Long-Term Planning in Restructured Power Systems

Dynamic Modelling of Investments in New Power Generation under Uncertainty

by

Audun Botterud

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Main advisor: Professor Ivar Wangensteen (NTNU)
Co-advisor: Professor Marija D. Ilic (Carnegie Mellon University/MIT)

PREFACE

This thesis is the result of a doctoral project in Department of Electrical Power Engineering at the Norwegian University of Science and Technology, lasting from January 2000 to December 2003. A substantial part of the research was accomplished during a visit of eighteen months to the Laboratory for Energy and the Environment at Massachusetts Institute of Technology (MIT) in Cambridge, MA USA.

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Acknowledgements
First of all I would like to express my sincere gratitude to the late Professor Øyvin Skarstein, who initiated this project. His forward-looking thinking and inspiring supervision gave me the best possible starting point for my doctoral studies. Unfortunately, his tragic disease made him pass away far too early. He could therefore not see the full results of his original research ideas for this thesis.

I am deeply indebted to Professor Ivar Wangensteen, who took over as my main academic advisor. He has given me invaluable advice throughout my studies. At the same time he has provided me with the necessary freedom and flexibility to pursue my own ideas. During my eighteen months at MIT I have benefited greatly from working with Professor Marija D. Ilic (now at Carnegie Mellon University) and Mr. Stephen Connors. Specifically, the inputs and advice from Professor Ilic have made very important contributions to the contents of this thesis. I am also grateful to Professor Rolf Marstrander, along with Mr. Connors, for establishing the links between NTNU and MIT, and thereby giving me the opportunity to visit this great research institution.

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My most precious feelings go to Bilge Yildiz, who opened up a new dimension in my life with her appearance more than two years ago. Bilge has played a crucial role in supporting me through the final stressful stages of my doctoral studies, something I am deeply grateful for.

In the end, most of all I want to thank my family and especially my parents. None of my achievements would have been possible without their enduring love and support.

Trondheim, November 2003.

SUMMARY

This thesis describes the development of three decision support models for long-term investment planning in restructured power systems. The model concepts address the changing conditions for the electric power industry, with the introduction of more competitive markets, higher uncertainty and less centralised planning. Under these circumstances there is an emerging need for new planning models, also for analyses of the power system in a long-term perspective. The thesis focuses particularly on how dynamic and stochastic modelling can contribute to the improvement of decision making in a restructured power industry. We argue that the use of such modelling approaches has become more important after the introduction of competitive power markets, due to the participants' increased exposure to price fluctuations and economic risk. Our models can be applied by individual participants in the power system to evaluate investment projects for new power generation capacity. The models can also serve as a decision support tool on a regulatory level, providing analyses of the long-term performance of the power system under different regulations and market designs.

In Chapter 1, we give a brief introduction to the ongoing development towards restructuring and liberalisation of the electrical power system. A discussion of the operation and organisation of restructured power systems is also provided. In Chapter 2, we look more specifically at different modelling approaches for expansion planning in electrical power systems. We also discuss how the contributions in this thesis compare to previous work in the field of decision support models for long-term planning in both regulated and competitive power systems. In Chapter 3, we develop a power market simulation model based on system dynamics. The advantages and limitations of using descriptive system dynamics models for long-term planning purposes in this context are also discussed. Chapter 4 is devoted to a novel optimisation model which calculates the optimal investment strategy for a profit maximising investor considering investments in new power generation capacity. The model is based on real options theory, which is an alternative to static discounted cash flow evaluations of investments projects

under uncertainty. In the model we represent load growth as a stochastic variable. A stochastic dynamic programming algorithm is applied in order to solve the investment problem. Prices and profits are calculated in a separate model, whose parameters can be estimated based on historical data for load, prices and installed capacity in the power system. In Chapter 5, we extend the stochastic dynamic optimisation model from Chapter 4, so that the investor now can choose between two different power generation technologies to invest in. An alternative representation of the power market is also implemented, which makes it possible to use either a profit or a social welfare objective in the optimisation. With this model we can compare the optimal investment decisions, and the dynamics of investments, prices and reliability, which follow from centralised and decentralised decision making.

The main scientific contributions in the thesis lie in the combined use of economic theory for restructured power systems and theory for optimal investments under uncertainty. With an explicit representation of the power market, the dynamic investment models can identify profit maximising investment strategies under different regulations and market designs. The use of physical state variables in the models also facilitates analyses of the long-term consequences for the power system, which result from the optimal decentralised investment decisions. Decision support models for expansion planning in the regulated power industry do not address the aspect of competition and decentralised decision making. At the same time, long-term uncertainties and their impact on optimal investment decisions are rarely represented in planning models for the competitive industry. The stochastic dynamic models in this thesis therefore provide a new framework for long-term analysis of investments and prices in restructured power systems.

Potential applications of the investment models are demonstrated in a number of illustrative examples in the thesis. Through the analyses in these examples we have gained increased insight into the complex dynamics of prices, investments and security of supply in competitive power systems.

CONTENTS

Chapter 1 INTRODUCTION

“The more I see, the more I see there is to see”
John Sebastian

The importance of a dependable electrical power system is ever increasing in the modern world of today. Almost all aspects of society are dependent on electrical power in one way or the other to function properly. At the same time, the technical complexity of power delivery increases, as new technologies are being introduced into power systems with growing demand and increasing geographical scope. The technical and societal changes nourish the ongoing debate about how the electrical power system should be organised, in order to best meet the various demands it serves in the society. Different structures for power system organisation are also being implemented in various parts of the world. This thesis will shed some light into some of the long-term challenges regarding the continued reliance on electrical power as a primary energy carrier.

In the introductory chapter we first discuss two fundamental drivers for changes in the electrical power system. Then we provide a short overview of the different participants involved in the operation of the electrical power system, their interaction and how they are regulated. Furthermore, we identify which aspects of this complex system that are addressed in this thesis. Finally, an outline of the thesis is provided along with the main scientific contributions in our work.

1.1 Two Fundamental Drivers for Changes in the Power System

Two fundamental trends in society are important drivers in the long-term development of the electrical power system. The first trend is the demand for cost efficiency, which has triggered a wave of deregulation and liberalisation initiatives in various industries that used to be operated under regulation (e.g. aviation, railway, telecommunication, gas, and electricity).

The second trend is the increased public awareness of the environmental consequences caused by the increasing use of energy in the world. This aspect drives the search for new and cleaner technologies to generate electricity. The two trends, economic efficiency and environmental responsibility, contribute to change the conditions under which the participants in the electrical power system operate. The objective behind power system liberalisation is to increase the competition, and thereby also the economic efficiency in the operation of the electrical power system. One important consequence of the liberalisation is that the traditional regulated utilities shift their focus from cost minimisation to profit maximisation in the segments of their operation where competition is introduced. At the same time, uncertainty plays a more prominent role, as stochastic factors are immediately reflected in the power market's spot prices. This is in contrast to the regulated system, where uncertainties very rarely have an effect on the regulated tariffs. Another general effect of the corresponding restructuring of the power industry, which can also add to the increased uncertainty, is a higher degree of decentralised decision making in the system. The increased environmental concern is mainly reflected in regulations whose aim is to curb polluting emissions from power generation. Tradable certificates for renewable power generation and limits, quotas, and taxes on emissions from power plants are examples of such environmental regulations. While the drive towards competitive markets in general induces fewer regulations in the system, the drive towards less environmental impact tends to introduce more regulations.

1.2 Operation and Organisation of Restructured Power Systems[1]

The shift towards liberalised and competitive power markets has led to a major change in how electrical power systems are being operated and organised. Electrical power systems are large-scale, integrated, and complex engineering systems which need a certain level of centralised coordination to function. Besides, electric power has a set of special features which makes it different from most other commodities that are traded in competitive markets. The list of special features includes instant and continuous generation and consumption, nonstorability, high variability in demand over day and season, and nontraceability (i.e. a unit of consumed

[1] The various expressions that are frequently being used to describe the change in how electrical power systems are organised can be somewhat confusing. Deregulation is a term that fits best to the ongoing reorganisation of power systems in the US, where the traditional regulatory structure has been privately owned utilities under public regulation. In contrast, the European tradition has been to have publicly owned utilities where the regulation has followed more from the direct public ownership. The terms restructuring and liberalisation are therefore more general expressions for the reorganisation of the power systems that takes place in different parts of the world, and these terms are used throughout this thesis.

electricity can not be traced back to the actual producer). At the same time electricity is an essential good for society, and we know that blackouts with huge detrimental effects can occur if the system is not maintained under control. Furthermore, generation and transmission of electricity are highly capital intensive businesses. Large up-front investments can easily deter new participants from entering the market, and thereby prevent efficient competition. It is therefore obvious that special attention is essential in the process of liberalising and restructuring the electrical power system. There is currently no real consensus among researchers and industry practitioners about what is the ideal organisation of a liberalised market for electricity. The optimal solution will necessarily depend on the physical character of the power system in question, and different market designs are implemented in various parts of the world. The purpose of this section is not to give an extensive presentation of all the aspects of the different market designs. However, we want to give an overview of the main participants that are typically involved in the planning and operation of a restructured power system, and how the participants interact and are regulated (Figure 1.1). With such an overview it is easier to understand the scope and limitations of the work presented in this thesis.

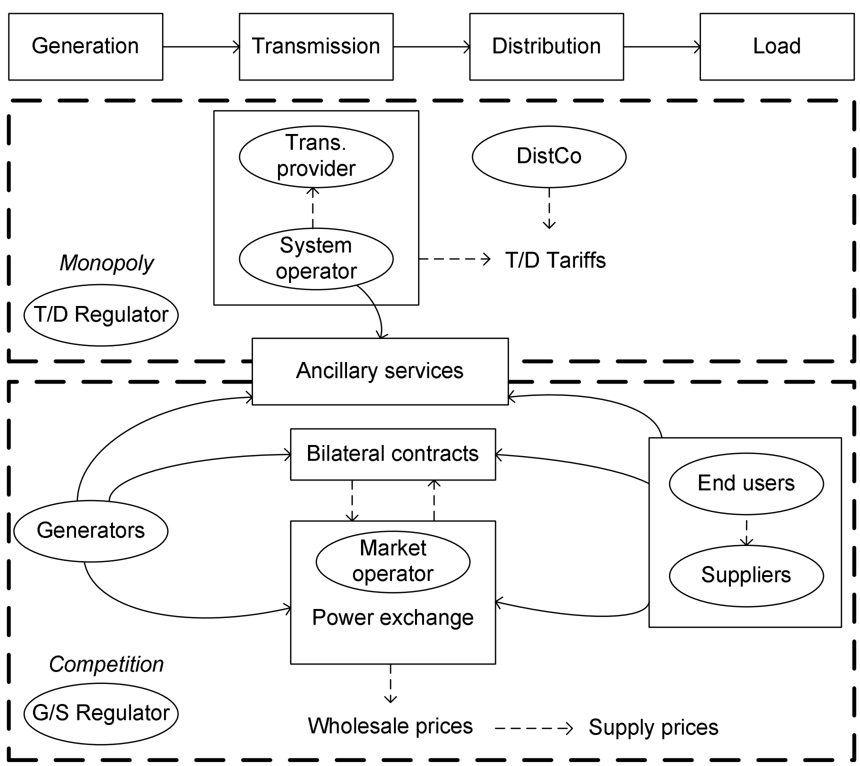

Figure 1.1 Illustration of the main participants involved in electric power delivery in a restructured power system.

Figure 1.1 shows a simplified picture of the interaction between the most important participants in a fully liberalised power system, with competition on the wholesale and supply levels. The organisation of the power system can be split into two separate parts, which are operated under different regulatory regimes. The transmission and distribution of electric power are natural monopolies, and usually subject to strict public regulation. The cost of operating the transmission and distribution system is therefore transferred to the end users in terms of tariffs. On the other hand, generators and end-users have open access to the grid and operate in a competitive market. The wholesale price of electric power is settled through market mechanisms, and transferred to end users through the supply prices. In order to facilitate such an arrangement the traditional utilities must be unbundled, i.e. the generation and supply parts are separated from transmission and distribution. The main participants in the system are briefly described below[2].

1.2.1 Transmission and Distribution

System operator

The system operator plays a very important role in the coordination and operation of the power system, and is responsible for always keeping supply equal to demand. Trading between generators and end users in the power market provides equilibrium between expected supply and demand. However, in order to keep the balance in real time under various contingencies, the system operator needs to purchase so called ancillary services. This is further discussed in section 1.2.3. Congestion management and transmission pricing are also the responsibilities of the system operator.

Transmission provider

The transmission provider owns and operates the high voltage transmission grid in the power system. The system operator and the transmission provider can be the same entity, like in the Nordic countries, where the system operators own the main grids in the respective countries. However, the grid can also be owned by separate companies and coordinated through an independent system operator (ISO), as is frequently the case in the US. The costs related to running the transmission grid (investments, operating costs, transmission losses etc.) are recovered from the transmission tariff.

[2] For a detailed description of power system operations for the regulated and competitive power industry, see Ilic and Galiana [1] chapter 2. Wangensteen [2] gives a comprehensive description of power system economics, with special attention to the restructured power system in Scandinavia.

Distribution company (DistCo)
The distribution companies are responsible for operating the lower voltage grids, and ensure that end users have access to their local network. This is also a monopoly service and total costs for investment and operation of the distribution grid is reflected in the distribution tariff.

T/D Regulator
Transmission and distribution (T/D) are regulated as natural monopolies. The T/D regulator controls that there is open access to the T/D grid, and also regulates the tariffs and revenues for the transmission provider and the distribution companies.

1.2.2 Generation and Supply

Generators
The generators are responsible for feeding sufficient electricity into the grid. With open access to the network there is wholesale competition between generators of various technologies and ownership. The generators bid their power generation into the market, either through an organised power exchange or via bilateral contracts.

End users
The end users usually participate in the power market through suppliers. Competition on the supply level ensures that the end users can buy their electricity from which supplier they want. Large scale customers with real time metering can also be able to participate directly in the wholesale electricity markets, by submitting their bids to the power exchange or directly to a generator.

