV.

2) The daily behavior of the PEV owners is important in this study. Since the number of vehicles is very large, statistical behavior is rather predictable, though individual drivers might behave erratically. The driving behavior data used in the chapter is from the Danish National Transport Survey data [93], [94]. The daily average driving distance is 29.48 km and about 75% of the car users drive equal or less than 40 km. The overall vehicle hour availability of one day is also obtained and analyzed. The vehicle availability is quite high if only the driving time periods are considered as the unavailability time periods. The vehicle availability is 100 percent or very close to 100 percent during the early morning and the late night. More than 94% of the vehicles are idle even during the peak hours of transport demand and most of the cars are driven some time during 06:00 to 17:00. Therefore, it is reasonable to assume that 50% of PEVs are always idle and connected to the grid. Another 50% of PEVs are driven in the period from 06:00 to 17:00 and connected to the grid immediately after the driving.

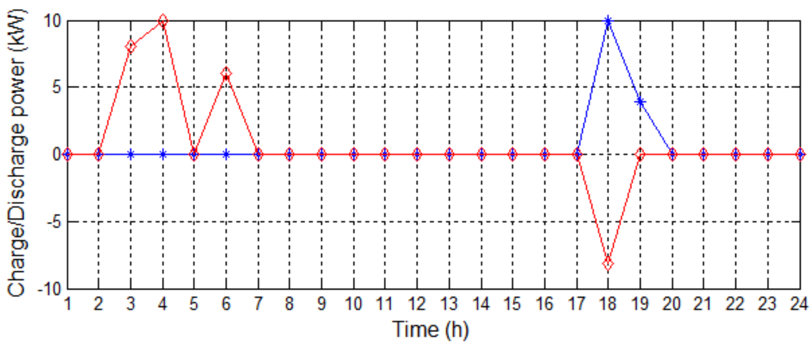
3) It is also assumed that the spot prices are not changed by the operation of the PEV. The reason has been discussed in the previous section.

The PEV owners may try to find the minimum value of objective function under the assumptions mentioned. Sequential quadratic programming method, which was discussed in the previous section, is used as the optimization method for this problem.

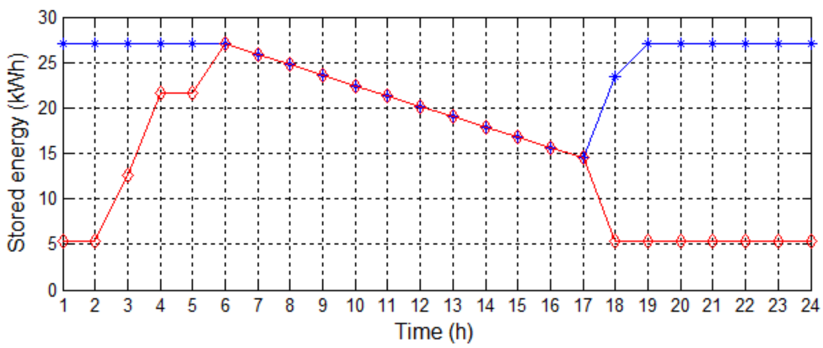
6.3.2 Case Study of PEV Optimal Operation in Spot Market

The same winter weekday is chosen as the study case. The spot price is illustrates in Fig. 6.1. There are two price peaks at about 09:00 and 18:00, respectively. It is assumed that the owner of the PEV drives 45 km in the study case.

The case that the battery of the PEV is charged immediately when it connects to the grid is chosen as the reference case (dumb charging) in the study. In the reference case, the battery of the PEV is charged immediately when it connects to the grid at 18:00. However, in the optimal case, the PEV is charged when the electricity price is low in the early morning. The PEV is discharged when the price is high at 18:00 in order to minimize its energy costs. The charge/discharge power of the PEV and the stored energy in the battery of the PEV in the winter weekday for both the reference case and the optimal case are shown in Fig. 6.11. From Fig. 6.11(b), it can be seen that the battery of the PEV is fully charged at 06:00 when the PEV is to be used by its owner. It is also assumed that the battery of PEV is discharged from 07:00 to 17:00 evenly due to driving in this figure. In the real life, the PEV may be only driven for half an hour in the morning and in the afternoon. But this will not affect the simulation results, because the driving time is not in the optimization algorithm. The net energy cost of the PEV in the winter weekday is 0.8 EUR for the reference case and 0.07 EUR for the optimal case, which means 91.6% of energy cost saving.



(a)

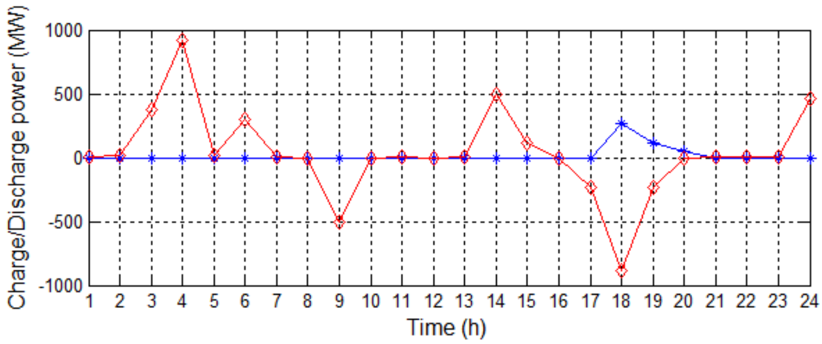


(b)

Fig. 6.11. (a) The charge/discharge power of the PEV in a winter weekday. (b) The stored energy in the battery of the PEV in a winter weekday (blue asterisk line: the reference case, red diamond line: the optimal case).

It is assumed that there are 100,000 PEVs in western Denmark, which corresponds about 10% of the total vehicles in Denmark. The statistical driving behaviors of the PEVs are assumed the same as for traditional vehicles, which has been investigated by the Danish

National Transport Survey. The assumptions and simplifications of the PEV hour availability is presented in Section 6.3.1. Fig. 6.12 illustrates the aggregated charge/discharge power and the stored energy of all the PEVs in western Denmark for both the reference case and the optimal case. In the optimal case, the PEV is charged when the electricity price is relatively low in the early morning and between 13:00 and 15:00 (due to the idle cars). The PEV is discharged near the two price peaks at about 09:00 and 18:00 in order to achieve the minimum energy costs.



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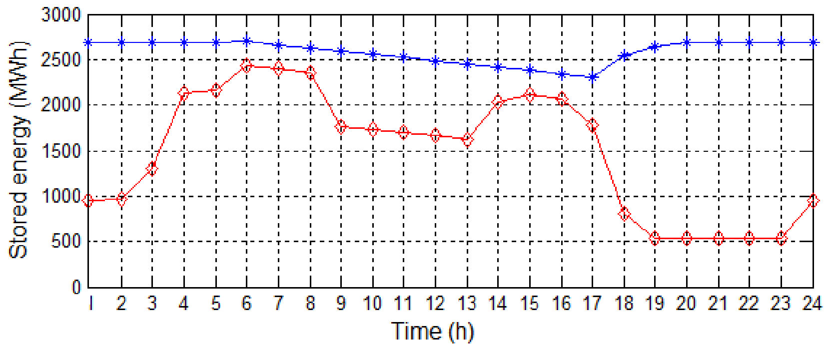


(b)

Fig. 6.12. (a) The charge/discharge power of the aggregated PEVs in the western Denmark. (b) The stored energy in the aggregated PEVs in the western Denmark (blue asterisk line: the reference case, red diamond line: the optimal case).

The overall PEV energy costs of each hour are shown in Fig. 6.13. It can be seen that the PEVs pay the lower energy costs when spot price is relatively low in the early morning, and earn a lot of money when the price is high at about 09:00 and 18:00 in the optimal case by selling the energy to grid. The overall PEV energy costs in the studied winter weekday decrease from 23.1 kEUR of the reference case to -26.2 kEUR (negative means PEV owners earn money) of the optimal case, which means that the owners of PEVs may earn money if they let their cars optimally participate in the spot market.

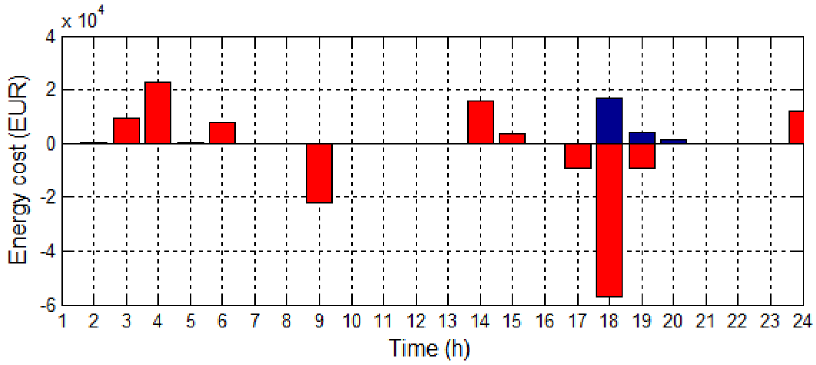
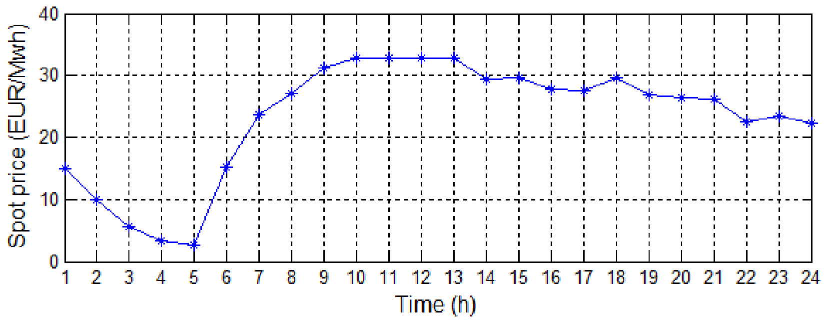


Fig. 6.13. The overall energy costs of the aggregated PEVs in the western Denmark (blue bar: the reference case, red bar: the optimal case).

Then a summer weekday is chosen as another study case. Fig. 6.14 illustrates the spot price, the charge/discharge power of the aggregated PEVs and overall energy costs for the PEV owners in western Denmark for both reference case and optimal case. The spot price is low in the early morning and high in the rest of the day. There are no significant price peaks compared with the spot price in the winter weekday. In the optimal case, the PEV is charged when the electricity price is relatively low in the early morning and discharged when the electricity price is relatively high in the day from 09:00 to 13:00 and from 17:00 to 20:00. The overall PEV energy costs in the studied summer weekday decrease from 12.1 kEUR of the reference case to -27.2 kEUR of the optimal case.