Suppliers
Suppliers represent end users in the wholesale market for electricity. Their bids into the market reflect the preferences of their customers. While the distribution company takes care of the physical transfer of power to the end users, the suppliers are responsible for the financial transactions between end users and generators. The metering of the end users is sometimes also the responsibility of the supplier. However, in the Norwegian system the distribution companies are mandated to take care of the metering.

Market operator
The market operator is responsible for organising a public power exchange. A range of different products will typically be traded at the power exchange, from physical day ahead contracts to financial forward contracts with delivery several years into the future. Bilateral contracts serve as

supplements to the contracts traded at the power exchange. A description of the products traded at the Nordic power exchange, Nord Pool, which is a separate entity owned by the system operators in Norway and Sweden, is provided in Appendix A[3]. In some other systems, for instance in the Northeast US (PJM, New York, New England), the system and market operator is the same entity.

G/S Regulator
Regulation is still needed, even if the supply and demand for electric power is organised through a competitive market. An important responsibility for the generation and supply (G/S) regulator is to define rules for how the power market is operated. This could for instance be in terms of deciding time resolution and curtailment policy in the close to real time physical markets for electricity. Furthermore, the G/S regulator is also responsible for preventing that participants can dominate the market and exercise market power. The regulation of G/S and T/D could be accomplished by the same regulatory body. However, this is not necessarily the case. In Norway there are two different entities involved in regulating the monopolistic and the competitive part of the electric power system.

The list presented here of participants in the competitive part of the power system is by now means exhaustive. *Brokers* and *traders* will for instance play important roles in maintaining liquidity for the products traded in the power market. Some of the participants in the power market also depend on separate *balance responsible entities* to keep track of the difference between scheduled and real time power consumption (or generation). The balance responsible entity serves as an intermediary between the market participant and the system operator.

1.2.3 Ancillary Services

The term “ancillary services” is an expression for the set of system services that the system operator relies on in order to maintain real-time balance and security of supply in the power system. Different definitions exist for what is included in the ancillary services, and the exact list of services will also depend on the physical characteristics of the power system[4]. However, the provision of operating reserves together with frequency and voltage control through balancing of real and reactive power in the system are always important elements of these services. The ancillary services are placed

[3] Appendix A also gives a brief history of the power system restructuring in Scandinavia, and presents an empirical analysis of prices in Nord Pool’s spot and futures markets.
[4] A hydro-dominated power system with a high fraction of generating units that can adjust their output on very short notice will typically need a different set of ancillary services than a thermal system with a majority of slowly responding generators.

between monopoly and competition in Figure 1.1. Some of the ancillary services, such as the instant balancing of real power in the system, can be organised through a market mechanism. However, a problem when it comes to introducing full competition in the provision of ancillary services is that the system operator is usually the only participant in the power system that can coordinate and determine the demand for these services in real time. While competition can be introduced on the supply side, it is difficult to create a market for ancillary services with an active and decentralised demand side. The cost of providing ancillary services therefore tends to be reflected in the transmission and distribution tariffs, although some of the costs could also be determined through competition.

1.2.4 The Balance between Competition and Regulation

Based on the description so far we see that the electrical power system is a demanding system to control, not only from an engineering perspective, but also from and economic and regulatory point of view. There is a fundamental trade-off between the use of competition and regulation in order to provide cost efficiency and lower environmental impact, and at the same time maintain the security of supply in the power system (Figure 1.2).

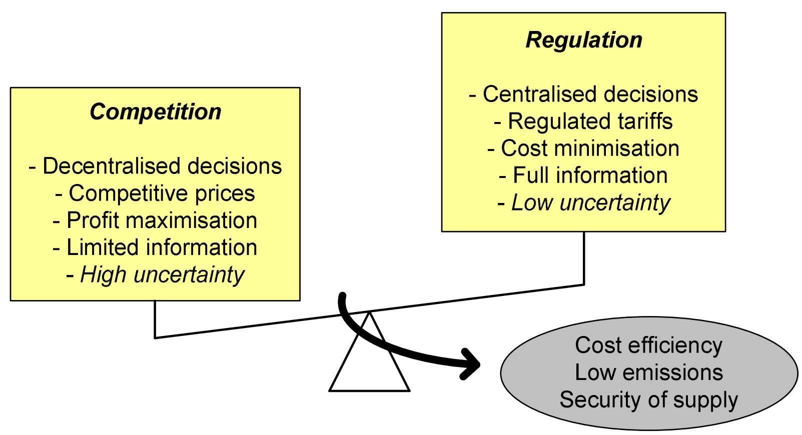

Figure 1.2 Illustration of the balancing trade-off between competition and regulation in the electrical power system.

Figure 1.2 can serve to illustrate trade-offs between competition and regulation in several parts of the electrical power system. Some of the most important trade-offs are:

- Establishing an appropriate line of separation between the monopolistic and competitive parts in the operation of the power system (Figure 1.1). This is particularly relevant for the organisation of ancillary services.

- Design of market rules that ensure efficient economic short-term operation of the electrical power system. Correct locational price signals and market power mitigation are important topics in this respect.

- Implementation of market rules and regulations that provide sufficient incentives for investments in the power system. Such incentives are crucial for the long-term security of supply.

- Design of incentives which ensure that environmental considerations are taken into account in operation and expansion of the system. This is necessary to lower the environmental impacts of power generation.

1.2.5 New Challenges for the Participants in the Power System

All the participants in the electrical power system will need to adapt to the changing regulative environment in which the system is operated. As illustrated in Figure 1.2, the participants that are making the shift from a regulated to a competitive regime will need to change their focus from cost minimisation to profit maximisation. This is the case for generators and suppliers in the restructured power system. Appropriate procedures for risk management now become more important as these participants are exposed to competitive prices with increased volatility. Participants in transmission and distribution will also be affected by increased uncertainty, since future decisions concerning investments in the power system are less predictable in a system with decentralised decision making. Long-term planning methods should be updated accordingly. The main challenge for authorities and regulators is to design a system with the correct balance between competition and regulation. The ultimate goal is to end up with an electrical power system where cost efficiency and low pollutions are achieved, without compromising the security of supply.

It is obvious that the participants in the restructured electrical power system need to adjust their planning methods in order to adapt to the changing environment in which they are operating. This has been pointed out by several authors (e.g. Hobbs [3] and Dyner and Larsen [4]). At the same time there is also a need for developing mathematical models that can provide better decision support under the new planning conditions.

1.3 Scope and Limitations of the Thesis

The discussion so far in this chapter illustrates the range of complexities involved in the organisation and operation of liberalised and restructured electrical power system. Naturally, this thesis only covers a limited part of all the challenges that the various participants in the system are facing.

The work presented in this thesis focuses on the competitive part of the restructured power system, as illustrated by the lower box in Figure 1.1. Our main attention is on investments in new power generation capacity, and on the long-term balance between supply and demand in restructured power systems. In a competitive power market the electricity prices are supposed to provide signals for investments in new power generation capacity. However, prices and investments depend on the rules and regulations that govern the market. In this thesis we study the long-term effects of environmental regulations (e.g. CO_2-taxation), direct investment incentives (e.g. capacity payments or subsidies) and market design (e.g. price caps). We also analyse how limited competition and high barriers to entry for new participants can possible influence investment levels, prices and system reliability. However, a number of important aspects are also left out of the analyses. For instance, we do not consider how the general rules for taxation of power generation companies' income influence profitability and investment behaviour. Corporate issues related to restrictions on capital and optimal equity/debt ratios are also left out of the analyses. We simply assume that sufficient capital at a certain interest rate is always available when favourable conditions for investment occur in the market. In addition, inflation is dealt with by using real interest rates in the investment models.

The objective in this thesis is to use mathematical modelling as a tool to increase the understanding of the complex dynamics of investments and prices in liberalised power systems. We develop a set of decision support models that generation companies can make use of in order to improve their investment strategies in the new competitive power systems. We are particularly concerned with the power generation companies' increased exposure to uncertainty, and how this affects their optimal investment strategies. The decision support models can be used to find optimal strategies for investments in new power generation capacity, but they can also simulate the development of supply and demand in the power system over a multi-year period. Hence, the models can also serve as a decision support tool for regulators that want to analyse the effect of various market designs and regulations.

The mathematical models presented in this thesis builds upon a number of simplifying assumptions. We are mainly concerned with modelling of the economic interaction between electricity prices and investments in new power generation plants. Decommissioning of existing plants is an important aspect which is not taken explicitly into account in our analyses. Less emphasis is also given to the representation of all the physical relations that determine the power flow between the different components in the power system. Transmission and distribution constraints are for instance disregarded, although they can have a major impact on the prices at constrained locations in the grid. The implementation of ancillary services can also influence the profitability of investments in new power generation, but this is not covered in extensive depth in the analysis presented here. Furthermore, the operation of the power plants is simply modelled with the assumption that units can be switched on and off according to their marginal costs. Inter-temporal constraints are neglected. Most of the modelling efforts are focused on the dynamics of supply and demand for electricity, and how new investments depend on the resulting prices in the power market. However, the model frameworks presented in this thesis are of a flexible nature, and can easily be extended to take into account at least some of the more technical aspects that are mentioned here.

1.4 Thesis Outline

After this brief introduction, we look more specifically at different modelling approaches for expansion planning in electrical power systems in Chapter 2. We also discuss how the contributions in this thesis compare to previous work in the field of decision support models for long-term planning in both regulated and liberalised power systems. In Chapter 3, we develop a power market simulation model based on system dynamics. The advantages of using system dynamics models for planning purposes in this context are also discussed. Chapter 4 is devoted to a new stochastic dynamic optimisation model which can calculate optimal timing of investments in new power generation assets for a profit maximising investor in the power market. The model is based on real options theory, which is an alternative to the use of static net present value evaluations of investment projects. The real options theory is presented in the beginning of the chapter, with focus on relevant applications to asset valuation in power markets. In Chapter 5, we extend the stochastic dynamic optimisation model from Chapter 4, so that the investor now can choose between two different power generation technologies to invest in. An alternative representation of the power market is also implemented, which makes it possible to use either a profit or a social welfare objective in the optimisation. With this model we can compare the investment dynamics which follows from centralised and decentralised decision making. Illustrative examples are provided for all the model concepts that are presented in the thesis. In the case studies in Chapter 3 and Chapter 4 we use the proposed models to analyse expansion projects which are currently relevant in the Norwegian power system.

In the appendices we have added four conference papers that have been written during this doctoral project. These papers can be read independently from the rest of the thesis. The first two appendices present material which is not extensively covered in the main text, since the content is slightly on the side of the main topics in our work. Appendix A and Appendix B are still referred to at relevant places in the text. The contents of Appendix C and Appendix D are incorporated into Chapter 3 and Chapter 4 respectively. The two papers give a compact presentation of the decision support models that are presented with more detail in the main chapters.

1.5 Main Scientific Contributions in the Thesis

The main scientific contributions in the thesis lie in the combined use of economic theory for restructured power systems and theory for optimal investments under uncertainty. With an explicit representation of the power market, the dynamic investment models can identify profit maximising investment strategies under different regulations and market designs. The use of physical state variables also facilitates analyses of the long-term consequences for the power system, which result from the optimal decentralised investment decisions. Decision support models for expansion planning in the regulated power industry do not address the aspect of competition and decentralised decision making. At the same time, long-term uncertainties and their impact on optimal investment decisions are rarely represented in planning models for the competitive industry. The stochastic dynamic models in this thesis therefore provide a new framework for long-term analysis of investments and prices in restructured power systems.

The specific contributions of the three decision support models proposed in the thesis can be briefly expressed as follows:

- Development of a descriptive system dynamics model for long-term analysis of demand, prices, and investments in different power generation technologies in a competitive power market.

- Formulation of the expansion planning problem under uncertainty for a decentralised profit-maximising investor in the power market. Development of a mathematical model based on real options theory and stochastic dynamic programming to solve the problem.

- Extension of the stochastic dynamic optimisation model to also calculate optimal investments under a social welfare objective, and thereby facilitating comparison of optimal investments under centralised and decentralised decision making.

Possible applications of the three models are illustrated in the case studies provided in the thesis. A number of interesting results also arise from these illustrative examples. These results are presented in detail throughout the chapters and in the conclusion of the thesis.

Chapter 2 DECISION SUPPORT MODELS FOR POWER GENERATION EXPANSION PLANNING

In this chapter we discuss planning methods and decision support models for expansion planning and long-term analysis of electrical power systems. First, we describe a number of planning methods that were developed for the regulated power industry. Particular attention is paid to multi-criteria trade-off analysis and how this planning concept can be adjusted to better fit the conditions in restructured power systems. We also discuss new and alternative planning methods that can contribute to improve decision making in competitive power markets. We then look more specifically at a set of general attributes for decision support models, and explain how they can address the changing planning conditions for the power industry. A list of model properties is presented, and used to illustrate how the new decision support models presented in this thesis compare to more traditional planning models. The discussion of model properties is also useful in order to understand how our model concepts can provide increased value to decision makers in the restructured electrical power industry. A final comment is made about the similarities between the problem of investing in new power generation under uncertainty, and the hydropower production planning problem.

2.1 The Power Generation Expansion Planning Problem

The general power generation expansion planning problem has at least three important dimensions that must be evaluated during the project assessment phase. Firstly, the project type must be considered, i.e. choice of technology and capacity size for the new plant. Secondly, the timing of the investment must be evaluated. Thirdly, the location of the new plant must also be decided. A full project evaluation is a large and complex task, which requires the use of various planning methods and decision support models.

In this thesis we are mainly concerned with the first two of these dimensions, while the question of optimal location in the electrical power system is not treated in any depth. The focus in our research is on developing mathematical models that are better capable of providing decision support in competitive power markets. As discussed in Chapter 1 the restructuring of the electrical power system has drastically changed the conditions under which the electrical power industry is operating, and this must also be taken into account in the planning methods and decision support models.

2.2 Long-Term Planning Methods under Regulation and Competition

We have seen that the planning conditions for the regulated electric power industry, with stable prices, centralised decision making and access to full information resulted in low uncertainty for the participants in the system Figure 1.2. Under these conditions, forecasting and optimisation are ideal long-term planning methodologies, and these methods were also frequently used in the regaled power industry, as pointed out by Dyner and Larsen [4]. Various planning techniques have been developed in order to optimise electricity supply systems under traditional regulation. We briefly present some common techniques below, with particular attention to the use of multi-criteria methods. A description of a Scandinavian project which builds upon theory for multi-criteria decision making is also included in Appendix B. At the end of this section we discuss how the competitive industry can respond to the new conditions by applying alternative planning methods.