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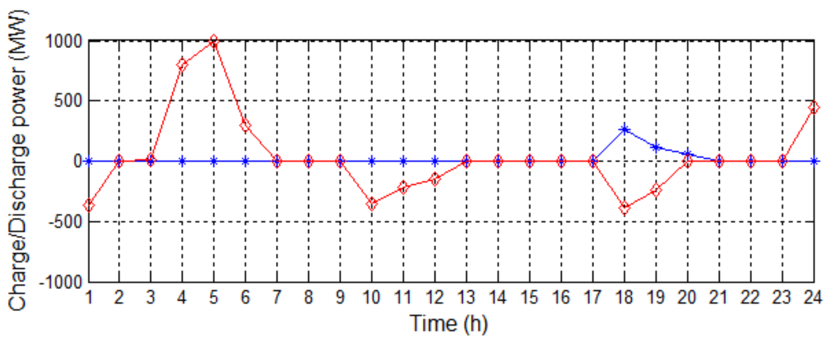

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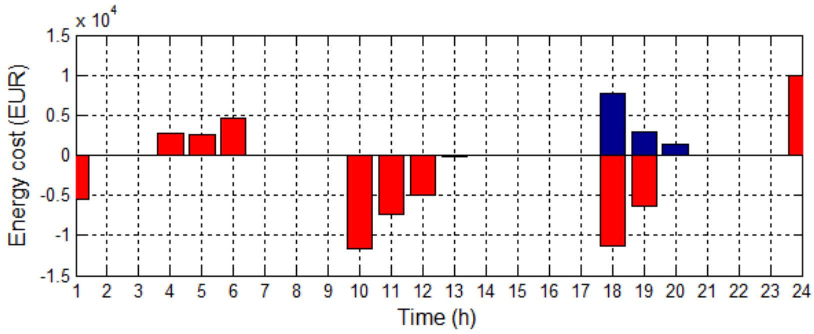


(c)

Fig. 6.14. (a) The spot price of west Denmark in a summer weekday. (b) The charge/discharge power of the aggregated PEVs in western Denmark. (c) The overall energy costs of the aggregated PEVs in western Denmark (blue bar: the reference case, red bar: the optimal case).

6.4 Plug-in Electric Vehicles as Regulation Service Provider

The secondary control possibility of PEVs is very important to some countries like Denmark with high wind power penetration. The battery of a PEV can act as a source of stored energy to provide the secondary control and make some money in the regulating market.

The larger power plants are either coal or gas based thermal units in the western Danish power system. More than 50% of the installed power capacities for electricity generation are land-based wind turbines and decentralized combined heat and power (CHP) units, which has been illustrated in Fig. 1.1. On average, the wind power supplies around 27% of the annual electricity consumption in West Denmark. Therefore, the western Danish power system with high wind power penetrations is chosen as the study case. The wind profile, fluctuating features of western Danish power system has been discussed in detail in [95]. The West Denmark transmission system is interconnected to the Union for the Coordination of Electricity Transmission (UCTE) system through Germany, where the generation capacity is dominated by thermal and nuclear power plants and fast growing wind power production. To the north, West Denmark is connected to Nordic synchronous area through HVDC links to Norway and Sweden [95], [96].

The western Danish power system operates as a single control area which is interconnected to the larger UCTE synchronous area. The total power deviations from the planned value of the power exchange between west Denmark and the UCTE control areas are the results of deviations from the planned electricity production, demand, and the power exchanges to the Nordic area. The LFC operation is accomplished through a tie-line control where the transferred power must be maintained at the scheduled values. The controller generates regulation power demand in order to minimize the power exchange deviations between the two control areas. The acceptable deviation is approximately ± 50 MW from the planned power exchange [97]. The secondary reserve power is normally provided by central power plants and large local CHP units now. This power balancing issue becomes more critical when more and more wind power plants replace the central power stations in the future. Therefore, the battery storage based PEVs with vehicle-to-grid (V2G) functions may be a possible solution to provide a flexible and fast regulation power in the near future.

The digital simulations are performed using the DIgSILENT Power Factory software. The model integrating the battery storage based PEVs, tries to minimize the power deviations from the planned value of the power exchange between west Denmark and the UCTE control areas. The aggregated PEV models and load frequency control strategies are similar to the models in [95]. The detailed models and parameters are presented in Appendix.

Time series data for simulations from the western Danish SCADA system are obtained from Energinet.dk, the TSO in Denmark. The data available is of 5-min resolution. The electricity profile of the western Danish power system obtained from the SCADA system for a winter weekday is shown in Fig. 6.15, where the wind power meets an average of 40% of the total daily electricity consumption and the total production exceeds the demand in West Denmark.

The power exchange deviation between West Denmark and UCTE control area from the simulation without PEV providing regulation power is shown in Fig. 6.16. In this case, only the thermal generators provide the regulation power. A positive power exchange deviation indicates that the actual transfer power is less than planned value and a negative deviation means that the actual transfer power is more than planned value. It can be observed that the power deviations exceed the acceptable levels of ±50 MW due to the power imbalance caused by the inaccuracy of the estimated wind power and load demand.

According to the Danish National Transport Survey data [93, 94], more than 94% of the vehicles are idle and could be connected to the grid even during the peak hours of transport demand. Therefore, it is reasonable to assume that all the 100,000 PEVs in western Denmark are connected to grid all the time and only provide regulation power in this study case. The initial battery state of charge is assumed as 50% for all PEVs. Fig. 6.17 illustrates the power exchange deviation between West Denmark and UCTE control area from the simulation when PEVs only provide regulation power. Comparing the case with and without PEV providing regulation power, it can be seen that the power exchange deviation between West Denmark and UCTE is reduced significantly when the battery based PEVs provide regulation power. The regulation power provided by the battery of aggregated PEV and the battery state of charge are shown in Fig. 6.18. The negative power exchange deviation means that more power is transferred than the planned power, the battery is charged in order to decrease the transfer power between West Denmark and UCTE. It can be observed that the battery is operated at charging mode most of time. This is because the production exceeds the demand due to the high wind power generation in this case and it requires the PEVs to provide the down regulation power. The total regulation power provided by PEVs is 517.3 MWh in the studied winter weekday.

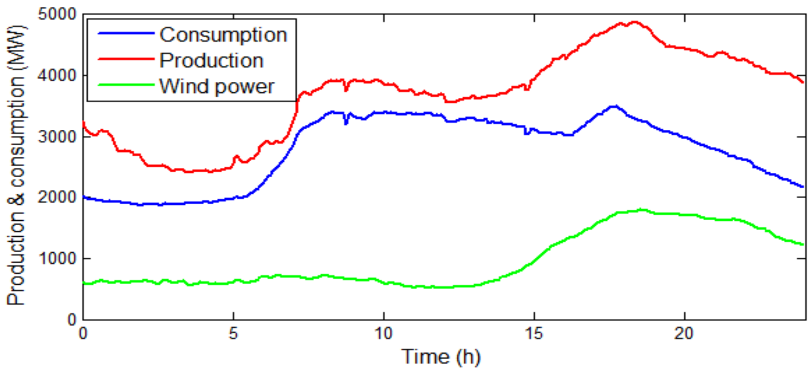


Fig. 6.15. The electricity profile of the western Danish power system obtained from the SCADA system for a winter weekday.

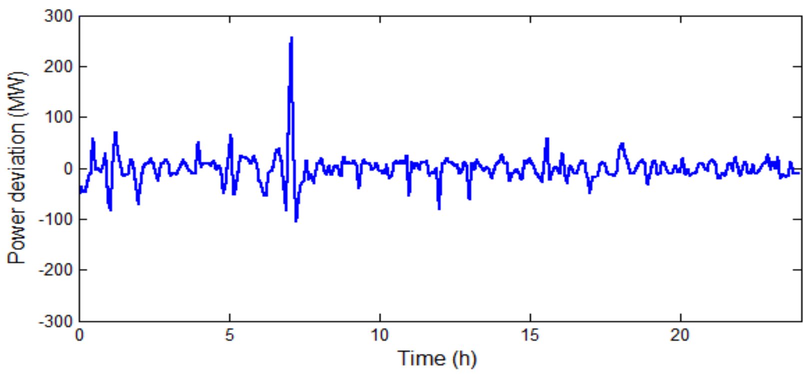


Fig. 6.16. The power exchange deviation between West Denmark and UCTE control area from the simulation without PEV providing regulation power.

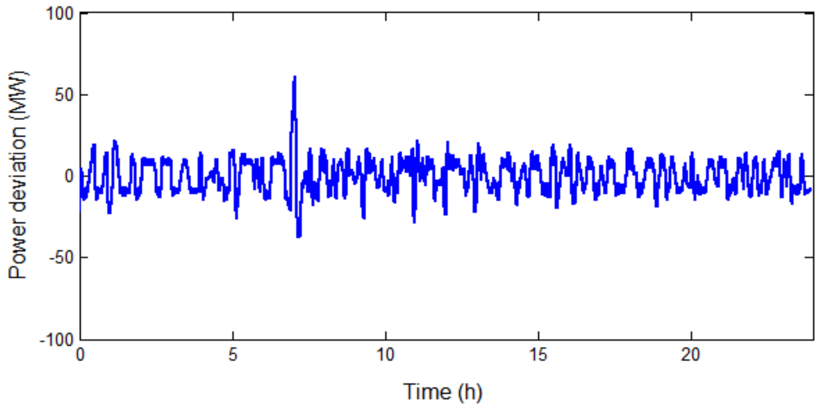
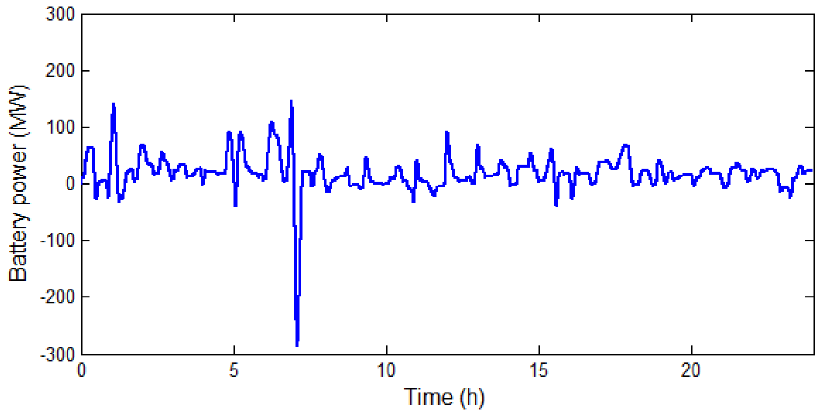


Fig. 6.17. The power exchange deviation between West Denmark and UCTE control area from the simulation when PEVs only provide regulation power.