2.2.1 Generation Expansion and Integrated Resource Planning

The traditional objective in power generation expansion planning was to minimise the cost of accomplishing required expansions of generation capacity. The focus was almost entirely on the supply-side of the power system, while demand was simply assumed to follow a forecasted growth rate. As a response to both increasing cost of electricity supply and also environmental constraints the concept of integrated resource planning was developed. While the objective of the traditional expansion planning was to meet demand for electricity at least cost, the principal goal in integrated resource planning is to meet the demand for energy services at least cost (Swisher et al. [5]). Hence, integrated resource planning also considers options on the demand side, such as energy efficiency programs and demand-side management, in order to find the optimal configuration of the power system. The concept of integrated resource planning was originally developed for the regulated utilities in the US. However, the same methodology can also be applied on different geographical and organisational levels. Integrated resource planning has been used for planning purposes from the local distribution level to national analyses of regulatory policies for the energy sector.

2.2.2 Multi-Criteria Trade-Off Analysis

The provision of energy services has a fundamental impact not only on the economy, but also on the environment and on the society in general. Conflicting objectives frequently arise in long-term infrastructure planning within the energy sector, since many interest groups are affected by the resource decisions. Planning methods that take into account several of these objectives are referred to as multi-criteria decision making methods. Multi-criteria methods are frequently applied for different planning purposes in the electrical power sector, for instance in combination with capacity expansion or integrated resource planning. The objective for the multi-criteria methods is to help decision makers evaluate the trade-offs between different system criteria, such as total costs, emissions and reliability. A systematic comparison of the various criteria makes it easier for the decision makers to make well-informed and appropriate decisions. The least-cost solution is not necessarily the optimal one, when other criteria are also taken into consideration.

Several analytical methodologies have been developed in order to aid in multi-criteria decision making[5]. The first step in the planning process is to select which system criteria to include in the analysis. This is done by the decision makers and possibly also other stakeholders in the system. A power system simulation model is then usually applied to estimate the outcomes of the selected criteria for different technological configurations of the power system. Note that the model does not find the optimal expansion plan itself, but simulates the operation of the system for a set of technological options that are specified by the people involved in the planning process. A set of assumptions about the future (load growth, fuel prices etc.) also has to be specified as input to the simulation model. Some of the multi-criteria methods are aiming at quantifying the decision makers' value judgements, and thereby finding an optimal system expansion plan. This can be done by assigning weights to the different system criteria, adding the weighted criteria up, and then compare the total result for the range of investment alternatives. Various weighting and multi-objective optimisation techniques have been developed for this purpose, as described by Hobbs and Meier [6]. An alternative approach is taken by Merrill and Schweppe [7], in their so called trade-off/risk method for multi-criteria planning under uncertainty. Their approach puts more emphasis on displaying tradeoffs and identifying

[5] A comprehensive description of multi-criteria decision support methods is given by Hobbs and Meier in [6].

plans which are robust for a range of assumptions about the future, instead of finding one single plan which might only be optimal under a specific set of assumptions. The methodology analyses trade-offs between the selected criteria and identifies investment strategies that are strictly or significantly dominant with regards to all the criteria. Robust investment strategies can be identified both with a deterministic and a stochastic representation of the future. Hence, by using the trade-off/risk approach decision makers can find strategies that are robust both in terms of selected system criteria and relevant future uncertainties. The methodology has been applied for integrated resource planning at the utility level several places, for instance at the Bonneville Power Administration in the US (Burke et al. [8]).

The principles in the trade-off/risk method have also been applied to electric power system planning on regional and national levels. Connors [9] uses the methodology for integrated resource planning in the New England power system and focuses on the effects of increasing wind power capacity and the extent of demand-side management programs. A similar multi-criteria analysis is also accomplished for the Swiss power system (Schenler and Gheorghe [10]). In the Swiss case study the trade-off approach is combined with life cycle analysis to examine environmental impacts for the entire life cycle of the power system. Another example of using an extended version of the trade-off/risk framework is found in a planning project from the Shandong province in China (Eliasson and Lee [11]). In all these projects there are several decision makers involved in the planning process (utilities, regulators, end-user groups etc.). This is in contrast to projects on the utility level, where the final decision is made by the utility itself. At the same time the total number of other stakeholders also increases when the geographical scope of the problem is extended. Therefore, when multi-criteria trade-off analysis is applied on regional and national levels, it serves first of all as a tool for facilitating discussions between stakeholders and decision makers, and for providing them with objective simulation results for a range of investment strategies. Identification of robust investment strategies is still important, in order to avoid counterproductive decision making. However, the search for an optimal strategy makes less sense in a setting with multiple decision makers.

A multi-criteria planning project, which builds upon the same principles as described for the regional and national projects above, is currently also being started for the Scandinavian region. The framework of analysis and initial assumptions for the project are further described in Appendix B. A discussion of the analytical approach and some preliminary simulation results are also provided by Bhattacharyya [12]. A new challenge when it comes to applying such a centralised planning method in this region is the high degree of liberalisation in the Scandinavian power system. As pointed out in Chapter 1, competitive power markets are characterised by decentralised decision making. Robust power system investment strategies which are identified through the multi-criteria trade-off analysis can therefore not be directly implemented, since the degree of centralised planning is low. Still, with an extensive and iterative dialogue with decision makers and other stakeholders, the discussions and information exchange which arise from such a project can serve as valuable inputs also to decentralised decision makers. The results from the multi-criteria trade-off analysis can also be a good source of information for the public in general. Besides, there will always be an extent of centralised planning in the power system, through the market rules and regulations in the power system. Authorities and regulators can use the outcomes of the multi-criteria trade-off project to create a system where the desirable results are achieved through regulations, investment incentives and appropriate market design. However, in order to facilitate such results the project must go beyond identifying robust strategies, and also analyse how these strategies can be accomplished in a competitive setting. The model concepts that are presented in this thesis can serve as useful tools in terms of analysing the investment dynamics in competitive power markets. Therefore, the use of our models in an extended multi-criteria trade-off analysis can contribute to make the project results more relevant in restructured power systems.

2.2.3 New Planning Methods for the Competitive Industry

Most of the long-term planning methods that were developed for the regulated electrical power industry were based on a centralised system optimisation perspective. Prescriptive methods, like the ones described above, were used to identify optimal expansion plans for the infrastructure in the power system. Decentralised decision making in a perfect market gives the same result as centralised system optimisation, according to welfare economics. A centralised system optimisation perspective can therefore still be used as the starting point for making a benchmark in long-term analysis of restructured power systems. However, alternative planning methods which focus more on how power markets can deviate from the long-run equilibrium, and also on how the individual participants can optimise their positions with respect to the rest of the system are needed. Below we discuss some methodologies which can be used to include the effects of decentralised and strategic decision making, and increased uncertainty into long-term planning strategies.

The shift towards decentralised and profit maximising decision makers in restructured power systems is likely to incur a higher degree of strategic decision making. Hence, strategic analyses of the industry as a whole and also of important competitors become more important for the individual participants in the power system. Such analyses can be based on purely qualitative considerations. However, various mathematical modelling techniques can also be applied in order to study the effects of strategic decision making. System dynamics is a descriptive modelling methodology where the focus is on behavioural simulation of systems at a high level of aggregation. The flexible and descriptive approach and the dynamic nature of system dynamics models make them well suited to analysis of strategic decision making. In Chapter 3 we apply system dynamics to develop a simulation model for long-term analysis of the power market. Multi-agent modelling is another tool for analysing the interaction between individual agents in a system. However, the multi-agent technique is designed for more detailed analysis of systems at a lower level of aggregation, where decisions occur frequently and decision makers are constantly learning and adapting their strategies. In the context of electricity markets multi-agent modelling is well suited for short-term analysis of bidding strategies in the spot market (Visudhipan [13]). Game theory is another approach which is frequently used for analysis of power markets with a limited number of participants (duopolies, monopolies), both in a short-term price and long-term investment perspective (Ventosa et al. [14]). Multi-agent modelling and game theory are not applied in the decision support models presented in this thesis.

The increased uncertainty following the restructuring of power systems can also be dealt with using both qualitative and quantitative methods. Some long-term uncertainties, such as political market regulations and public opinion, are difficult to quantify and describe by probability distributions. The effect of these uncertainties can still be incorporated into scenario planning techniques, where the purpose is not to identify optimal investment strategies, but rather to gain increased insight into the range of outcomes that the future might bring. On the other hand, quantifiable uncertainties can be included formally into decision support models. An extensive literature exists on optimisation of investments under uncertainty. The models in Chapter 4 and Chapter 5 are inspired by the real options theory, where uncertain factors are described by stochastic processes and taken explicitly into account in the calculation of optimal investment strategies. Increased uncertainty, combined with large-scale irreversible investment decisions, makes the real options approach particularly relevant for investments in the electrical power system.

2.3 Classification of Decision Support Models

In this section we look more specifically at some important attributes of decision support models for long-term planning in electrical power systems. We discuss a number of dimensions along which long-term planning models can be classified. Our discussion of model attributes is not meant to cover all aspects of expansion planning models. However, we focus on the dimensions that are of particular concern in a competitive setting, and which can be used to illustrate the contributions of the planning models proposed in this thesis. In the next two sections we use the model properties discussed here to describe and classify existing models for long-term planning in power systems, and compare them to the new decision support models presented in this thesis.

2.3.1 Model Purpose and Algorithm

A decision support model for long-term planning can be either prescriptive or descriptive. Prescriptive models are based on optimisation, and their purpose is to identify optimal investment strategies. Most planning models for the regulated industry are prescriptive. In contrast, a descriptive model does not find optimal investment strategies directly. The purpose of descriptive models is to increase decision maker's knowledge, by simulating the future development of the system under a set of different assumptions. Better knowledge will, in turn, result in improved decision making. The relevance of descriptive models has increased following the restructuring and decentralisation of decision making in electrical power systems. Geographical scope is another model attribute which depends on the problems the model is designed to analyse. The geographical system boundary can typically vary from a very local area to a multi-national region. A range of other properties also define the model's system boundaries. For instance, some models consider the electric power system only, while others also include the transportation and demand for alternative energy carriers such as gas and district heating.

The objective function in prescriptive decision support models developed for the regulated power industry is usually minimisation of total cost, or in some cases maximisation of social welfare. In the competitive power industry a more appropriate objective for individual participants is the maximisation of their expected profits from investing in the system. Descriptive models do not have an explicit mathematical objective function. However, the simulated investment decisions must still be based on assumptions about investors' priorities and objectives. Another important model attribute is the mathematical algorithms which are used to solve the model. A planning model can use more than one solution algorithm. For instance, the representation of the short-term operation of the power system and the power market is typically a separate part of the planning model, which can be based on a different algorithm than the investment decisions. Several optimisation methods from operations research (linear/non-linear programming, dynamic programming etc.) are frequently used in expansion planning models. The planning model's solution algorithms depend on the purpose of the model, and the range of other attributes that are included in it. For instance, the extent to which different mathematical algorithms can efficiently include representation of uncertainty varies substantially.

2.3.2 Representation of Investment Decisions

The representation of investment decisions in long-term planning models plays a central role in this thesis. Regulated power system are characterised by centralised decision making. Therefore, in traditional prescriptive expansion planning models it is usually assumed that all decisions are made by one centralised decision maker, which controls the entire system (Figure 2.1A). As already pointed out, a centralised optimisation can also serve as a benchmark for a perfectly competitive market. However, it is also possible to explicitly model decentralised decision making, in order to describe the conditions in competitive power markets with more realism. In this thesis we use two different approaches to represent decentralised decision making in planning models. In the first approach the interaction between a number of decentralised participants with their own investment strategies is modelled. The participants interact through the power market (Figure 2.1B). The second approach is to take the perspective of an individual participant who wants to optimise his position in the system. The other participants are now represented as an aggregate decision maker, whose decisions could also depend on feedback from the power market (Figure 2.1C).

Another important dimension in the modelling of investment decisions is how the timing of new investments is taken into account. With a static representation it is assumed that a new investment must be undertaken immediately. Hence, the only concern is to decide whether or not to invest, and then also which project to invest in if there are several alternatives. In contrast, with a dynamic representation of investment decisions, the timing of new projects is also taken into account. Modelling of uncertainties, construction delays and investor foresight are also important for the investment decision. Long-term trends, such as changes in demand, fuel prices etc., can be represented either as deterministic or stochastic variables. The representation of investment timing, long-term uncertainties, and construction delays can have a substantial impact on the optimal investment decisions, as will be shown in this thesis. This is discussed in much more detail when the real options theory is presented in Chapter 4.

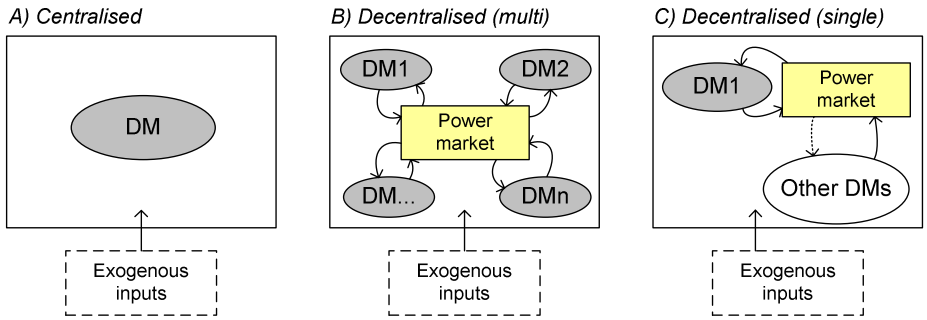

Figure 2.1 Representation of centralised and two types of decentralised decision making in long-term expansion planning models. DM – decision maker.

2.3.3 Representation of Supply, Demand and Electricity Market

The level of detail in the representation of supply and demand in the power system is rather limited in most long-term planning models. This is mainly because the gain from adding details in a long-term analysis is usually low, while the increase in computational burden can be substantial. The number of power generation technologies that can be added to the power system is a supply-side attribute which can be very important for the mathematical dimension of the expansion planning problem. Technology learning is another aspect, which by time can substantially reduce investment costs for emerging technologies. Technology learning can be included in expansion planning models by using learning rates for the various technologies. On the demand side, the time resolution decides how much of the short-term demand fluctuations (seasonal, weekly, daily) that can be included in the model. Another important dimension is whether or not price elasticity of demand is represented. The introduction of competition and increased exposure to prices in the power system makes it important to include how the demand-side influences and responds to the fluctuating prices. This is dependent on the market design. Explicit representation of the power market is needed in a competitive market setting, in order to be able to analyse the effects on prices and investments of various market designs. In a competitive and decentralised setting the market plays a crucial role in coordinating the actions between the various participants, as illustrated in Figure 2.1. In a model with centralised decision making there is no explicit representation of the market, although an exogenous price can be included in the input to the model to represent prices outside of the region which is included in the model.

2.4 Expansion Planning Models in Norway

In this section we present four existing models that have been used for long-term analysis and expansion planning in the Norwegian power and energy systems. All the models have a bottom-up description of the power system.

2.4.1 DYNKO

DYNKO is a centralised and prescriptive expansion planning model which minimises the total cost of expanding the energy system within an area. Operating costs for different system configurations (combined heat and power, gas/oil/electricity boilers etc.) are calculated with merit order models for the production of district heating and electricity. The expansion planning module uses dynamic programming (DP) to identify the least cost solution, based on a deterministic forecast of future load. DYNKO was developed by the Norwegian Research Institute of Electricity Supply (EFI) in Trondheim for planning purposes at the regulated utility level in the late 1980s (Johansen and Wangensteen [15]).

2.4.2 SDP Model

The SDP model for expansion planning proposed by Mo et al. [16] is an extension of the DYNKO framework. The objective is still to minimise the total cost of providing electricity and heating services within a local area. However, load growth and oil price are now represented as stochastic variables. Stochastic dynamic programming (SDP) is used to find the optimal investment plan. The SDP algorithm takes into account the long-term uncertainties and also the dynamic flexibility in investment timing. Construction delays are explicitly represented in the model and will also affect the optimal investment strategy.

2.4.3 MARKAL

MARKAL is a large-scale linear programming (LP) model which optimises the supply of energy services in a region or country, also including the transportation sector. The objective function is normally to minimise the total cost of meeting the energy demand, although alternative objective functions can also be used, such as minimisation of the total emissions from the energy system or the total use of fossil fuels. Energy demand is represented in the model with a deterministic projection of demand for different sectors of society. Operations and expansions of the system are jointly optimised with a huge linear programming algorithm. There is no explicit representation of the electricity market in the model, but marginal operating costs can be found from the dual variables of the restrictions in the LP algorithm. The model was originally developed at Brookhaven National Laboratory and is used for regional energy system studies in a range of countries including Norway (Johnsen and Unander [17]).

2.4.4 Normod-T

Normod-T is a partial equilibrium model developed for analysis of the Nordic electricity market. The model simulates electric load, generation and prices in Norway, Sweden, Denmark and Finland, based on exogenous and deterministic demand forecasts. Normod-T is a multi-area model and includes transmission constraints between the countries. Power system dispatch and prices are found for each year by maximising the social welfare in the system for the given transmission and capacity constraints. The short-run price elasticity of demand is also taken into account in the model. New generation capacity is added as soon as the simulated prices exceed the long-run marginal cost of available technologies. Hence, new capacity additions in the system are not part of a formal optimisation. Normod-T therefore has a more descriptive nature than the other models presented here. However, the decision rule for capacity additions makes sure that the system is always kept close to the long-run economic equilibrium. Hence, the simulated expansions are not allowed to deviate far from the social welfare optimum. The model has been developed and used by Statistics Norway (Johnsen [18]).

2.5 The Model Concepts in this Thesis

In this thesis we propose three new decision support models for long-term analysis and investment planning in restructured power markets. The models are developed to address the impact of decentralised decision making and increased uncertainty following the introduction of competition in generation and supply of electricity. The effects of environmental regulations, investment incentives and market design can also be analysed with the planning models in this thesis. The three model concepts are briefly described below. A summary of model properties for the existing and new models are summarised at the end of this section in Table 2.1. The selection of model properties is based on the discussion in section 2.3.

2.5.1 System Dynamics Model (SysDyn)

In Chapter 3 we develop a descriptive simulation model based on system dynamics for long-term analysis of a regional power market. The model simulates investments in a set of power generation technologies, where each technology is represented in the model as a separate decision maker with a profit maximising objective (Figure 2.1B). The demand is also represented as a decision maker which responds to the prices in the electricity market. Both short- and long-term price elasticity of demand is included in the model. The market is described with linear supply and demand curves, and linear programming is used to calculate the market price at the intersection of the two curves for each simulated year. New investments in the different generation technologies are based on profitability assessments of total costs for the new technologies compare to deterministic projections of the simulated prices. Individual construction delays and technology learning rates for the various technologies are represented in the model and contribute to the simulated investment dynamics.

2.5.2 Real Options Model 1 (RealOpt1)

In Chapter 4 we look at investments in new power generation capacity from the perspective of an individual decision maker in the power system (Figure 2.1C). Real options theory is used to develop a prescriptive planning model, which optimises the participant's timing of investments in a specified power generation technology. The investment optimisation model is based on stochastic dynamic programming, where load growth is represented as a stochastic variable. The solution algorithm and description of uncertainty in our model is similar to what is used in the SDP model described in [16]. However, the objective in the model is now to maximise the profits of an individual participant, instead of minimising the total cost of the entire system. Other participants in the system can be represented in the model, by assuming that their investment decisions are also dependent on the prices in the power market. The electricity price is modelled as a probability distribution which depends on the load level and the total installed capacity in the system. The parameters in the price model can be estimated based on historical data. A simulator is also implemented in order to analyse the long-term investment pattern which follows from the model's proposed investment strategies.

2.5.3 Real Options Model 2 (RealOpt2)

The planning model in Chapter 5 is an extension of the model concept in Chapter 4 for investments in power generation assets under uncertainty. The model has been extended to include investments in two new generation technologies, and can therefore calculate the optimal technology choice in addition to the optimal timing of the investment. At the same time demand is modelled with more detail, by introducing sub periods for base, medium and peak demand. The representation of demand is based on the theory of peak load pricing. An alternative market description is also included in the model, where the electricity price is derived from the intersection of linear supply and demand curves. With this representation of the market the model can either optimise the investments of a decentralised profit maximising participant (Figure 2.1C), or it can optimise the entire system from a centralised social welfare perspective (Figure 2.1A). Hence, we can use the model to compare investments, prices and reliability under centralised and decentralised decision making.

Models/ properties		**Existing models**				**Models in this thesis**		
		DYNKO	*SDP*	*MARKAL*	*Normod-T*	*SysDyn*	*RealOpt1*	*RealOpt2*
Purpose & Algorithm	*Purpose*	Prescriptive	Prescriptive	Prescriptive	Descriptive	Descriptive	Prescriptive	Prescriptive
	Scope	Local heat/ electricity	Local heat/ electricity	Regional energy	Regional electricity	Regional electricity	Regional electricity	Regional electricity
	Objective	Min. total cost	Min. total cost	Min. total cost (or fuels etc.)	Total social welfare	Investor profit	Max. inv-estor profit	Max. inv. profit or tot. social welf.
	Algorithm (invest-ments/operation)	DP/ merit order	SDP/ merit order	LP/ LP (joint)	NPV rule/ NLP	NPV rule/ LP	SDP/ price.dist.	SDP/ merit order
Investment decision	*Perspective of decision maker*	Centralised	Centralised	Centralised	Decentral. (multi)	Decentral. (multi)	Decentral. (single)	Central. or Dec.(single)
	Decision	Dynamic	Dynamic	Dynamic	Static	Static	Dynamic	Dynamic
	Long-term uncertainties	Determin-istic	Stochastic	Determin-istic	No	Determin-istic	Stochastic	Stochastic
	Foresight	Perfect	Probabil-istic	Perfect	No	Limited	Probabil-istic	Probabil-istic
	Construction delay	No	Yes	No	No	Yes	Yes	Yes
Supply	*No. of technologies to invest in*	Multiple	Multiple	Multiple	Multiple	Multiple	One	Two
	Technology learning	No	No	Yes	No	Yes	No	No
Demand	*Time resolution*	Weekly	Weekly	6 periods per year	12 periods per year	Annual	Annual	3 periods per year
	Price elasticity of demand	No	No	No	Short-term	Short-term/ long-term	No	Short-term
Electricity Market	*Market description*	Exogenous price series	Exogenous price series	No explicit represent-ation	Supply - demand equilibrium	Supply - demand equilibrium	Probability dist. (state dependent)	Supply - demand equilibrium

Table 2.1 Properties for existing planning models (DYNKO, SDP, MARKAL, Normod-T) and the new models proposed in this thesis (SysDyn, RealOpt1, RealOpt2).

2.6 A Similar Problem: Hydro Power Production Planning

In the end of this chapter we comment briefly on the similarities between the problem of investing under uncertainty and the hydropower production planning problem. The objective in hydropower production planning is to optimise the allocation of limited hydro resources. Precipitation determines the inflow of water to the reservoirs and is an important stochastic variable along with the future electricity price. Just like there is a value in waiting for more information about uncertain long-term trends in the investment planning problem, there is also a value of waiting for more information about future precipitation and prices in the hydropower problem. From a mathematical point of view, installed generation capacity and demand level are the main state variables in the investment problem, while the reservoir level is the most important state variable in the hydropower production planning problem. The time horizons are of course different, but the problems' structures, with sequential decision making and gradual unfolding of new information, are the same. Therefore, the two problems lend themselves to the same analytical approaches, since the common aim for their decision support models is to capture the value of having a flexible and dynamic strategy in an uncertain environment. It is not a coincidence that stochastic dynamic programming, which are used in Chapter 4 and Chapter 5 in this thesis, are also frequently applied for hydropower production planning, both in Scandinavia and other parts of the world (Fosso et al.[19]).

Chapter 3 A SYSTEM DYNAMICS MODEL FOR LONG-TERM ANALYSIS OF THE POWER MARKET

In this chapter we present a new model concept for long-term analysis of liberalised power markets. In the model we try to capture the main factors influencing the long-term development of supply and demand in the power system. In liberalised power markets, investment decisions are no longer part of centralised planning and optimisation. Investors' lack of perfect foresight, together with permissions and construction delays, could possibly result in periods of overcapacity or capacity deficits in the system. By using a dynamic description of investments in new power generation capacity we are able to include these effects into our model. The average spot price in the power market is calculated from year to year, using a linear optimisation algorithm based on marginal costs. The price for electricity, in turn, influences investments in different technologies, both on the generation and end-use sides of the electric power system. System dynamics, which is a general dynamic modelling technique with a wide range of applications, is used to model these investment decisions. Companies in the electric power industry and public authorities are potential users of the model, for learning and decision support in scenario planning and policy design. A summary of results from a case study of the restructured power market in Norway are included to illustrate potential use of the model.

The dynamic investment model outlined in this chapter was presented at the 14th Power System Computation Conference, PSCC 2002, (Botterud et al. [20]). The paper from the conference proceedings is included in Appendix C.

3.1 Introduction

This chapter presents a new model concept for long-term analysis of the power market which is based on system dynamics. The model is a possible tool for increasing the understanding of the dynamics of supply and demand in restructured power markets. It is specifically suitable for scenario planning, and we argue that both energy companies and public authorities could make use of such dynamic models in their long-term strategic planning. In the model we calculate the annual average electricity price using a linear optimisation algorithm, while the description of investment decisions is based on system dynamics. In the first part of the chapter we briefly discuss investment dynamics in the power market, and how this is incorporated into traditional and new power market models. The main part of the chapter is devoted to a detailed presentation of our new model concept. At the end we also briefly present results from a case study of the Norwegian power market, to illustrate potential use of the model. Further applications and extensions of the model concept are also discussed.

3.2 Investment Dynamics in the Power Market

3.2.1 Decentralised and Imperfect Decision Making

As pointed out in Chapter 1, one important consequence of power market restructuring is that many decisions related to operation and planning of the power system are now made at more decentralised levels in the system. This is indeed also the case for decisions regarding investments in new power generation. The introduction of competition in the market has shifted the investment focus for utilities and power generation companies from meeting load to maximising profits. Under these circumstances it is no longer certain that installed generation capacity is always ahead of the development in demand. Power plants have a long lifetime and a substantial fraction of the total costs are paid up front. At the same time there is high uncertainty regarding the future electricity prices. Consequently, investors might be reluctant to invest in new generation capacity in time to meet increasing demand. Delays caused by the time it takes to obtain construction permits and to construct new plants will also contribute to the likelihood for an imbalance between load and generation capacity.

The demand side of the power market consists of a large number of consumers. Small consumers, such as single households, do not necessarily base their investment decisions on purely economic arguments. Their behaviour is more likely to be described by bounded rationality[6]. The direct

[6] Bounded rationality is a term which is used in behavioural economics to describe real decision making processes, where limitations of both knowledge and cognitive capacity

link between electricity price and investments in new end-use technology is therefore less clear than on the supply side of the market. It is still reasonable to assume that there is a level of price feedback also to demand, both in a short- and long-term perspective. The short-term price elasticity of demand arises because parts of the electricity consumption can be substituted by other energy carriers. There is usually also a potential for short-term electricity savings in the system. In the long run investments can be made in technologies that change the demand level and also the temporal pattern of electricity use. Energy-intensive industries are for instance a consumer group that will typically be very sensitive to changes in the electricity price, and optimise their production facilities accordingly. At the same time, construction delays are also present on the demand side when it comes to investments in new end-use technologies. All these factors contribute to the dynamics of investments on the demand side of the power market. However, the long-run development of electricity demand is also to a large extent determined by macro factors such as growth in population and changes in economic activity within a region. Such factors are difficult to include as endogenous variables in a power market simulation model.