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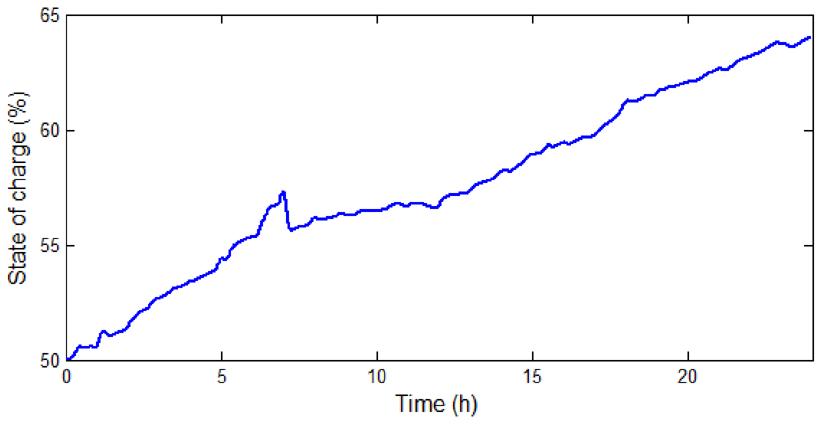
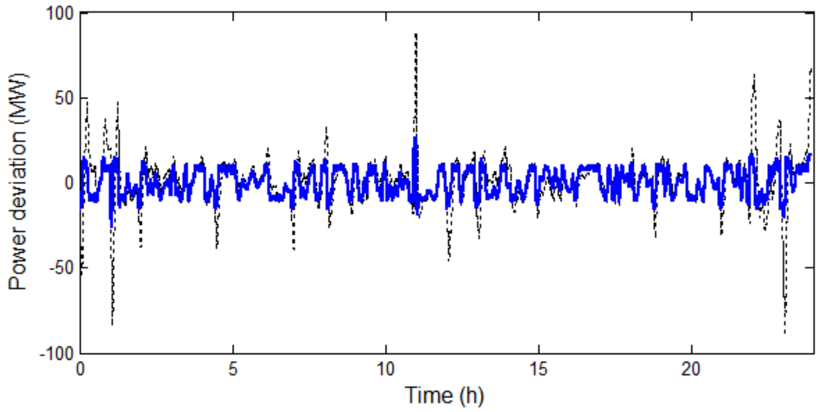


(b)

Fig. 6.18. (a) The regulation power provided by the battery based aggregated PEVs. (b) The battery state of charge.

Then a summer weekday is chosen as another study case. The wind speed is quite low in that day. Fig. 6.19(a) illustrates the power exchange deviation between West Denmark and UCTE control area without PEV (dash line) and with PEV (solid line). It can be seen that the power exchange deviation is reduced significantly when the battery based PEVs provide regulation power. The regulation power provided by the battery of aggregated PEV and the battery state of charge are shown in Fig. 6.19(b) and 6.19(c). When power exchange deviation is positive which means that less power is transferred than the planned power, the battery is discharged in order to increase the transfer power between West Denmark and UCTE. It can be observed that the battery is operated at discharging mode most of time, because the wind speed is quite low and it requires the PEVs to provide the down regulation power. The total regulation power provided by PEVs is 411.6 MWh in the studied summer weekday. It can be concluded that the battery storage based aggregated PEV is a possible regulation services provider in the western Danish power system. The economic benefits in this case will be discussed in the next section.



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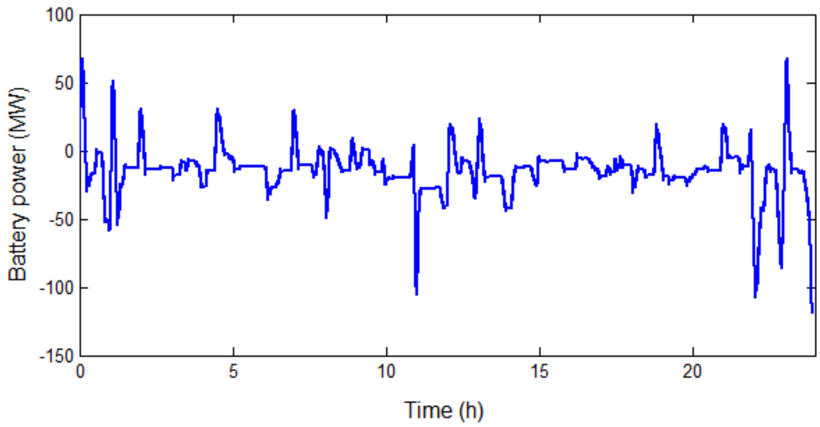

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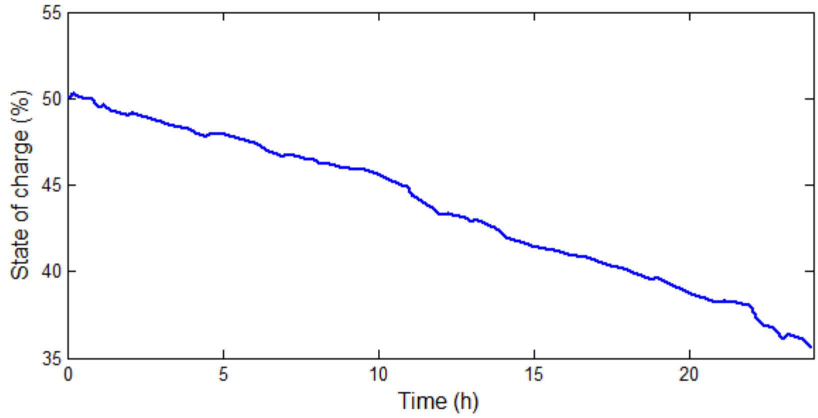


(c)

Fig. 6.19. (a) The power exchange deviation between West Denmark and UCTE control area in the summer weekday (dash line: without PEV, solid line: with PEV). (b) The regulation power provided by the battery based aggregated PEVs. (c) The battery state of charge.

6.5 PEV Operation in Both Spot Market and Regulation Market

The regulation power provided by the battery based aggregated PEVs is relatively small compared with the charge/discharge schedule in the spot market. So it may be possible to operate the PEVs in both the spot market and the regulation market at the same time. It is assumed that the PEVs have the same driving behavior as traditional vehicles. The optimal charge/discharge strategies are adopted in order to achieve minimum energy costs in the spot market, which has been discussed in Section 6.2. The PEVs are charged/discharged based on the optimal strategies but they also provide regulation power based on LFC at the same time.

The power exchange deviation between West Denmark and UCTE control area in the winter weekday from the new simulation is shown in Fig. 6.20, where PEVs optimally charge/discharge and provide the regulation power at the same time. The spot market price is available to PEV owners one-day ahead of the actual operation hour and the optimal charge/discharge schedule may also be made one-day ahead. The optimal charge/discharge schedule can then be taken care of by adjusting the generator output power. So the optimal charge/discharge schedule will not affect the power exchange deviation and the power exchange deviation is almost the same with the case that PEV only provide the regulation power (see Fig. 6.17).

Fig. 6.21 illustrates the aggregated battery power and battery state of charge from the simulation when PEVs optimally charge/discharge in the spot market and provide regulation power at the same time. It can be observed that the battery power is a combination of the optimal charge/discharge power in the spot market (see Fig. 6.12(a)) and the relatively small regulation power (see Fig. 6.18(a)). The battery state of charge is almost the same with the case that PEV optimal charge/discharge in the spot market (see Fig. 6.12(b)) except that the total energy in the battery increases about 14% by participating in the regulation market.

Then a summer weekday, when the wind speed is quite low, is chosen as another study case. The simulation results are shown in Fig. 6.22. It can be then concluded that the PEVs not only optimally charge/discharge in the spot market to minimize their energy costs, but also provide regulation power at the same time for both high and low wind speed days.

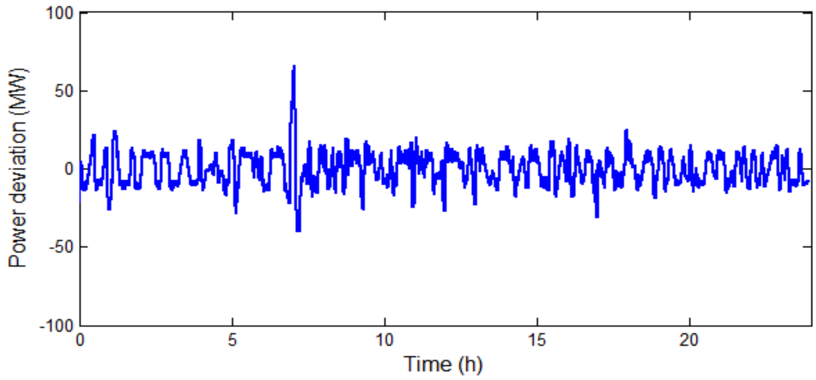
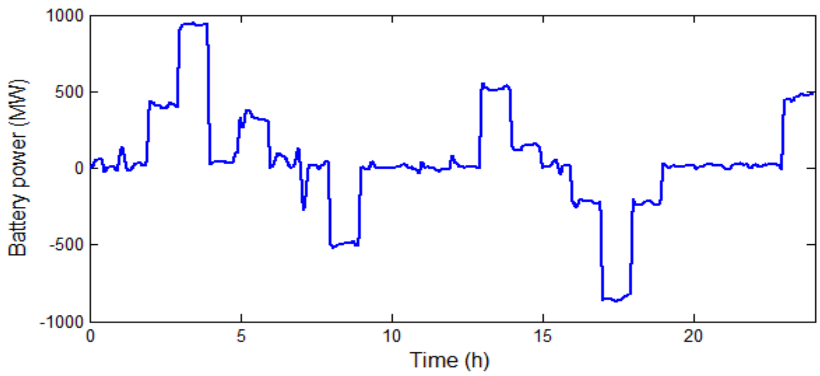


Fig. 6.20. The power exchange deviation between West Denmark and UCTE control area in the winter weekday when PEVs optimally charge/discharge in the spot market and provide the regulation power at the same time.



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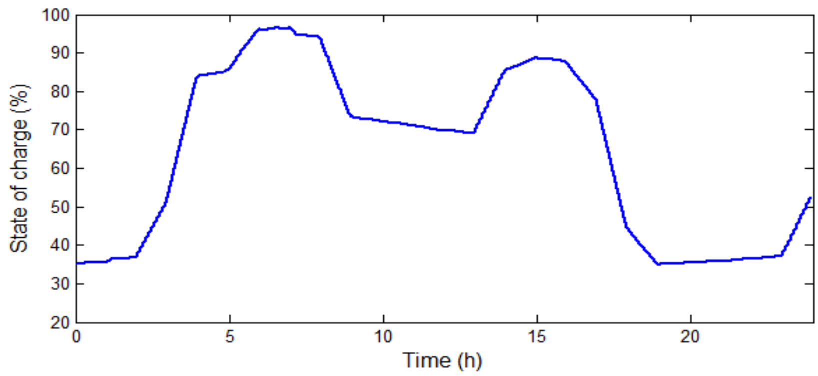
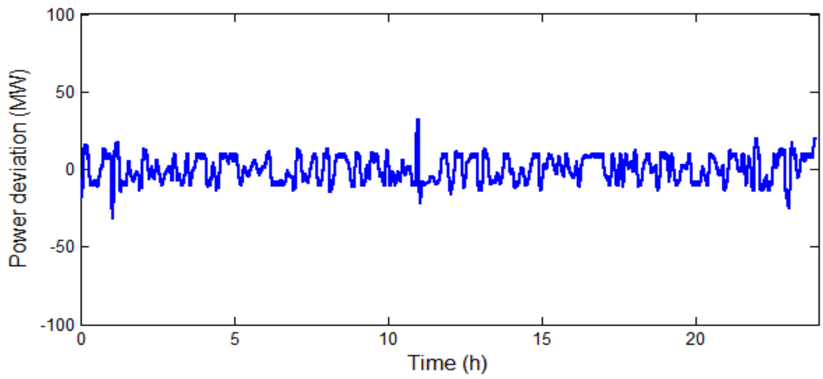


(b)

Fig. 6.21. (a) The aggregated battery power when PEVs optimally charge/discharge in the spot market and provide regulation power at the same time. (b) The battery state of charge.



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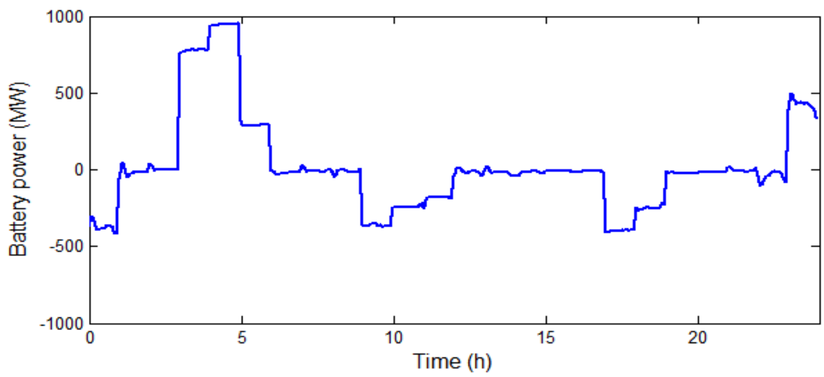

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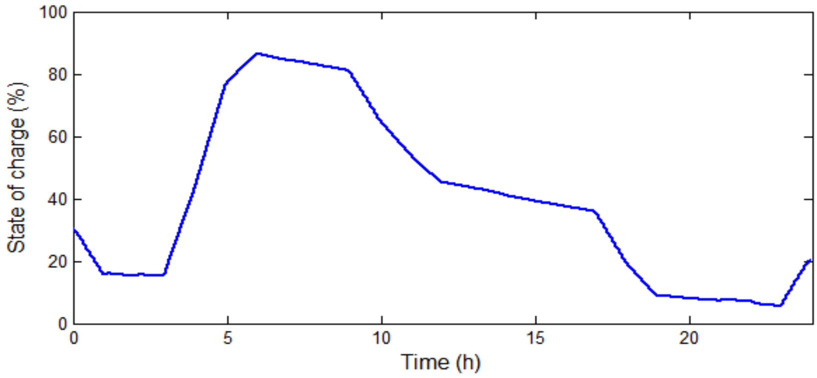


(c)

Fig. 6.22. (a) The power exchange deviation in the summer weekday when PEVs optimally charge/discharge and provide the regulation power at the same time. (b) The aggregated battery power. (c) The battery state of charge.

Regulation reserves are normally purchased by TSO from selected central power plants to ensure stable and reliable operation of the electricity systems. Regulation power in Denmark is usually paid both as a reservation price (fixed capacity price) and an activation price (energy price). The energy price is the same as the regulation price in Denmark, which is set as bidding price of the last activated unit. The current fixed capacity price is 10 million DKK per Month for all the regulation sources, which is equivalent to 44.4 kEUR per Day, and the regulation price is 100-125 DKK/MWh, which is equivalent to 13.3-16.7 EUR/MWh [34]. It is assumed that the energy price for PEVs is the average value of the regulation price (15 EUR/MWh) in order to simplify the calculation. If we assume that PEVs provide half of the regulation capacity and central power plants provide the other half, the revenue of PEV owners is 30.0 kEUR for providing regulation power in the studied winter weekday and 28.4 kEUR for providing regulation power in the studied summer weekday. Fig. 6.23 summaries the daily energy costs for different operation strategies. The positive value indicate that the owners of PEVs pay for using energy and the negative value indicate the owners of PEVs get money for providing services. The annual revenue is estimated to be 204 EUR per PEV, if all the PEV owners would optimally charge/discharge in the spot market and provide regulation power at the same time.

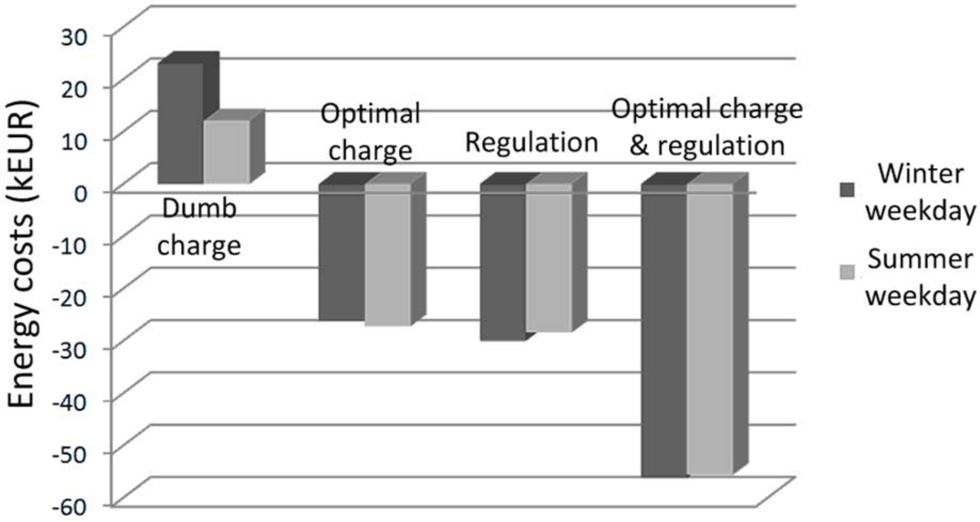


Fig. 6.23. The daily energy costs for different operation strategies.

Now many consumers in Denmark, especially small businesses and private households, operate on fixed electricity price contracts and they may not get paid by providing the regulation service. Therefore, now the PEV owners will not earn as much money as the calculated value in this chapter. In the future, when the private households could also participate in the competitive electricity market, the PEV owners may earn more money by making optimal charge/discharge schedule and providing regulation service, as reflected in the chapter. And also for the time being, these consumers will not have the spot market price as their price, their real expected fluctuation in the price will be lower due to tax and other tariffs. However, it is likely that the future price for the private costumers could be proportional to the spot price to give an incitement for shifting their consumption. The charge/discharge behaviors of PEVs would be similar with the simulation results in the chapter.

However, the optimal charge/discharge of PEVs will reduce the lifetime of the batteries in PEVs. The battery lifetime is a very complicated issue. Many factors contribute to the cycle life of a PEV battery in a given application. These include depth of discharge, ambient temperature, discharge rate, charging regime and battery maintenance procedures [98]. It can be seen that the depth of discharge is much smaller in the case of PEVs only providing regulation power (see Fig. 6.18), compared with the case of PEVs optimally charging/discharging in the spot market (see Fig. 6.12). So the PEV owner may be more willing to provide regulation service so that they can make some money and at the same time the lifetime of their PEVs will not reduce much. Another important factor is ambient temperature. It is reported that the lifetime of PEV is much longer in UK than in China for the same application, because the average temperature is lower in UK [99]. So the proposed operation and control strategies for PEV are more suitable for Denmark. In the end, it is also important that some development happens with the lifetime of the batteries, but this is not the scope of this chapter.

6.6 Summary

This chapter first presents an optimal operation strategy of battery energy storage systems to the spot market electricity price in order to achieve maximum profits of the BESS. Two kinds of BESS based on PSB battery and VRB battery technologies are studied in the chapter. Although the annual revenue of the VRB battery is higher than the annual revenue of the PSB battery, the payback period of the PSB battery is shorter than the payback period of the VRB battery. So the PSB battery is the best investment choice for the time being. The payback period of the PSB battery is around 14 years if the power capacity and energy capacity of the PSB battery are chosen appropriately.

This chapter then describes a study of integration of plug-in electric vehicles in the power systems with high wind power penetrations. An optimal operation strategy of PEVs in relation to the hourly spot price in competitive electricity markets is proposed in order to achieve minimum energy costs for the PEV owners. The total daily energy costs of all PEVs are decreased from 23.1 kEUR to -26.2 kEUR (negative means PEV owners earn money) in the studied winter weekday, if the proposed optimal operation strategy is used. The application of battery storage based aggregated PEV is then analyzed as a regulation services provider in the western Danish power system with high wind power penetrations using LFC. It can be concluded from the simulation results that the power exchange deviations are significantly reduced between West Denmark-UCTE interconnections with the use of PEV regulation power. The PEVs not only optimally charge/discharge in the spot market to minimize their energy costs, but also provide regulation power at the same time for both high and low wind speed days. The daily revenue for PEV owners is 30.0 kEUR for providing regulation power in the studied winter weekday. The annual revenue is estimated to 204 EUR per PEV, if the PEV owners would optimally charge/discharge in the spot market and provide regulation power at the same time.

The main work of this chapter has also been reported in the author's previous publications [P10-P13].

Chapter 7

Interaction between Electricity Price and System Demand

7.1 Introduction

The demand-side response is widely considered as an effective method to increase the economic efficiency in electricity markets and improve the power system operations [100]. It can bring many benefits to consumers and power system operators, such as electricity bill saving [101, 102] and peak load reduction [103], as discussed in the previous chapters. Furthermore, the demand-side response can be also used to allow system demand to respond to the wind power generation in a power system with high wind power penetrations and therefore increase the utilization of wind power plants [104]. However, the spot market price is normally assumed not changed after the demand-side response, which will not be the case when a large proportion of the system demand responds to the spot price.

In this chapter, the interaction between electricity price and system demand is studied when PEVs are optimally charged/discharged and consumers optimally shift their loads according to the spot market price. The chapter is organized as follows. The impact of different PEV charging/discharging strategies on the spot market price is presented in Section 7.2. Then Section 7.3 studies the interaction between the electricity price and the system demand. Finally, Section 7.4 summarizes the main conclusions.

7.2 Impact of PEV on the Spot Price

7.2.1 Problem Formulation

The Nord Pool spot market exchanges the power of Norway, Sweden, Finland and Denmark [34]. The Nord Pool receives bids from generation companies, big consumers and representative companies of small consumers for each hour one day ahead. The purchasing and selling curves are constructed by aggregating all the bids from generator side and demand side, respectively. The point where they cross determines the spot market price of each hour in the next day. Fig. 7.1 illustrates the principle for spot price calculation.