In the model presented in this chapter we try to capture the most important relationships that influence the dynamics of supply and demand in the power system. We assume that the objective for participants on the supply side of restructured power markets is to maximise the market value of the company. Investments in new power generation plants will therefore be triggered by expectations about future profits. The expected profitability on new investments is in turn determined by the future price of electricity. Thus, the expected electricity price is clearly the main feedback signal for investments on the supply side of a competitive power market. Moreover, we argue that the electricity price is also important for the demand side of the power market, although the change in demand will also be highly dependent on other factors in the society. Interventions from regulating authorities, in terms of taxation, subsidies and concession policy, can contribute to change the dynamics of both supply and demand in the market. By development and use of the dynamic model presented here, we are aiming at improving the knowledge about the complex relationships that are likely to determine the long-term development of the power market.

3.2.2 Traditional and New Modelling Approaches

An overview of modelling approaches for generation expansion planning in regulated and restructured power markets is given in Chapter 2. Most of the

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prevents decision makers from making rational choices based on maximisation of their expected utility.

long-term planning models for the traditional power industry are based on centralised system optimisation, where the objective is to minimise the total cost of meeting load within a region. These models usually have an underlying assumption of perfect investor foresight. The effect of bounded rationality and imperfect decision making that contribute to the investment dynamics described above are rarely represented. The substantial delays during permit approvals and under construction of new power plants are usually also omitted in these models.

Alternative modelling approaches are therefore needed to study the long-term consequences of decentralised decision making in restructured power markets. However, so far most of the models that are being developed for the new competitive environment seem to focus on shorter-term issues like operation planning, trading, economic risk management and market power in the spot market. One of the power market modelling approaches developed for the restructured industry that also address the long-term investment dynamics on the supply-side of the market is proposed by Skantze and Ilic [21]. A model of the spot market for electricity with stochastic descriptions of supply and demand is here extended to also include investments in new generation capacity. The rate of investments in new capacity depends on the relation between the electricity price and the total unit cost of new capacity. This is similar to the approach taken in the model presented here. However, the model in this chapter focuses more on the relations between investments in different technologies and less on the stochastic elements of supply and demand. Other recent approaches to modelling of investments in liberalised power markets include game theory, as described for instance by Chuang et al. [22] and Ventosa et al. [14]. These models are designed for analysis of capacity expansions in markets which can not be considered as fully competitive, but more realistically described as duopolies or oligopolies.

3.2.3 System Dynamics

In our model we use system dynamics as a tool for analysing investments in the power system. A short introduction to the field is therefore provided below[7]. The theory of system dynamics was developed during the fifties and sixties by Jay W. Forrester as a policy design tool for complex management problems [23]. System dynamics draws upon control-, organisation-, and decision theory, and can be used to model interactions within and between social, economic and technological systems. Instead of analysing the details

[7] A comprehensive description of system dynamics is provided by Forrester [23] and Sterman [24]. Forrester lays out the founding principles behind the theory of system dynamics in [23], while Sterman gives an up to date description of the field, with examples of applications in a range of different industries in [24].

of individual elements in a system, the emphasis in system dynamics is on the relationships between the elements that create dynamics in a system. Consequently, system dynamics models usually have an aggregate level of detail, while the scope of the models can reach beyond what is usually included in traditional analytical methods. Systems thinking[8], which has its foundation in the field of system dynamics, has made an important contribution to organisational theory and management. The focus in systems thinking is also on understanding how the components of a system interact with each others, but with less attention to the development of a mathematical formulation of the problem that is being studied.

When developing a system dynamics model, a substantial amount of time should be spent in the beginning to develop an understanding of the problem that is being investigated. It is very important that the decision makers, which are actually going to utilise the results from the model, are involved already at the beginning of the analysis. The project group's mental models of the system must be spelled out, and the most important variables in the relevant system identified. Causal loop diagrams, which are sketches of the causal relationships between the different components of a system, can be very useful as a tool of communication in this stage of the model development. Such diagrams are used later in this chapter to illustrate the main relationships on the supply and demand side of the power market. The next step in the analysis is to formalise the causal relations into a mathematical model. When sufficient testing is performed, the final model can be used to evaluate different policies and decision strategies.

Mathematically, system dynamics is a set of differential equations. The state variables in the system are referred to as stocks, while the control variables are dependent on the decision strategies and the structure of information feedback loops in the system. A system dynamics model is usually solved numerically, and can handle both delays and nonlinearities. A number of specialised software tools have been developed specifically for system dynamics models. The possibility of including optimisation and uncertainty into the models is limited. Advanced decision strategies based on optimisation can therefore be difficult to implement within the framework of system dynamics. However, the purpose of developing a system dynamics model is usually to gain better insight into a real world system. As pointed out above, real decision makers are rarely entirely rational about their decisions. Simulation models based on system dynamics is therefore still a valuable tool for descriptive analyses, which in turn can result in increased knowledge and thereby improved decision making.

[8] An important contribution in the field of systems thinking is given by Senge in [25].

System dynamics has been used to analyse dynamic patterns in a range of different industry sectors, including the electrical power industry. Bunn and Dyner [26] argue that system dynamics can serve as an important tool for analysis of the changing conditions in the energy industry. Results from a simulation study of consumer choice of electricity substitution by gas in Colombia are presented. Market forces in the UK electricity industry are also analysed by simulating investments in new power generation capacity. It is shown that increased exchange of information between market participants can have a stabilising effect on investments and the reserve margin. Gary and Larsen also [27] develop a system dynamics model for investments in generation capacity in the UK electricity market. Different investment strategies are simulated, and the interaction between the electricity and gas markets is also included in the model. The results from the study are compared to a situation where a constant long-term equilibrium price is assumed for gas. Not surprisingly, the results from the feedback simulation model deviates substantially from the equilibrium prediction. Ford [28] [29] analyses cycles in power plant constructions in the western US. Results from a system dynamics model shows that boom and bust cycles are likely to occur due to investor's limited foresight and delays in permitting and constructing new plants. However, a capacity payment can contribute to dampen these construction cycles.

The model presented in this chapter is in many respects similar to the ones mentioned above. However, our model focuses more on the competition between different power generation technologies, and therefore on the causal relationships that determine technology choice. Although most of our attention is also given to modelling the investment dynamics on the supply side of the market, we improve the representation of electricity demand by introducing feedback from price to demand.

3.3 The Simulation Model

3.3.1 General Characteristics

The model simulates the development of the power system within a region for a long period of time (20-50 years). We model the power market with a supply and demand curve, and the electricity price is derived from the intersection of the two curves. The time resolution in the model is one year, using the simplifying assumption that investment decisions can only be made at the beginning of each year. New investments in generation and demand-side technologies result in a change in the supply and demand for electricity. Consequently, we end up with a dynamic description of the supply and demand curve, with electricity price as the main feedback mechanism.

The level of detail in the model is aggregated. Instead of going into details on the different parts of the system, we try to focus on the relationships that we see as most important for the long-term development of supply and demand in the power system. The model is a tool for generating scenarios to analyse what is likely to happen under certain circumstances (e.g. about the development of fuel prices, taxation, technological improvements etc.). Development and use of the model can contribute to learning and improved decision making for participants in the power industry. To facilitate communication of the model and its results to decision makers we have used Powersim[9] to implement the dynamic description of the supply and demand curves. The price calculation is carried out in Visual Basic with a corresponding Excel spreadsheet interface.

3.3.2 List of Variables and Parameters in the Model

The list below shows the main variables and parameters in the model, which are further referred to in the presentation of the model below. Generation, demand and power exchange are represented with a number of capacity groups, where each group has a fixed bid in the electricity market. This is explained in more detail in the sections below.

General variables:

$p(t)$	wholesale electricity price	[NOK/MWh][10]
t	discrete time	[years]

Supply, M generation groups, $i \in [1,M]$:

$g_i(t)$	annual power generation	[TWh/year]
$ncap_i(t)$	new capacity rate	[MW]
$acap_i(t)$	approved capacity rate	[MW]
$\hat{p}_i(t)$	price forecast	[NOK/MWh]
$RC_i(t)$	remaining energy reserves	[TWh/year]
$GC_i(t)$	annual generation capacity	[TWh/year]
$EIC_i(t)$	unit energy investment cost	[NOK/MWh]
$VC_i(t)$	variable generation cost	[NOK/MWh]
$MC_i(t)$	marginal generation cost	[NOK/MWh]
$OC_i(t)$	operation and maintenance cost	[NOK/MWh]
$FC_i(t)$	fuel cost	[NOK/MWh]
$II_i(t)$	investment incentives	[NOK/kW]
$OI_i(t)$	operating incentives	[NOK/MWh]

[9] Powersim is one of the software packages developed specifically for system dynamics models. The graphical user interface facilitates communication of the model to decision makers involved in planning projects. A comprehensive documentation of the software is found in [30].
[10] NOK is the Norwegian currency. Currency rate (October 2003): $ 1 ≈ 7 NOK.

$CF_i(RC_i)$	expected capacity factor of new capacity	[hours/year]
$PF_i(t)$	profitability factor	
ir_i	internal rate of return on investment	
rr_i	investors' required rate of return	
δ_i	deviation in required rate of return	
ic_i	investment cost for initial capacity	[NOK/kW]
k_i	technology improvement factor	
n_i	expected lifetime for new plants	[years]
$amax_i$	maximum permit applications per year	[MW]
ad_i	approval delay	[years]
cd_i	construction delay	[years]
ap_i	permit approval fraction, $ap_i \in [0,1]$	
ab_i	project abandonment fraction, $ab_i \in [0,1]$	
$w(u)$	adjustment factor for marginal value of regulated hydropower, $w \in [0.5,2.5]$	
u	stochastic relative inflow, u~N$(1,\sigma_u)$	

Demand, N demand groups, $j \in [1,N]$:

$d_j(t)$	annual load	[TWh/year]
$MD_j(t)$	marginal willingness to pay	[NOK/MWh]
$DC_j(t)$	max annual demand	[TWh/year]
$DTOT(t)$	max total annual demand	[TWh/year]
$fp(t)$	flexible fraction of $DTOT(t)$, $fp(t) \in [0,1]$	
$tax(t)$	electricity end use tax	[NOK/MWh]
dg_{ref}	annual demand growth reference	
ε	long-term price elasticity of demand	
dd	demand adjustment delay	[years]
p_{curt}	curtailment price	[NOK/MWh]

Power exchange, O import and export groups, $k \in [1,O]$:

$im_k(t)$	annual import	[TWh/year]
$ex_k(t)$	annual export	[TWh/year]
$IMP_k(t)$	import price	[NOK/MWh]
$EXP_k(t)$	export price	[NOK/MWh]
$EXC_k(t)$	power exchange capacity	[TWh/year]

3.3.3 Supply Side Description

The power generation is divided into *M* generation groups, with each group representing one specific technology. The main relationships included in our modelling of investments in new generation capacity follow the same structure for all the generation groups. The causal loop diagram in Figure 3.1 illustrates this structure.

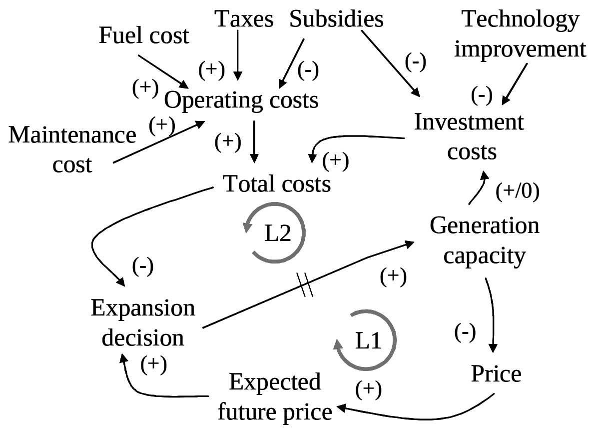

Figure 3.1 The main factors and relationships influencing investments in new power generation capacity. The signs on the arrows indicate the signs of the feedbacks for the relations between the variables. L1 and L2 represent feedback loops.

There are two feedback loops in Figure 3.1, and the expansion decision can be considered as the control variable for both loops. The first feedback loop (L1) states that when generation capacity is increased the electricity price is likely to fall. This lowers expectations of future prices, which in turn reduces the likelihood of future expansion decisions. L1 is therefore a balancing loop that limits the investments in new generation. The second feedback loop (L2) is caused by the connection between current installed capacity and investment costs. The sign and magnitude of this relationship varies for different generation technologies. For renewable technologies like hydropower and wind power we assume that locations with the best energy resources, or the highest expected capacity factor, are utilised first. The investment cost is therefore a function of remaining reserves, which in turn are directly linked to installed capacity. Hence, there is a positive link between installed capacity and investment costs, so that L2 becomes a balancing loop for these technologies. On the other hand, fossil-fuelled power plants do not have the same clear link between generation capacity and investment cost, since there is usually no constraint on the amount of fuel supplied to these plants. The capacity factor for thermal power plants is a function of the dispatch of the power plant. The change in dispatch due to new installed generation capacity is dependent on the overall power system characteristics. We are treating the capacity factors for thermal technologies as constants in the investment part of the model. As a result, there is no link between installed capacity and investment cost for these technologies in the model. However, by including more details in the modelling of the power system operation, we could include the relation between installed capacity, the expected capacity factor and thereby the unit investment cost for thermal technologies.

The two bars on the line between expansion decision and generation capacity in Figure 3.1 represent a delay. An expansion project goes through several stages before it eventually comes on line, as illustrated in Figure 3.2. All these stages are represented as stocks (i.e. state variables) in the model. The two main delays are concerned with obtaining a permit to build a new plant and the time it takes to construct it. These two delays are included in the model, and will therefore influence the simulated investment dynamics in the system. Furthermore, we assume that the fractions of the permit applications that are denied (ap_i) and the construction permits abandoned (ab_i) are constant. These parameters represent the regulating authorities' support and the investors' willingness to invest in the various technologies.