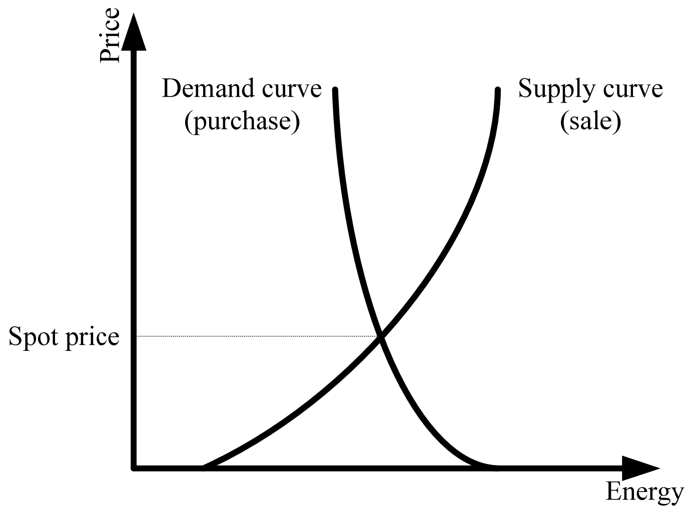


Fig. 7.1. The principle for spot price calculation.

When a lot of PEVs are integrated into the power system, it may also have some impacts on the spot market price. Fig. 7.2 shows the principle for spot price calculation after the PEV integration. The consumers will bid higher than their original bids, when many PEVs charge at this specific hour. Therefore, the aggregated demand curve will move to the right side, which is shown as the blue line in the figure. A higher spot price will then be calculated when the PEVs charges at this hour.

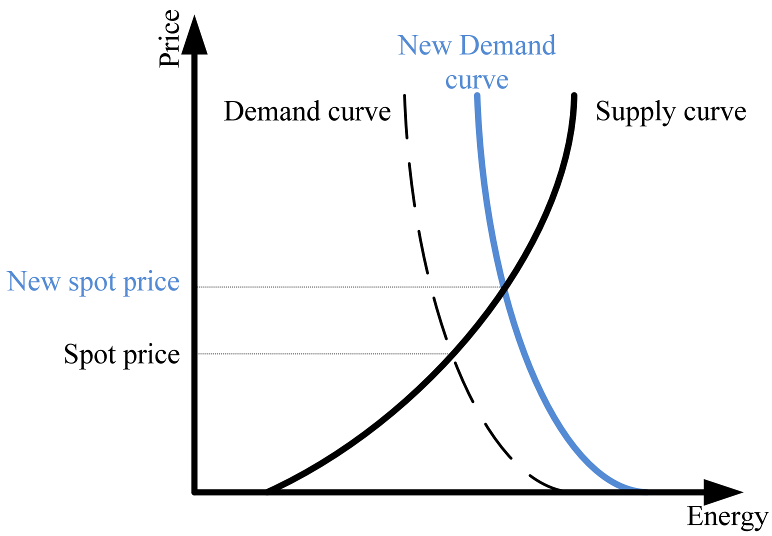


Fig. 7.2. The principle for spot price calculation after the PEV integration.

Some necessary limitations and assumptions have to be made as follows.

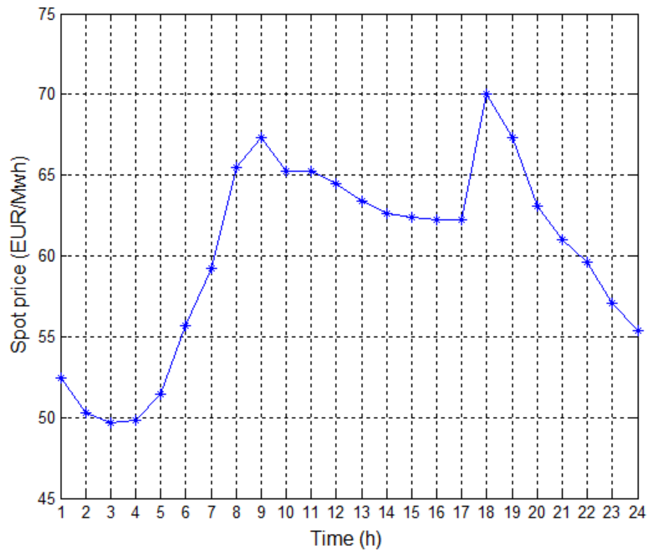
1) Because the spot market price is calculated in the Nord Pool market, all Nordic countries have to be taken into consideration. It is also assumed that there is no congestion between these countries in this study in order to simplify the problem, which means that there is only one spot price for all countries.

2) It is assumed that there are 500,000 PEVs in the Nordic countries, which corresponds about 5% of the total vehicles in these countries. The statistical driving behaviors of the PEVs are assumed the same as for traditional vehicles, which has been investigated by the Danish National Transport Survey and discussed in details in Chapter 6 [93], [94].

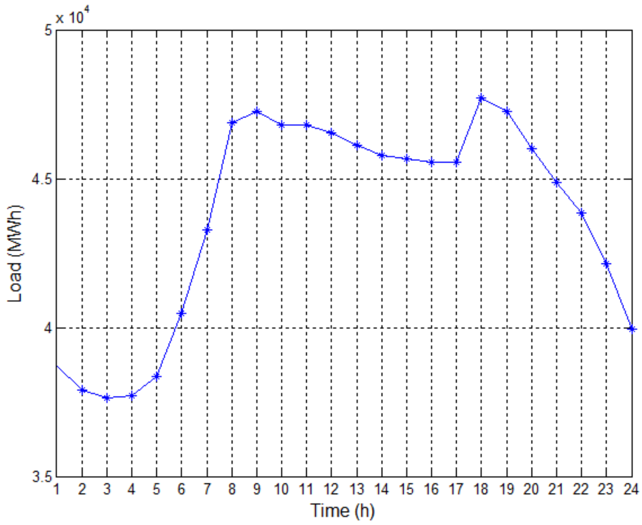
3) It is assumed that the generation curve is not changed and the demand curve only moves according to the amount of PEVs aggregated charge/discharge energy at the specific hour, as illustrated in Fig. 7.2.

7.2.2 Case Study of PEV Impact on the Spot Price

A winter weekday in the year 2010 is chosen as the study case. The spot price, the system demand, the generation curve and the demand curve are collected from the Nord Pool market [34]. Fig. 7.3 illustrates the spot price and the system demand of the winter weekday.



(a)



(b)

Fig. 7.3. (a) The spot price of the winter weekday. (b) The system demand of the winter weekday.

The case that the PEV is charged immediately when it connects to the grid is chosen as the reference case (dumb charging) in the study, which is the same as the previous chapter. The optimal operation strategy of PEVs and assumptions are also the same as the previous chapter. Fig. 7.4 illustrates the aggregated charge/discharge power of all the PEVs in Nordic countries for both the reference case and the optimal case. In the reference case, the battery of the PEVs is charged immediately when it connects to the grid at 18:00. However, in the optimal case, the PEVs is charged when the electricity price is low in the early morning and discharged when the price is high at around 18:00 in order to minimize its energy costs, as discussed in the previous chapter. The total energy cost of all the PEVs in Nordic countries in the studied winter weekday is 145.6 kEUR for the reference case and 83.3 kEUR for the optimal case, which means 42.8% of energy cost saving.

The total system demand in Nordic countries after the PEV integration can be calculated by adding the system demand (see Fig. 7.3. (b)) and the aggregated charge/discharge power of all the PEVs (see Fig. 7.4). Fig. 7.5 illustrates the total system demand in Nordic countries after the PEV integration in the winter weekday for the different cases. In the reference case, the total system demand increases at around 18:00 when all PEVs charge at that time. In the optimal case, the total system demand increases in the early morning and decreases at around 18:00 due to the optimal charge/discharge of the PEVs.

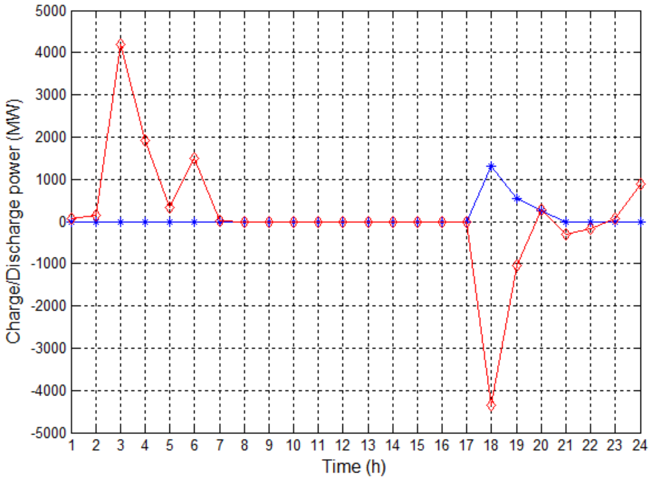


Fig. 7.4. The aggregated charge/discharge power of all the PEVs in Nordic countries (blue asterisk line: the reference case, red diamond line: the optimal case).

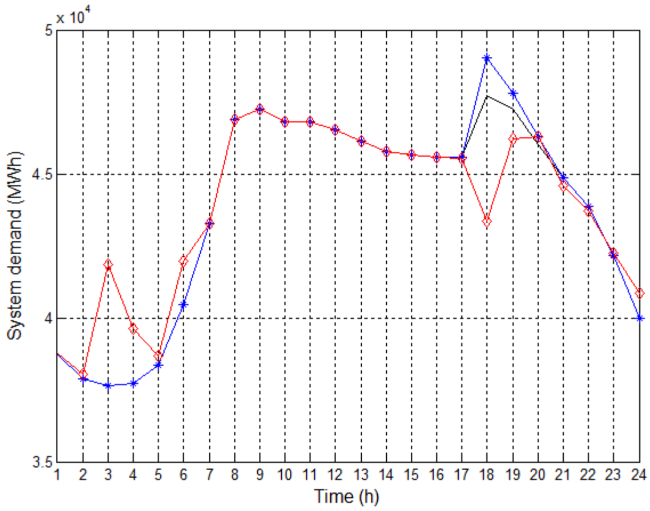
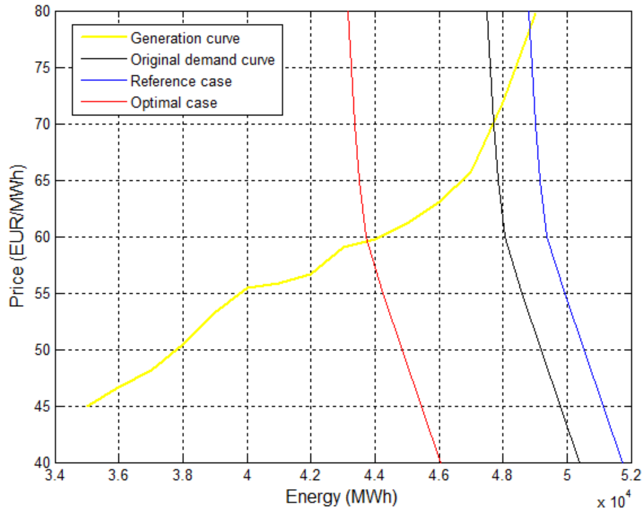
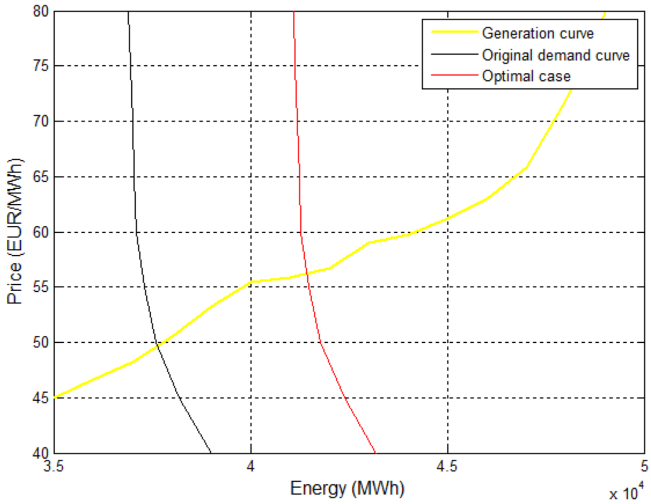