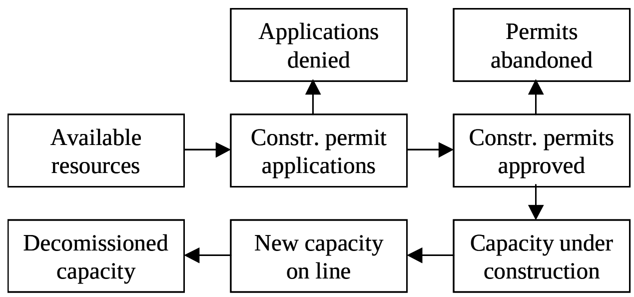

Figure 3.2 The stages in a power plant's life cycle.

A technology group's total cost is of course one of the main input factors when investments in new generation plants are considered. We therefore need a description of how investment and operating costs are likely to change over time. The investment cost per energy unit (EIC_i) in the model depends on initial investment cost, technology learning, expected lifetime, capacity factor and possibly also subsidies, as shown in (3-1).

$$EIC_i(RC_i,t) = \frac{ic_i \cdot e^{-k_i(t-t_o)} - II_i(t)}{n_i \cdot CF_i(RC_i(t))} \tag{3-1}$$

The variable costs of a generation group (VC_i) are the sum of fuel, and the variable part of maintenance and operating costs. The authorities could possibly also impose operational incentives such as subsidies for renewable power generation or CO_2 taxation of generation from fossil fuels. All these elements are exogenous inputs to the model, but can still change as a function of time, as shown in (3-2).

$$VC_i(t) = FC_i(t) + OC_i(t) - OI_i(t) \tag{3-2}$$

We assume that investments in the new power generation capacity are based on purely economic arguments. Power companies invest in the available technologies if the expected profitability is high enough to cover their required rate of return on capital. The expected profitability on a new investment is dependent on total costs of the project and the expected future price. We employ a first order exponential smoothing process to forecast the price a specific number of years into the future[11]. The time periods used in the backward-looking trend calculation and the forward-looking price extrapolation, can be defined individually for each single technology. It is for instance reasonable to assume that investors in wind power have shorter time horizons for their price forecast than hydropower investors, due to the shorter lifetime and construction time for wind power.

With values for investment cost, variable cost and expected future price we can find the expected internal rate of return on investments in new power generation capacity for the different technologies. This is simply done by setting the expected net present value (NPV) of the project to zero, as shown in (3-3). The expected price and variable costs are treated as constants within each time period. Hence, we can derive a profitability factor as shown in (3-4), which is used as an indicator for the quantity of new permit applications and plant constructions. The profitability factor can be expressed either in terms of expected price and cost figures, or as a function of internal rate of return and lifetime. By using figures for the technology's lifetime and the investor's required rate of return in the last part of (3-4), we can therefore calculate the required profitability factor for investments in different generation technologies to take place. The required profitability factors are compared to the simulated ones, as given by the first part of (3-4), and determine the rate of investment in the various technologies.

$$\mathrm{NPV}_i \quad = \quad -n_i \cdot CF_i \cdot EIC_i(t) + CF_i \sum_{l=1}^{n_i} \frac{\hat{p}_i(t) - VC_i(t)}{(1+ir_i)^l} \quad = \quad 0 \qquad (3\text{-}3)$$

$$PF_i(t) = \frac{\hat{p}_i(t) - VC_i(t)}{EIC_i(t)} = \frac{n_i}{\sum_{l=1}^{n_i} (1+ir_i)^{-l}} \qquad (3\text{-}4)$$

Figure 3.3 shows how approval applications and new constructions are modelled as a function of the simulated profitability factor. We assume that a higher profitability factor for a technology *i*, corresponding to a higher expected rate of return, results in an increase in the rate of applications for construction permits for that technology. The rate of new constructions

[11] This is a built-in value forecasting function in Powersim.

started is also an increasing linear function of the profitability factor, but with a less steep slope. There is an exogenously defined limit to the rate of new permit applications equal to $amax_i$ in Figure 3.3. The corresponding limit to the rate of new constructions is lower, and equals the fixed approval fraction for the technology (ap_i) times $amax_i$. Furthermore, we assume that investors require a higher rate of return to start the construction of new plants than what is required to apply for permits. The required rate of return (rr_i) and its deviation (δ_i), as shown in Figure 3.3, should be set to resemble the assumed behaviour of investors in the various power generation technologies. The model allows the use of different rr_i's and δ_i's for the different groups of power generation technologies. Differentiated rate of return requirements can be used in the case that the risk concerned with investing in different technologies varies considerably[12]. The installed generation capacity, GC_i, is updated for each time step. (3-5) shows how the construction delay is taken into account in the model. The permit approval delay is modelled in the same way. Construction and approval delays can also vary between the power generation technologies, resulting in different patterns of investment dynamics for the different generation groups.

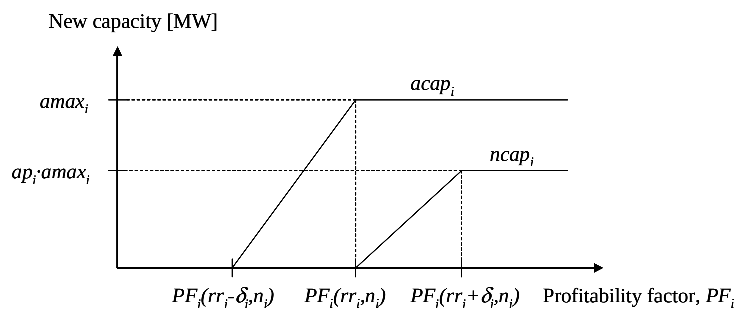

Figure 3.3 Illustration of the rate of applications for construction permits ($acap_i(t)$) and new constructions started ($ncap_i(t)$) as function of the profitability factor ($PF_i(t)$).

$$GC_i(t) = GC_i(t-1) + ncap_i(t - cd_i) \qquad (3\text{-}5)$$

As explained above, the rates of permit applications and new power plant constructions determined by a price extrapolation which is in turn dependent on the simulated prices. Capacity under construction and the level of permission already granted are not taken into account in the investment strategies. Furthermore, the investment decisions are based on static assessments where future trends and uncertainties are not taken into account

[12] A technology's expected lifetime and the relative proportion of investment costs and operating costs are two of the factors that are likely to influence investors' perceived risk.

other than through the price extrapolation. Investment decisions for the different technologies are also uncoordinated, in the sense that the rate of investment for one technology is independent of investment decisions for other technologies. This is clearly a simplified representation of the investment strategies that occur in real power markets. However, the representation of investment decisions in the model should still be sufficiently detailed to gain useful insight in the long-term dynamics of supply in a liberalised power market. After all, investors have limited foresight about future events and can not be expected to always act according to rational expectations. The focus in this chapter is on modelling of the main causal relationships for investments in the power system. In the following chapters we pay more specific attention to how investors can optimise their investments in power generation assets in restructured power markets, where the level of uncertainty is increased.

3.3.4 Demand Side Description

Our description of the demand curve is more aggregate than the supply curve, and a substantial part of the demand in the model is described by exogenous input parameters. We still try to capture the most important connections between electricity price and demand, both in the short and long run. Figure 3.4 illustrates how demand is treated in the model. The feedback loop states that increasing demand results in higher end-user prices. This will in turn give incentives for energy savings, and will contribute to lower the total demand after a time delay (*dd*). L1 is therefore a balancing loop. The dynamic description of total demand is based on a model proposed by Sterman in [24][13]. We assume a constant long-term price elasticity of demand (ε). When the simulated end-user price deviates from the reference price, the long-term price elasticity contributes to change the development in total demand away from the underlying reference growth, dg_{ref}.

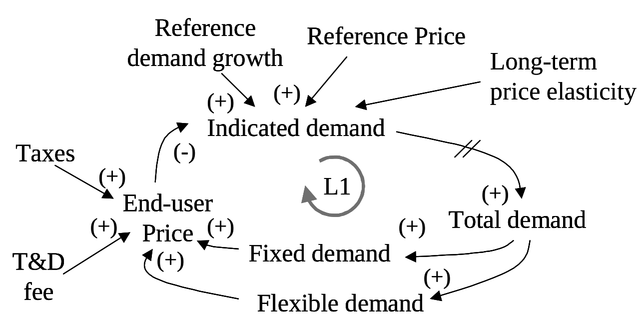

Figure 3.4 The main causal relationships on the demand side.

[13] See [24], pp.811-813, for a further description.

We distinguish between fixed and flexible demand. Flexible demand is defined as the demand that can respond quickly to price signals in the short term without additional investments in the system. Hence, the flexible demand represents the short-term price elasticity in the model. For instance, switching from electricity to oil heating in dual fuelled heat systems represents parts of this flexibility. On the other hand, the fixed part of demand does not have any substitute in the short run. It still changes in the long run, partly due to the underlying general load growth. Investments in energy saving technology such as heat pumps and improved insulation would also influence the total load development. This is represented in the model by the long-term price elasticity of demand

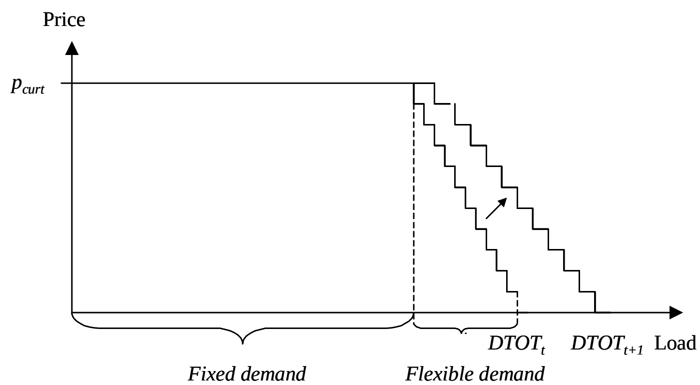

Figure 3.5 Representations of the demand curve at two different time steps.

Figure 3.5 shows how the fixed and flexible demand is represented in our model in terms of a demand curve. The total demand, *DTOT(t)*, is updated for each time step, while the fixed and flexible demands follow as fractions of the total demand. The proportion of flexible demand, *fp(t)*, is an input parameter, but can still change as a function of time to describe the expected development of the flexibility on the demand side. Figure 3.5 illustrates a shift in the demand curve, where the total demand as well as the variable fraction increases. For the fixed demand we assume that there is a curtailment price, p_{curt}. The flexible demand is represented by a number of linear price steps. Hence, the whole demand curve has a linear representation, and can be described by a number (*N)* of demand groups with corresponding prices (MD_j) and capacities (DC_j) for each group.

3.3.5 Exchange of Power with Outside Region

Import of power to the region is handled by adding a number (O) of additional supply steps to the supply curve. Similarly, a number of export steps are added to the demand function to represent electricity demand outside of the region. The exchange capacity is determined by the capacity of the transmission lines to surrounding regions, and is an exogenous variable that could be allowed to change with time. The capacity and price of each import and export step should be defined to resemble the power market conditions in the connected regions. The lowest import price must always be higher than the highest export price, to fit into the price calculation as described below.

3.3.6 Electricity Price Calculation

The average annual price, *p(t)*, in the wholesale electric power market is calculated for each simulated year. The price is determined by maximising the short-term socio-economic surplus in the market, including imports and exports, as illustrated in Figure 3.6.

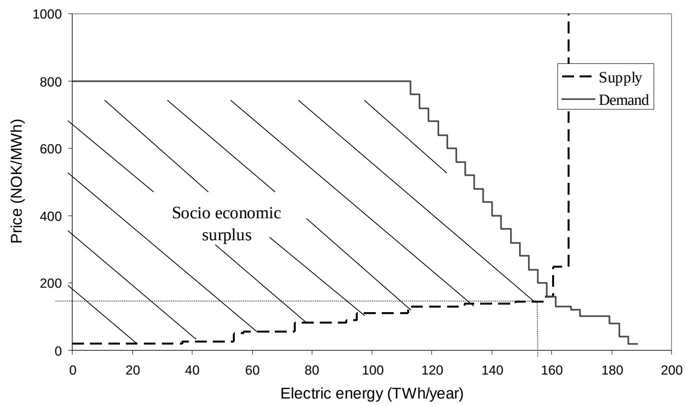

Figure 3.6 The power market is described by the supply and demand curves for each simulated time step.

The variable costs for the generation groups go directly into the price calculation, where they are treated as marginal costs (i.e. $MC_i = VC_i$), for all generation technologies except regulated hydropower. The regulated hydropower is divided into five separate supply steps, where the marginal value of the most expensive step equals a factor *w* times the lower import price, as shown in (3-6). The marginal values of the other steps are fixed fractions of the most expensive step. This is to take into account that regulated hydropower is dispatchable, and therefore scheduled according to the price of alternative generation. The alternative generation is usually thermal power, and its marginal cost depends on how much of the system load it has to serve. This is in turn dependent on the annual inflow to hydropower reservoirs. The *w* value is therefore a function of the inflow, *u(t)*, which is drawn from a normal distribution for each time step. *w* is low when inflow is high and vice versa. The representation of the marginal value of hydropower is meant to resemble the so-called water value calculations that are frequently used in hydropower production planning, as explained by Fosso et al. in [19].

$$MC_{hydropower,max}(t) = w(u(t)) \cdot IMP_{lowest}(t) \tag{3-6}$$

Strictly speaking, the shaded area in Figure 3.6 is not the true socio-economic surplus, due to the use of alternative costs instead of real marginal costs for regulated hydropower. The description still serves as a good approximation of the bidding process in the power market, if we assume perfect competition[14]. The linear description with constant marginal values for each load and generation group is clearly a simplification of the real world. Marginal costs of thermal power plants vary as a function of output for both a single plant as well as for a group of plants. The correctness of the market description can, however, be improved by increasing the number of generation groups.