Fig. 7.5. The total system demand in Nordic countries after the PEV integration in the winter weekday for different case (black line: original system demand, blue asterisk line: the reference case, red diamond line: the optimal case).

The total system demand in Nordic countries after the PEV integration is different from the original system demand and it will naturally lead to the different electricity price. Fig. 7.6 shows the bidding curve at 18:00 and 03:00 of the studied winter weekday for different cases. The demand curve in the reference case moves to the right and the demand curve in the optimal case moves to the left at 18:00, because the total system demand in Nordic countries increases in the reference case and decreases in the optimal case at this hour. From this figure, it can be observed that the spot price increases in the reference case and decreases in the optimal case at 18:00. The spot price increases in the optimal case at 03:00, because the total system demand in Nordic countries increases in the optimal case at this hour.



(a)



(b)

Fig. 7.6. (a) The bidding curve at 18:00 of the studied winter weekday. (b) The bidding curve at 03:00 of the studied winter weekday (yellow line: generation curve, black line: original demand curve, blue line: demand curve in the reference case, red line: demand curve in the optimal case).

The bidding curve can be drawn for each hour in the studied day and the new spot price for both the reference case and the optimal case can be calculated. Finally, Fig. 7.7 illustrates the original spot price, the spot price for the reference case and the spot price for the optimal case in the studied day. There is a higher peak in the spot price for the reference case at around 18:00 due to all PEVs charging at this time. The spot price for the optimal case increases in the early morning and decreases at around 18:00 due to the PEV optimal charge/discharge operations. However, the PEV charging/discharging behavior will change again according to these new electricity prices. This issue will be discussed in the next section.

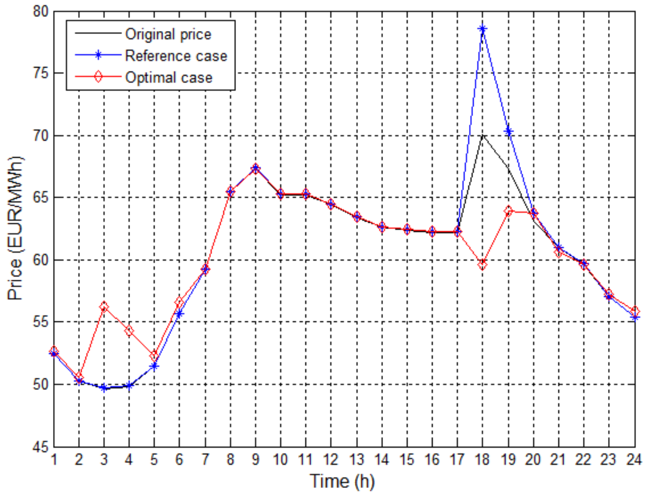


Fig. 7.7. The original spot price, the spot price for the reference case and the spot price for the optimal case in the studied day (black line: original price, blue asterisk line: the reference case, red diamond line: the optimal case).

7.3 The Interaction between Electricity Price and System Demand

7.3.1 Problem Formulation

The charging/discharging behaviors of PEVs have some impacts on the spot price as discussed in the Section 7.2. However, the new spot price will also affect the charging/discharging behaviors of PEVs again. So it can be formulated as an interaction problem. In this section, the interaction between electricity price and system demand will be studied.

Fig. 7.8 illustrates the flow chart of the proposed algorithm to this interaction problem. The parameters of the algorithm, such as the original system demand, the spot price and original bidding curve from both generation side and demand side, are initialized in the first step. Then the PEVs charge/discharge optimally according to the electricity price in order to achieve the minimum electricity costs in the day as discussed in Chapter 6. The consumers also shift their other loads according to the electricity price in order to achieve the minimum electricity costs in the same day as discussed in Chapter 3. The total system demand in Nordic countries is then calculated based on the PEV optimal charging/discharging energy and shifted load by consumers. Finally, the new price will be calculated according to the total system demand as discussed in Section 7.2. The algorithm makes a lot of iterations in order to find the final solution until the stopping criterion is satisfied. The stopping criterion is no further energy cost saving can be achieved for both PEV owners and consumers or that the maximum number of iterations is reached.

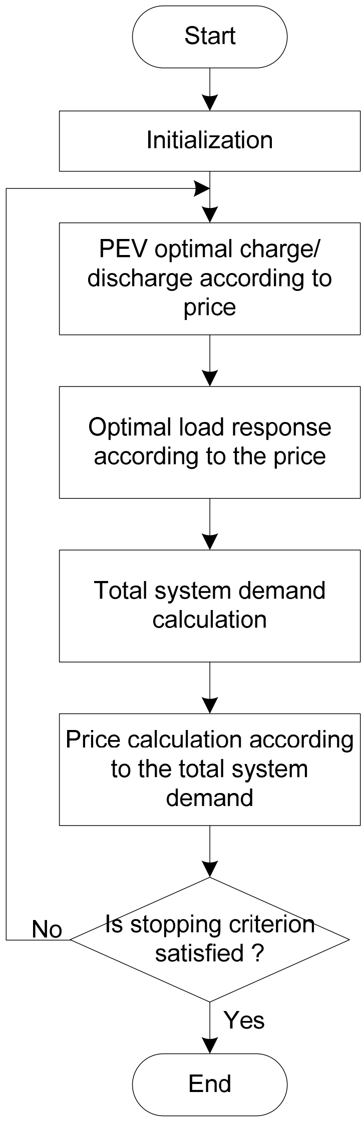
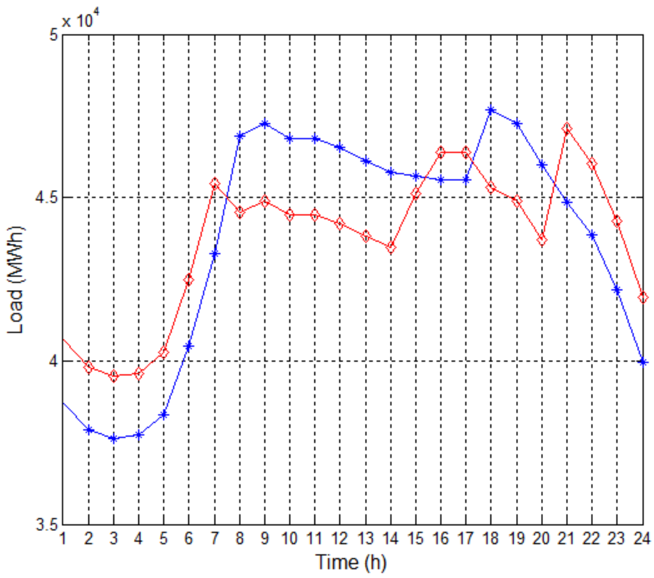


Fig. 7.8. The flow chart of the proposed algorithm to this interaction problem.

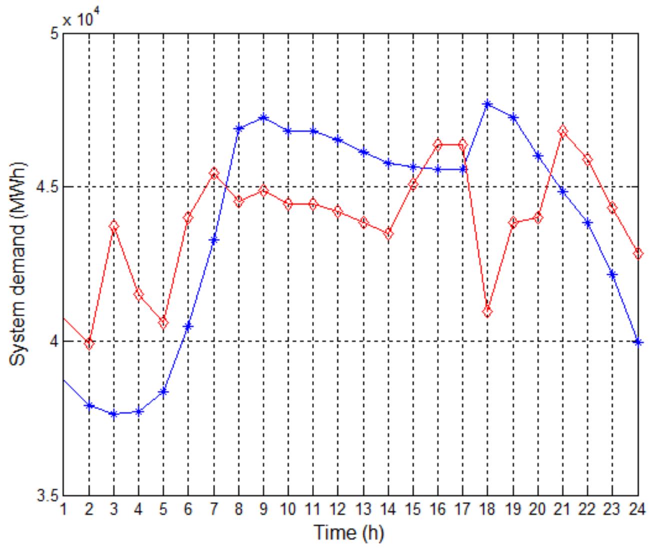
7.3.2 Case Study of The Interaction between Electricity Price and System Demand

The same winter weekday in the year 2010 is chosen as the study case. The spot price and the system demand of the winter weekday have been shown in Fig 7.3. It is assumed that the consumers can shift their other loads in the range (-5%~5%) of their original demand at each hour according to the electricity price. Fig. 7.9 shows the optimal load response without PEVs according to the electricity price and the total system demand in Nordic countries with PEV integration after the first iteration. It can be seen that the consumers shift their loads from high price periods to the low price periods in order to save their energy costs. The total system demand increases a lot in the early morning and late night when the electricity price is lower during these periods. The total system demand generally decreases in the day time due to the optimal load response to the electricity price and optimal charge/discharge of the PEVs. The total system demand increases at 16:00 and 17:00 during the day time, because the electricity price is relatively low at the 2 hours during the day time.

Then the bidding curve can be drawn for each hour using the new total system demand in the studied day and the new spot price can be calculated. Fig. 7.10 illustrates the original spot price and the spot price for each hour in the studied day after the first iteration. It can be observed that the new electricity price increases in the early morning and late night, and generally decreases in the day time. The new electricity price has similar pattern as the new total system demand in Nordic countries. It can be also observed that the new electricity price becomes flatter compared with the original electricity price.