The annual power generation (g_i), consumption (d_j) and exchange (im_k or ex_k) are found directly by applying Visual Basic's built-in algorithm for linear optimisation on the optimisation problem described in (3-7)-(3-12). All the other variables in the equations are treated as constants in the optimisations, which take place at each simulated time step. However, these variables might also change between each time step, due to the dynamics of the supply and demand curve in the system. The electricity price, $p(t)$, occurs as the dual value, or shadow price, of the electricity balance in (3-8). Other technology specific figures, like capacity factors and generation costs are easily derived from the results of the optimisation. Macro economic figures, such as consumer's and producer's surplus, also follow from the solution of the optimisation problem.

$$\textbf{\textit{max}} \quad \sum_{j=1}^{N} d_j \cdot MD_j - \sum_{i=1}^{M} g_i \cdot MC_i + \sum_{k=1}^{O} (im_k \cdot IMP_k - ex_k \cdot EXP_k) \tag{3-7}$$

subject to

$$\sum_{i=1}^{M} d_i - \sum_{j=1}^{N} g_j + \sum_{k=1}^{O} (im_k - ex_k) = 0 \tag{3-8}$$

$$g_i \leq GC_i, \quad i = 1..M \tag{3-9}$$

$$d_j \leq DC_j, \quad j = 1..N \tag{3-10}$$

$$im_k, ex_k \leq EXC_k, \quad k = 1..O \tag{3-11}$$

$$g_i, d_j, im_k, ex_k \geq 0 \quad \forall \quad i, j, k \tag{3-12}$$

[14] Modelling of imperfect competition and strategic bidding is more relevant for shorter time horizons where peaking effects from daily and seasonal load variations are included. We assume that these effects make a negligible impact on the average annual electricity price.

The model is, in its current form, an energy model, and does not address problems concerning peak demand and short-term capacity deficits. It is also a single area model, where transmission losses and reserve margins are assumed to be included in the demand groups. Consequently, there is one single electricity price for the overall region. Price differences within the region due to transmission congestion are not taken into account in the model. The aggregate annual price calculation is motivated from the fact that it is the average electricity price over the year that is relevant for most of the investments we consider, both on the supply and demand side in the power system. However, a more detailed market description could easily be implemented within the current framework, for analysis of effects that requires a shorter time resolution, as for instance investments in peak power plants.

3.4 Illustrative Example: Norwegian Case Study

To test the model we developed an input dataset for the Norwegian power market based on information in [31] and [32]. The initial conditions in the system describe year 2000, and the model is simulated for a period of 30 years. The most important assumptions for the supply and demand side are shown in Table 3.1 and Table 3.2. On the supply side the initial generation capacity consists almost entirely of hydropower. 4 different power generation technologies can be added to the system (hydro-, wind-, gas- and gas power with CO_2-capturing). Investments in all of these technologies are currently under consideration in the Norwegian power system. The demand side is described by a few key variables. The system load is slightly above average generation capacity in the initial year, and we assume a reference relatively low growth in demand of 1 %. The price flexible part of demand in assumed to be constant and equal to 14 % of total demand throughout the simulation period.

We first run a business as usual scenario (reference), where we assume that the authorities take a passive approach and leave it to the market to decide on the timing and technology for new generation. In the second scenario (green) we assume that the authorities take a more active approach and intervene in the market with CO_2 taxation (125 NOK/ton from 2002). They also show preferences for renewable power generation when giving construction permits. This is represented in the model with higher permit acceptance fractions for hydro and wind power than for gas power plants. All the other assumptions are the same in the two scenarios. In both scenarios we assume constant average inflow to the hydro reservoirs. Hence, price fluctuations due to the variable precipitation are not taken into account.

Table 3.1 Input parameter values for new generation technologies in the case study of the Norwegian power market. [1]Gas power with CO_2-capturing. [2]Values for the two scenarios ref/green. [3]CO_2 tax introduced in 2002 for gas power.

	Hydro	*Wind*	*Gas*	*Gas cap*[1]	*Unit*
GC_{init}	118	0.5	0	0	TWh/year
RC_i	30	80	100	100	TWh/year
OC_i	20	35	25	40	NOK/MWh
FC_i	0	0	100	120	NOK/MWh
$OI_i^{2,3}$	0/0	0/0	0/-45	0/0	NOK/MWh
CF_i	$CF_i(RC_i)$	$CF_i(RC_i)$	8000	8000	hours/year
ic_i	5000	8000	6000	10000	NOK/kW
II_i	0	0	0	0	NOK/kW
n_i	40	20	30	30	years
ad_i	3	2	3	3	years
cd_i	3	1	2	3	years
k_i	0.002	0.014	0.005	0.012	
rr_i	0.07	0.07	0.07	0.07	
δ_i	0.02	0.02	0.02	0.02	
ap_i^2	0.5/0.7	0.5/0.7	0.5/0.3	0.5/0.3	
ab_i	0	0	0	0	

Table 3.2 Input parameter values for the demand side in case study of the Norwegian power market. The parameters are constant throughout the simulation period.

dg_{ref}	p_{curt}	ε	*dd*	*fp*	*tax*
1 % pa.	800 NOK/MWh	-0.31	2 years	0.14	100 NOK/MWh

Figure 3.7 shows that the simulated price fluctuates throughout the 30 years in the reference scenario. Capacity expansions are triggered during the periods with high price, but delays cause the expansions to lag behind the price development. Most of the expansions are in large-scale gas power, as shown in Figure 3.9, since the other technologies are not able to compete. The cyclical pattern of prices and investments are similar to the ones detected by Ford in [28] and [29]. However, in our model the load also responds to the price and shows a similar fluctuating pattern, due to short- and long-term price elasticity. The price elasticity of demand contribute to lower the price peaks in the system.

In the green scenario the price increases immediately after the CO_2-tax is introduced in 2002 (Figure 3.8). The price also fluctuates here, but at a higher price level and with less regularity than in the reference scenario. The generation development is smoother because of a higher fraction of small-scale renewable generation technologies. Figure 3.10 shows a substantial shift from investments in gas power towards the renewable technologies.

Wind power is given a major boost due to the reduced competitiveness of the gas power technology. Investments in gas power with CO_2 capturing also occur in the green scenario, although not until close to the end of the simulation period. The demand shows a similar trend as in the reference scenario, but with lower growth, especially right after the price increase following the introduction of the CO_2-tax. Note that the generation is always lower than load in both scenarios. This is due to an assumption of excess import capacity throughout the simulation period.

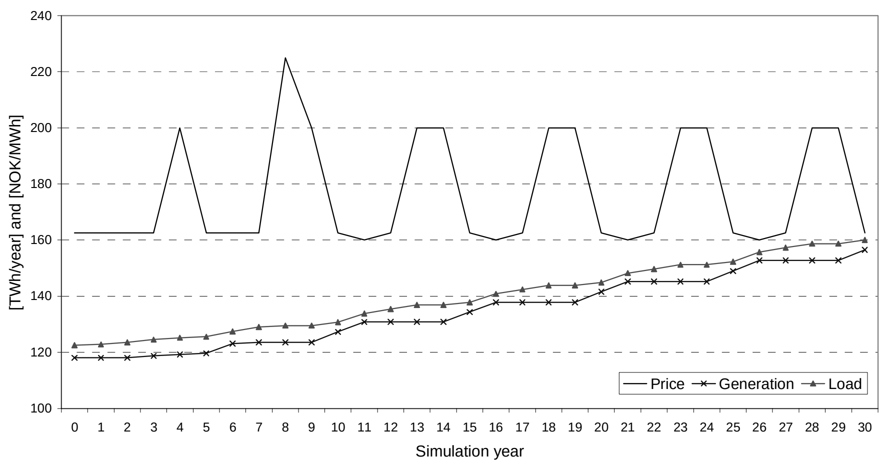

Figure 3.7 Simulated electricity price, generation and load in the reference scenario, 2000-2030.

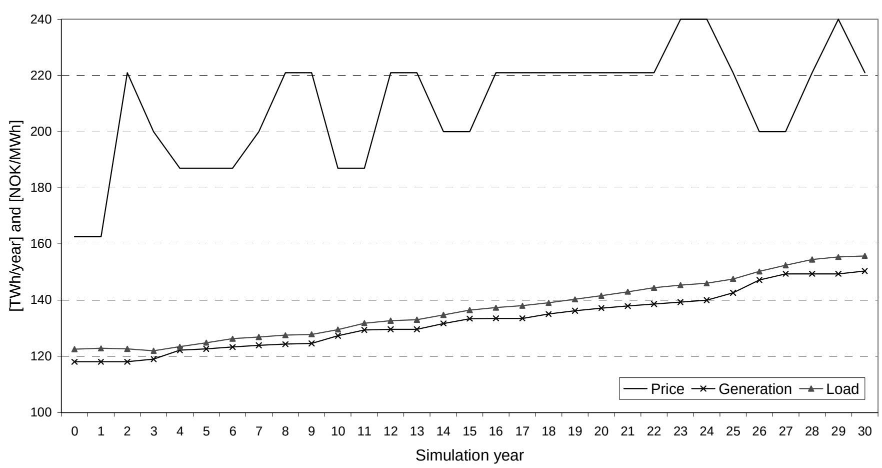

Figure 3.8 Simulated electricity price, generation and load in the green scenario, 2000-2030.

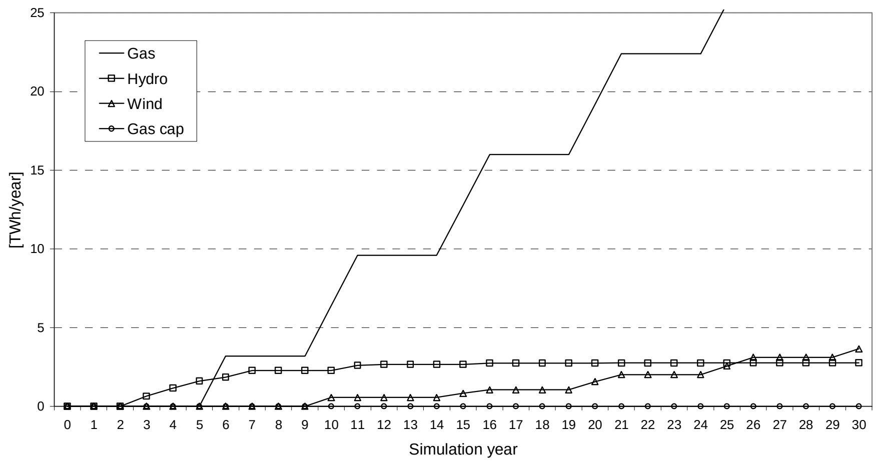

Figure 3.9 Simulated new generation capacity for the four different technologies in the reference scenario, 2000-2030.

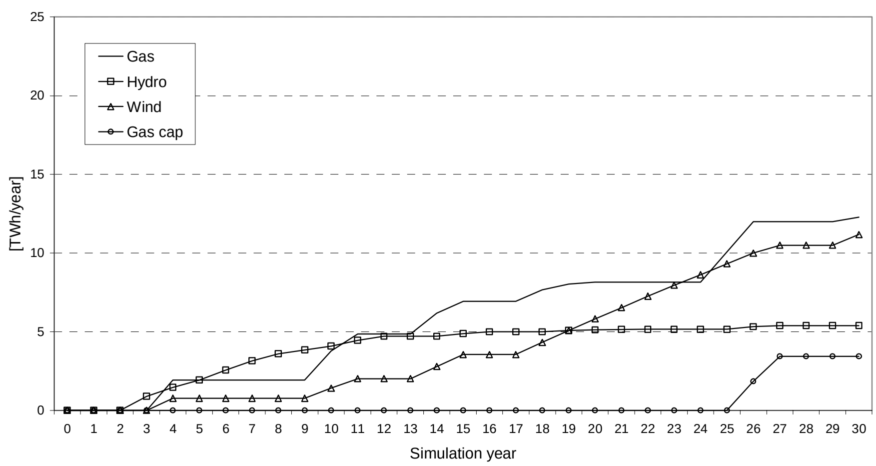

Figure 3.10 Simulated new generation capacity for the four different technologies in the green scenario, 2000-2030.

We only show a limited number of results here, as our main focus is on the presentation of the system dynamics model concept and the underlying theory. However, by changing the input variables to the model it is possible to study different topics, ranging from natural effects like stochastic inflow, to effects from authority regulations like subsidies of certain generation technologies and changes in end-use taxation. System consequences of different investment strategies can also be examined, by modifying the decision rules for investments in the various technologies in the model. The simulation model can be a useful tool for scenario analysis of the long-term development of the power market. The results from such scenarios can serve as input to investor's decisions regarding investments in new power generation assets. Politicians and regulators, who want to enhance their understanding of the investment dynamics in restructured power market, can also use scenario results as input to their decisions regarding market design and investment incentives. However, in order to achieve improved decision making through such scenario analysis it is of high importance that decision makers are also involved in defining the scope and assumptions for the study, and also in the development of the simulation model itself. The full value of using system dynamics as a tool for decision support is only achieved by actively taking part in the aggregation of knowledge which takes place through the different phases of the model development.

3.5 Extensions of the Model

The simulation model presented in this chapter was developed in an early stage of the doctoral project. Later on, the original model concept has been extended in several directions. Vogstad et al. [33] and Maribu [34] introduces a finer time resolution in the model so that seasonal variations can be taken into account. An alternative formulation for the price formation in the spot market is also proposed. Furthermore, the geographical scope of the input data set is extended to include Sweden, Finland and Denmark in addition to Norway. However, the main feedback loops for capacity addition and demand development are still the same as in the model presented above. A range of scenarios for the long-term development of the power market in Scandinavia are examined in these analyses, with focus on economic and environmental consequences of different energy policy options. Vogstad et al. [35] and Slungård Kristensen [36] also extend the scope of the model to include the interaction between a restructured electricity market and a possible market for tradable green certificates. The complexity of the feedback loops and investment dynamics in the system are further increased when green certificates are introduced as an incentive to increase investments in renewable power generation technologies.

3.6 Chapter Summary and Concluding Remarks

In this chapter we have presented a simulation model for long-term analysis of the power market. The model is based on the field of system dynamics. It simulates the development of supply and demand in a competitive power market, where the electricity price is the main feedback signal for new investments in the system. In the model we have tried to include the main causal relationships that give rise to the long-term investment dynamics in the power system. Less attention is paid to detailed representation of short-term operation of the system. The dynamic simulation model can serve as a tool for learning and decision support for participants in the power market who want to adapt quickly to the changing conditions caused by the recent trend towards liberalisation and competition. The strength of the modelling approach lies in its ability to dynamically simulate feedback systems where decisions are decentralised and not necessarily based on perfect foresight and rational expectations. Scenarios which resemble real world decision making can therefore be analysed.