(a)



(b)

Fig. 7.9. (a) The optimal load response without PEVs according to the electricity price after the first iteration (blue asterisk line: original load, red diamond line: optimal load). (b) The total system demand in Nordic countries with PEV integration after the first iteration (blue asterisk line: original system demand, red diamond line: new system demand).

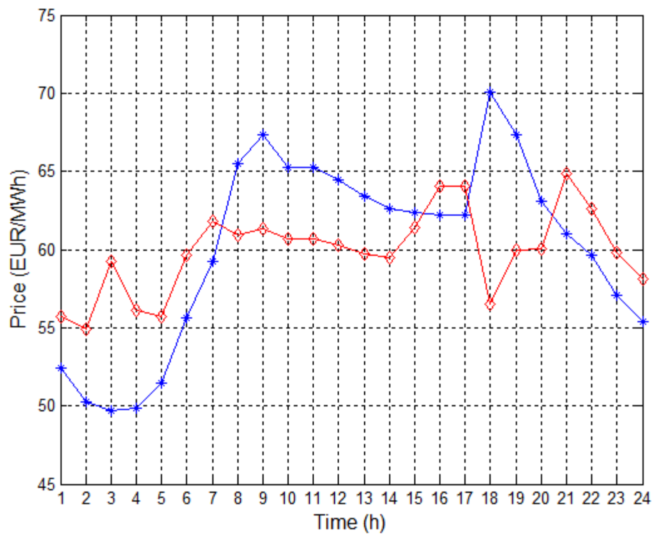


Fig. 7.10. The original spot price and the spot price for each hour in the studied day after the first iteration (blue asterisk line: the original price, red diamond line: the new calculated price).

The consumers may then shift their load optimally and charge/discharge their PEVs optimally according to the new electricity price again, which has been illustrated in Fig. 7.10. The same procedures can be adopted at each iteration, as shown in Fig. 7.8. Fig. 7.11

illustrates the original electricity price and the final new electricity price for each hour in the studied day. It can be observed that the final new electricity price becomes even flatter through the whole studied day compared with the electricity price after the first iteration. The original system demand and the final new system demand for Nordic countries for each hour in the studied day are shown in Fig. 7.12. It can be concluded that both the electricity price and the system demand will become flat in a long run, when the PEVs can be optimally charged/discharged and the load can be optimally shifted to other time periods.

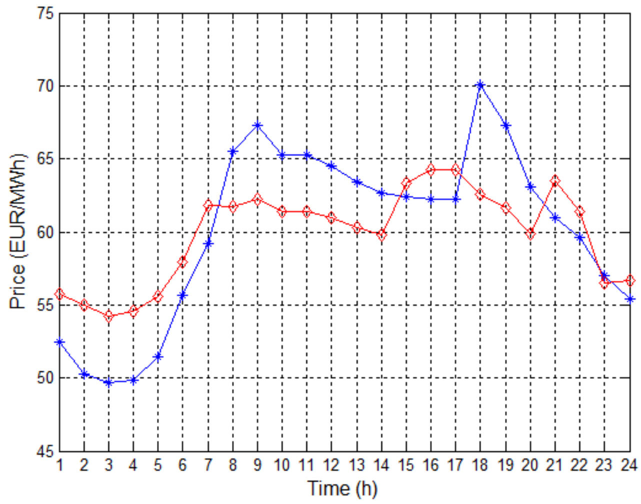


Fig. 7.11. The original electricity price and the final new electricity price for each hour in the studied day (blue asterisk line: the original price, red diamond line: the final new calculated price).

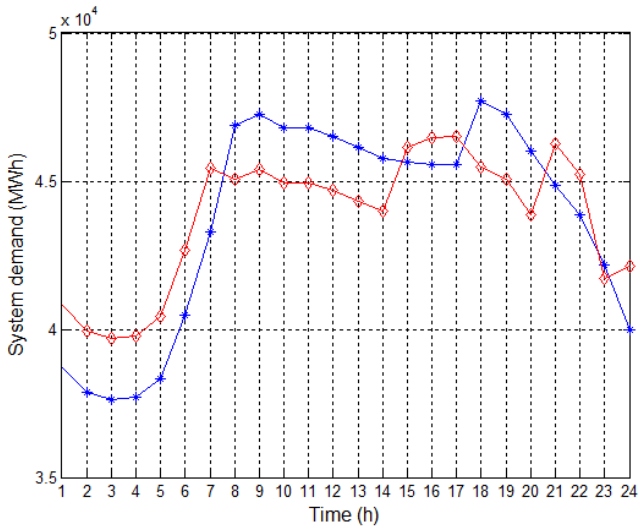


Fig. 7.12. The original system demand and the final new system demand for Nordic countries for each hour in the studied day (blue asterisk line: the original system demand, red diamond line: the final new system demand).

7.4 Summary

This chapter first presents the impact of different PEV charging/discharging strategies on the spot market price. When the dumb charging is adopted for all PEVs in Nordic countries, there is a high spot price peak in the late afternoon. When the optimal charging/discharging strategy is adopted for all PEVs in Nordic countries, the spot price increases in the early morning and decreases in the late afternoon.

In this chapter, the interaction between the electricity price and the system demand is also studied. Both the optimal PEV charging/discharging strategy and the optimal load response according to the electricity price, which have been proposed in the previous chapter, are adopted in this chapter. It can be concluded from the simulation results that both the electricity price and the system demand will become flat in a long run, when the PEVs can be optimally charged/discharged and the load can be optimally shifted to other time periods according to the electricity price.

Chapter 8

Conclusions and Future Work

8.1 Conclusions

This dissertation has investigated the characteristics of a distribution system under a dynamic electricity-pricing, load management system and under a large number of distributed generation units. The characteristics of a power system with wind turbines, DG units, loads and electricity prices have been studied. Further, the effects of energy storage systems have been considered, and an optimal operation strategy for energy storage devices in a large scale wind power system in the Danish competitive electricity market is proposed. Finally, the interactions between the electricity market and the system operation and control strategies have been explored.

The Danish power system is currently the grid area in the world that has the largest share of wind power in its generation profiles, with around 20% of its annual consumption generated by wind turbines. In this thesis, the Danish power system, which may represent the future of competitive electricity markets in some ways, is chosen as the studied power system. 10 year actual data from the Danish competitive electricity market are collected and analyzed. The relationship among the electricity price, the consumption and the wind power generation in the electricity market is investigated. The spot price and the regulation price generally decrease when the wind power generation in the power system increases or the consumption of the power system decreases. The statistical characteristics of the spot price and the regulation price for different consumption periods and wind power generation are analyzed. These findings are useful for wind power generation companies to make an optimal bidding strategy so that the imbalance cost of trading wind power on the electricity market can be reduced.

The formulation of an imbalance cost minimization problem for trading wind power in the Danish short-term electricity market is presented in the thesis. Because of the uncertainty of the regulation price, the activated regulation of the power system and the forecasted wind power generation, stochastic optimization and a Monte Carlo method are adopted to find the optimal bidding strategy for trading wind power in the Danish short-term electricity market in order to minimize the imbalance costs for regulation. Simulation results show that the stochastic optimal bidding strategy for trading wind power in the Danish short-term electricity market is an effective measure to maximize the revenue of the wind power owners.

Then the load response to electricity price using demand side management is studied in the thesis. Consumers may shift their loads from high price periods to the low price periods in a day in order to save their energy costs. A load optimization method to save the consumers' energy costs as much as possible is proposed. Optimal load responses of 3 typical loads in Denmark are studied. A distribution system where wind power capacity is 126% of maximum loads is chosen as the study case. The optimal load response to the electricity price generates different load profiles. Simulation results show that these kinds of load patterns have some good impacts on the power system constrains in the distribution system with high wind power penetrations. The overloading percentage of the transformer in the distribution system decreases from 3.23% to 1.69% with the optimal load response to the electricity price.

Power loss minimization in a distribution system may be realized by using the optimal load response according to the electricity price. In this thesis, an idea of power loss minimization in a distribution system by choosing an optimal hourly electricity price is proposed. The power loss minimization problem in distribution systems is modeled into two layers: load optimization to electricity prices (the inner layer) and power loss minimization with optimal electricity prices (the outer layer). The objective functions and the necessary assumptions of each optimization layer are presented. On the basis of the developed 2 layer model of the optimization problem, a fuzzy adaptive particle swarm optimization algorithm is presented as a tool for power loss minimization in distribution systems. Around 12% power loss reduction in the studied distribution system can be achieved when the proposed idea and algorithm are employed. It can be concluded from the simulation results that optimal choosing of electricity prices using the FAPSO algorithm is an effective measure to minimize the power loss in the distribution system.

The optimal load response according to electricity prices for different hours for demand side management will generate different load profiles. When the power system operates near its physical boundaries, a different electricity price for different hours may be given to consumers in order to motivate them to reduce or reschedule their demands. Consequently, the power flow may be changed and the power systems will be operated in a good condition, when appropriate electricity prices are given to consumers. The ideas and algorithms of power system operation improvement using demand side management are proposed in this thesis. Three different cases are studied to solve power system constraints, improve power system small signal stability and power system transient stability by deciding appropriate electricity prices for different hours. It can be concluded from the simulation results that optimal choosing of electricity prices is an effective measure to improve operation conditions of power systems with high wind power penetrations.

Then the benefits of using energy storage systems in the Danish competitive electricity market are researched in the thesis. An optimal operation strategy of battery energy storage systems to the spot market electricity price in order to achieve maximum profits of the BESS is proposed in this thesis. Two kinds of BESS based on PSB battery and VRB battery technologies are studied. Although the annual revenue of the VRB battery is higher than the annual revenue of the PSB battery, the payback period of the PSB battery is shorter than the payback period of the VRB battery. So the PSB battery is the better investment choice for the time being. The payback period of the PSB battery is around 14 years if the power capacity and energy capacity of the PSB battery are chosen appropriately.

This thesis also describes a study of integration of plug-in electric vehicles in the power systems with high wind power penetrations. An optimal operation strategy of PEVs in relation to the hourly spot price in competitive electricity markets is proposed in order to achieve minimum energy costs for the PEV owners. The total daily energy costs of all PEVs are decreased from 23.1 kEUR to -26.2 kEUR in the studied winter weekday, if the proposed optimal operation strategy is used. The application of battery storage based aggregated PEV is then analyzed as a regulation service provider in the western Danish power system with high wind power penetrations using LFC. It can be concluded from the simulation results that the power exchange deviations are significantly reduced between West Denmark-UCTE interconnections with the use of PEV regulation power. The PEVs can not only optimally charge/discharge in the spot market to minimize their energy costs, but also provide regulation power at the same time for both high and low wind speed days. The daily revenue for PEV owners is 30.0 kEUR for providing regulation power in the studied winter weekday. The annual revenue is estimated to 204 EUR per PEV, if the PEV owners would optimally charge/discharge in the spot market and provide regulation power at the same time.

Finally, the impacts of different PEV charging/discharging strategies on the spot market price are studied in this thesis. When the dumb charging is adopted for all PEVs in Nordic countries, there is a high spot price peak in the late afternoon. When the optimal charging/discharging strategy is adopted for all PEVs in Nordic countries, the spot price increases in the early morning and decreases in the late afternoon. The interaction between the electricity price and the system demand is also researched. It can be concluded from the simulation results that both the electricity price and the system demand will become flat in a long run, when the PEVs can be optimally charged/discharged and the load can be optimally shifted to other time periods according to the electricity price.

The consumers are assumed very sensitive to the electricity price and smart enough to make the optimal decisions, which have been illustrated in the research project. And also for the time being, private consumers will not have the spot market price as their price, their real expected fluctuation in the price will be much lower due to tax and other tariffs. Therefore, the real consumer behaviors may be different from the optimal ones as discussed in this thesis. However, the results presented in the thesis can be considered as the best performance from the private consumers, if they are subject to the variable spot market prices.

8.2 Future Work

Some other interesting and relevant topics are identified during the process of the research work. The important research topics that could be considered for further investigation in the future are listed as follows.

1) The relationship among the electricity price, the consumption and the wind power generation in the Nordic intra-day balancing market (Elbas) needs to be investigated. A better market structure and mechanism for the Elbas needs to be designed in order activate this market.
2) The other economic benefits of the battery energy storage system (BESS) by providing spinning reserve, frequency regulation and renewable energy support needs to be studied.
3) The operating and maintenance cost of the BESS and its effects on the optimal operation strategy of the BESS needs to be researched.
4) The lifetime of the batteries in PEVs needs to be evaluated when the PEVs are optimal charged/discharged and provide regulation power to the power systems.
5) The customers' responding characteristics, such as attitudes towards the new technology, sensitivity to electricity price, needs to be further studied. The effects of tax issue in the customers' energy costs also need to be addressed.
6) The proposed optimal operation and control strategies needs to be further validated in a much larger power system. Other physical constraints which affect the possibilities to implement the proposed control strategies, such as information and communications technology (ICT) and automatic control system, etc., need

to be researched. A Real Time Digital Simulator (RTDS) will be used to test and verify the proposed algorithms.

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[P6] Weihao Hu, Zhe Chen, Birgitte Bak-Jensen, "Fuzzy Adaptive Particle Swarm Optimization for Power Loss Minimization in Distribution Systems Using Optimal Load Response," *IET Generation, Transmission & Distribution*, (Status: Submitted).

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Appendix

Detailed Models of PEV in DIgSILENT

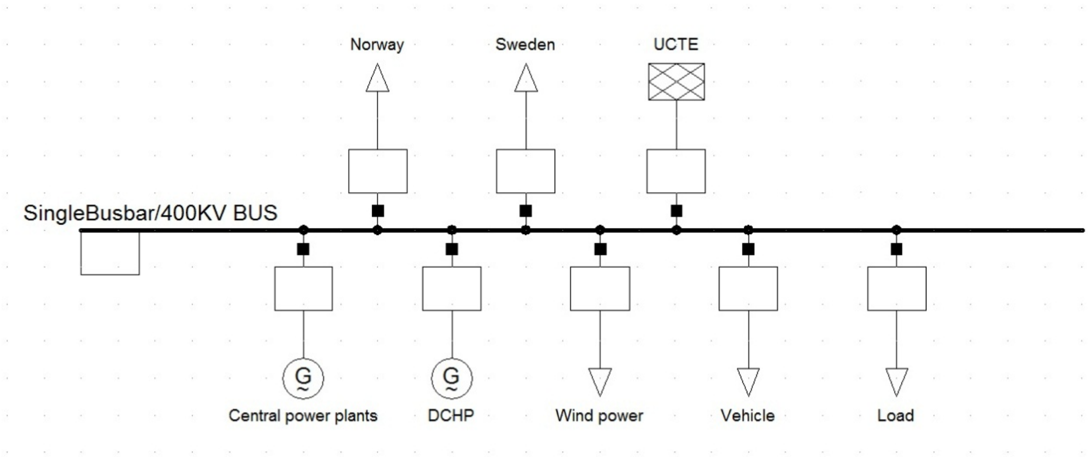

Fig. A.1. The single bus bar model for Western Danish power system.

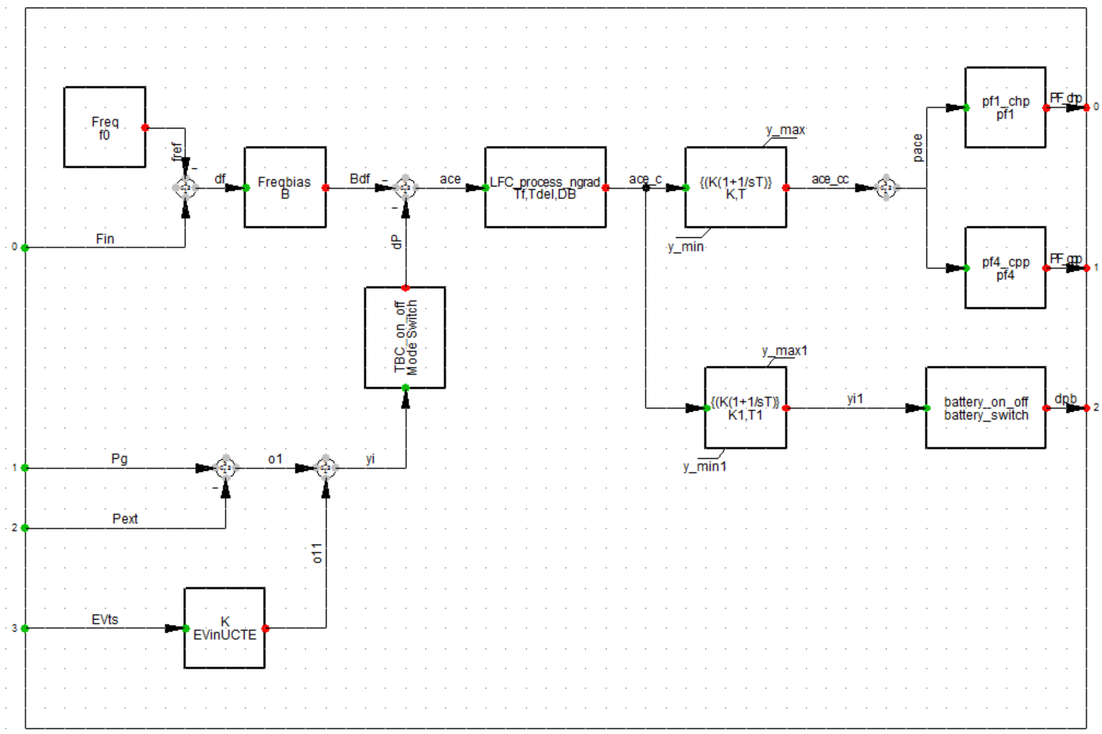

Fig. A.2. The model of load frequency control in DIgSILENT PowerFactory.

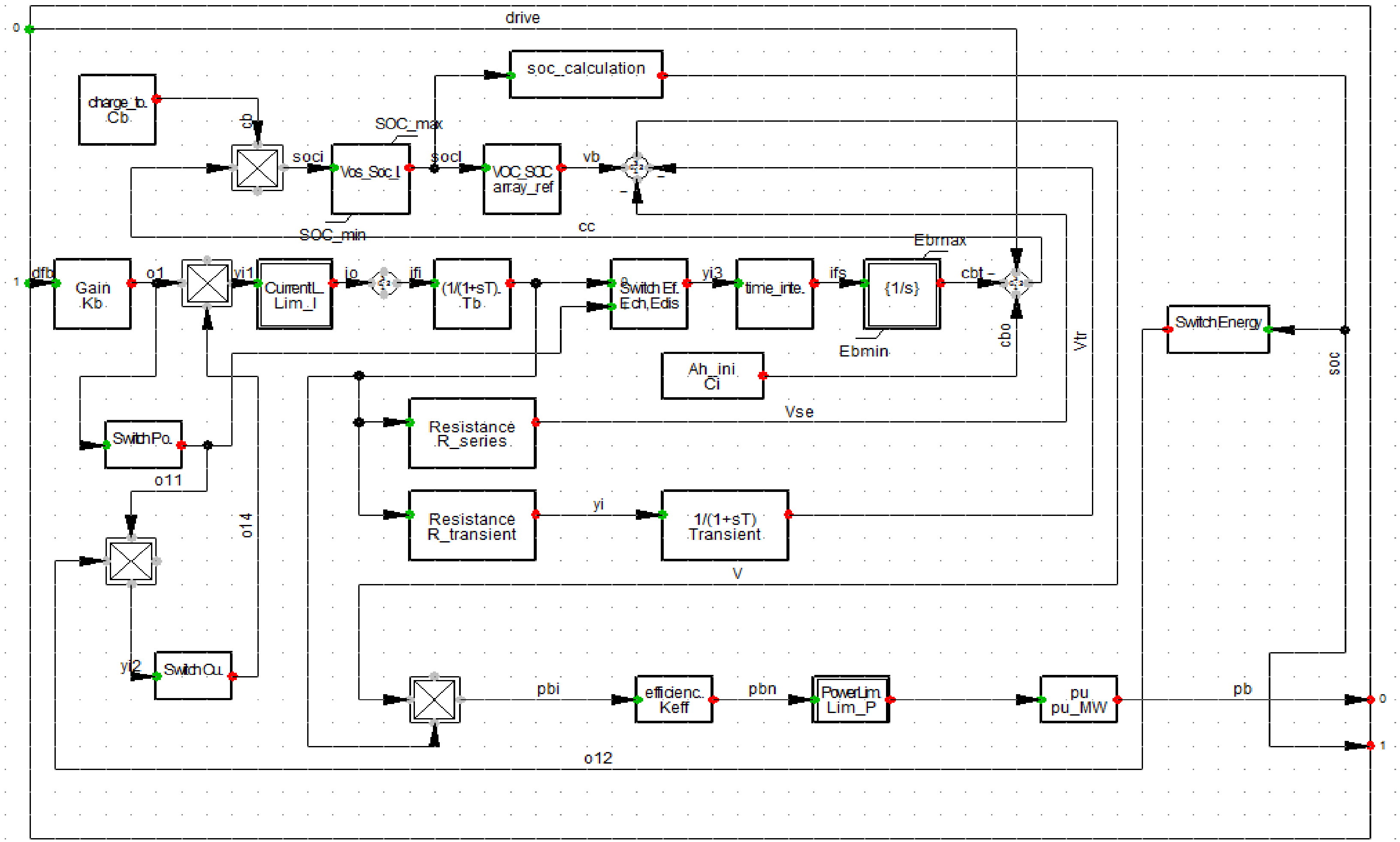

Fig. A.3. The detailed model of the aggregated PEV battery in DIgSILENT PowerFactory.