The model is well suited for scenario planning. The results from the Norwegian case study show that the model is able to capture at least parts of the long-term dynamics that is likely to occur on both the supply and demand side of the power market. We see that cycles of power plant constructions can easily occur in competitive power markets. This has also been pointed out in previous studies. Not surprisingly, the results also show that regulatory intervention in the market, e.g. in terms of taxation and permitting policies, can substantially change the choice of new power generation technologies. The changes in investment patterns also change the price dynamics in the system.

A system dynamics model is mainly a tool for improving decision makers' qualitative understanding about a complex problem. Increased insight will, in turn, result in better decision making. However, improved knowledge can only to a limited extent be achieved by studying the results from the simulation model. In order to obtain the best results from using system dynamics for planning purposes, decision makers should be involved in all the stages of the model development.

As we have seen, the investment decision rules that are applied in the model in this chapter are of a static and rather simplistic nature. In the following chapters we will focus on how decision makers can optimise investments in a competitive power market, where they are faced with increased levels of uncertainty. However, we still use the optimal investment strategies to simulate the system over a period of time, in order to gain insight in the long-term dynamics of investments and prices in the power system.

Chapter 4 OPTIMAL INVESTMENTS IN POWER GENERATION UNDER UNCERTAINTY

In this chapter we develop a stochastic optimisation model for investments in new power generation capacity under uncertainty. The model builds upon real options theory, which has been developed over the last two decades in order to improve how uncertainty can be taken into account in economic evaluations of investment projects. The real options theory is outlined in the beginning of the chapter, with focus on its relevance and applicability for investment planning in a restructured power system. We also discuss the main uncertain factors that will influence the future price of electricity, and how these short- and long-term uncertainties influence optimal investment decisions. The decision support model in this chapter calculates optimal investment strategies for a decentralised investor in the power system. When developing the model we first assume that the investor has an exclusive permission to construct a new power plant. Under this assumption we develop the mathematical framework of the optimisation model, which is based on stochastic dynamic programming. More realistic assumptions are added to the model, by also representing the investment decisions of other participants in the system. In the illustrative examples we use the model to identify at which load and price levels it is optimal to invest in a new gas power plant in Norway. The analysis is repeated for different assumptions about regulatory incentives for investments. We also study the resulting effect on capacity and energy balances in the power system. Differences in the optimal investment decisions from using stochastic versus deterministic, and dynamic versus static project evaluations are also illustrated.

The investment model in this chapter was first presented at the 12th Intelligent Systems Applications to Power Systems Conference, ISAP2003 (Botterud et al. [37]). The paper from the conference proceedings is included in Appendix D.

4.1 Investment Theory and Real Options

4.1.1 Shortcomings of Discounted Cash Flow and the Static NPV Rule

According to traditional finance theory the net present value (NPV) is the best indicator and decision-aid for companies evaluating a new investment project. The static form of the NPV rule states that a project should be undertaken as long as the sum of discounted cash flows from the project (i.e. the NPV) is positive, while projects with a negative NPV should be rejected. However, it has become apparent that the traditional static discounted cash flow techniques have severe shortcomings (Dixit and Pindyck [38], Brennan and Trigeorigis [39]). First of all, the static assessment only compares the two alternatives of making an investment today or not to invest at all. In most cases the decision maker has the choice of deferring an investment, and then to invest later in the event of favourable investment conditions. In addition, the result from applying the static NPV rule is heavily dependent on the discount rate applied in the calculation. At the same time we know that estimating an appropriate discount factor in many situations can be very difficult. A new direction within investment theory has emerged in the 1980s and 1990s, which is trying to mitigate the shortcomings of the static discounted cash flow techniques. The new approach, frequently referred to as real options theory, is based on a dynamic analysis of investment projects. In the real options theory a new invest project is regarded as an option, and it is recognised that the value of such a real option comes from three sources (Ross [40]). Firstly, the static NPV given that the project is undertaken immediately. Secondly, the value of the embedded options built into the project. These embedded option values arise because of uncertain future changes in the value of the project itself. Thirdly, the option value which is caused by possible future movements in capital costs (i.e. the interest rate).

The valuation of an investment opportunity can change considerably if the option values are taken into account in addition to the static NPV in project evaluations. In order to do so a stochastic dynamic approach is needed. A deterministic project assessment based on discounted cash flows can also give results that are better than the static NPV rule, as long as the dynamic aspect is included. Deterministic dynamic methods[15] is frequently applied

[15] A good theoretical overview of expansion planning methods for the power industry in Norway is given by Faanes in [41]. Dynamic programming (DP) is here considered as the best method to determine the optimal choice of timing, size and technology for new investments in generation capacity. Deterministic DP models find an optimal investment plan for the entire planning horizon and do not take the effect of uncertainty into account in the optimisation. Stochastic DP models, on the other hand, find the optimal first stage investment decision, while future decisions are dependent on how uncertainties unfold.

within the electrical power industry, and can be used to find optimal investment plans under certainty. The main advantage of the real options theory compared to these deterministic approaches is its improved capability of dealing with risk, uncertainty, and flexibility in the timing of investment projects. Dixit and Pindyck [38], Brennan and Trigeorgis [39] and Ross [40] give comprehensive descriptions of the real options theory. An overview of the main principles is given in the sections below.

4.1.2 Real Options, Managerial Flexibility and Irreversible Decisions

An investment project can have several embedded properties that can be viewed as options. The most common options for investment projects are listed by Trigeorgis [42]: the option to defer an investment, the time to build option (for staged investments), the option to alter operating scale, the option to abandon a project, the option to switch inputs or outputs from a process and different forms of growth options (e.g. investments in R&D). In some projects there are interacting effects between several of these options. In addition to the options embedded in the project itself there is always an uncertainty in future cost of capital. This will also contribute to the value of the option to invest in a new project. The total value of an investment option before it is exercised, i.e. the value of a project before an investment decision is made, is illustrated in Figure 4.1 and can be expressed as:

$$\left(\begin{array}{c}\textit{Total value of}\\ \textit{investment option}\end{array}\right) = \begin{array}{c}(\textit{Static NPV}) \quad + \\ (\textit{Value of options from managerial flexibility})\end{array}$$

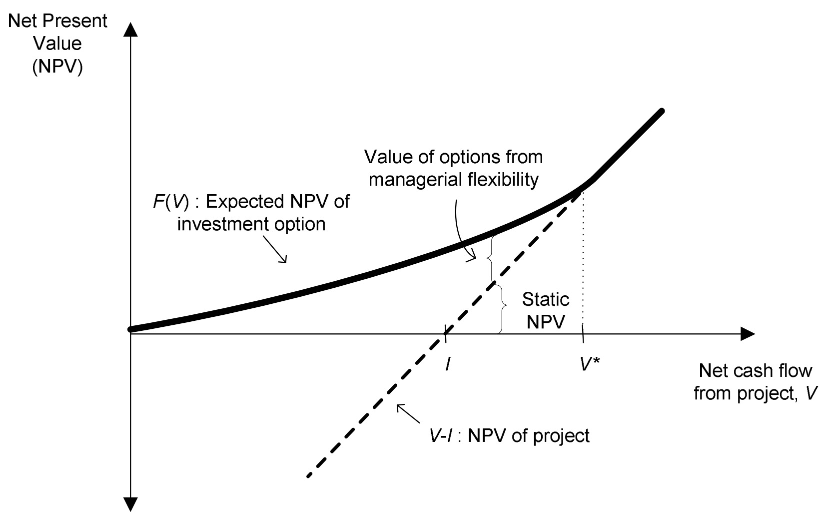

Figure 4.1 Illustration of the real options principle. The figure shows the expected NPV of the investment option, F(V), and the NPV of the project itself, V-I, as functions of the net cash flow from the project, V, which evolves as a stochastic process. I is the investment cost, while V is the threshold where immediate investment becomes optimal.*

According to the static NPV criterion, it is optimal to invest as soon as the NPV of the project turns positive, i.e. when the net cash flow, V, exceeds the investment cost, I, in Figure 4.1. However, V is uncertain and can change in the future. By investing immediately the investor is unable to take advantage of favourable changes in V. The value of having the option to invest, i.e. $F(V)$ in Figure 4.1, is therefore higher than the NPV of investing immediately, also after the project's NPV turns positive. Therefore, according to the real options theory the optimal investment criterion does not occur until the cash flow from the project reaches V^*. At this point the value of investing immediately becomes more profitable than the expected value of holding the option to invest and thereby be able to wait for more information about the future to unfold.

When calculating the total value of an investment opportunity the total net cash flow, V, can be represented directly as an exogenous stochastic variable, as illustrated in Figure 4.1. In more detailed models the value of the investment project is usually modelled as a function of one or more underlying variables, e.g. product demand or price if the project is a factory. Note that both growth and uncertainty in the net cash flow can contribute to the option value from managerial flexibility. A deterministic dynamic model can capture the part of the option value, which is due to the growth in underlying variables. However, a stochastic dynamic model is required to also take into account the option value that arises from uncertainty.

In the example illustrated in Figure 4.1 the option value from active management is positive, and therefore contribute to the postponement of the investment decision. In certain cases the option value might also be negative, resulting in earlier investments than what the static assessment suggests. This is typically the case when an investment decision develops future growth opportunities (growth options).

The part of the total project value that arises from the option value of managerial flexibility is highly dependent on the irreversibility of the investment decision. In some cases, as for instance investment in a new office building or a fleet of transportation vehicles, the investment can be at least partially reversed by selling off the assets to other investors. In the case of reversible investments the additional option value is low and the static NPV criterion would still be appropriate. However, large-scale capital investments are very often firm or industry specific and the investment decision is therefore to a large extent irreversible due to the projects' limited value for other investors. Irreversibility increases the option value of and investment opportunity, and therefore also the importance of taking this into account in the project appraisal. New power plants would usually fall into the irreversible category of investment opportunities, as the possibility of selling a newly constructed power plant without substantial financial losses is very low. Another important factor that influences the value of an investment opportunity is the duration of the investment option. A power generation company might receive approval from the authorities for constructing a new plant, but the permit is usually valid only for a limited number of years. In this situation, the option value of the investment opportunity would be large in the beginning of the period, while it would gradually decrease as the expiration of the permission approaches.

4.1.3 The Use of Dynamic Programming in Real Option Valuation

Dynamic programming (DP) is one of the optimisation techniques that is appropriate for solving investment problems in accordance with the real options theory. DP is a general optimisation technique with applications within a range of different areas, including power system planning. The central idea in DP is Bellman's principle of optimality which states that [38]: "*An optimal policy has the property that, whatever the initial action, the remaining choices constitute an optimal policy with the respect to the subproblem starting at the state that results from the initial actions*". A DP optimisation problem is therefore often solved stepwise, starting either from the beginning or the end of the period of consideration. The theory can also be extended to infinite horizon problems and continuous time. A continuous time version of the so called Bellman equation, as shown in (4-1), can be used to solve an investment optimisation problem when the underlying uncertainty is described by a continuous stochastic state variable. The equation states that under an optimal investment policy the sum of immediate payoff from the project and the change in the value of the investment option (the right-hand side of the equation), must equal the required risk-adjusted return on the investment project (the left-hand side of the equation).

$$\rho \cdot F(x,t) = \max_{u} \left\{ \pi(x,u,t) + \frac{1}{dt} E(dF) \right\} \qquad (4\text{-}1)$$

where

$F(x,t)$	value of the investment opportunity (option)
$\pi(x,u,t)$	immediate payoff from the investment
ρ	risk-adjusted discount rate for the investment project
x,u,t	state variable, control variable (investment decision), and time

The following simple example illustrates the use of the DP algorithm for an investment optimisation problem. A power generation company is considering construction of a new hydropower plant. The owners of the company have not taken the final investment decision yet, as they are not convinced about the profitability of the new plant. The value of the power plant is highly dependent on the future price in the power market, and the problem is to decide at what price level it is optimal to build the new plant. For simplicity we only consider price uncertainty here, although there are a number of other uncertainties that also influence the profitability of the power plant. We assume that the uncertain electricity price can be represented by a state variable, P, which follows a stochastic process as shown in (4-2)[16]. We also assume that the operating costs for the hydropower plant can be neglected. The expected value, $V(P)$, of the hydro power plant after the investment decision is taken is therefore as shown in (4-3), i.e. $V(P)$ can be expressed as the price for electric power, P, times a constant factor, k.

$$dP = \alpha \cdot P \cdot dt + \sigma \cdot P \cdot dz \tag{4-2}$$

$$\begin{aligned} V(P) &= E\left[cf \cdot ic \cdot \int_0^T (e^{-\rho t} \cdot P)dt \right] = cf \cdot ic \cdot \int_0^T (e^{-\rho t} \cdot P \cdot e^{-\alpha t})dt \\ &= P \cdot k, \quad k = \frac{af \cdot ic}{\rho - \alpha}\left(1 - e^{-(\rho-\alpha) \cdot T}\right) \end{aligned} \tag{4-3}$$

where

α, σ	expected growth rate and variance rate for price, P
dz	Stochastic Brownian motion process, i.e. $dz \sim N(0,dt)$
af, ic, T	capacity factor, installed capacity, and lifetime for the new power plant
ρ	risk-adjusted discount rate for the new power plant

We know that the price has to reach a certain level, P^*, before it becomes optimal to invest. At this price level the value of the investment option equals the NPV of the project (i.e. $V(P^*)-I$). Now consider the price interval below P^*. In this price interval we know that it is not optimal to invest. Hence, there is no immediate payoff from the project and the general Bellman equation in (4-1) can be restated as $\rho F dt = E(dF)$. By using Ito's lemma[17] to expand dF, combined with (4-2) for the underlying stochastic state variable, P, a differential equation for the optimal investment problem is derived, as shown in (4-4). This is a second-order homogenous

[16] This stochastic process is called geometric Brownian motion, and is frequently used within finance theory to describe the behaviour of financial assets. The famous Black and Scholes equations [43] for option pricing are for instance based on the assumption that the underlying asset follows a geometric Brownian motion.

[17] Ito's lemma is often used in financial mathematics when the stochastic state variable is an Ito process, i.e. a stochastic processes of the form $dx = a(x,t)dt + b(x,t)dz$. The lemma states that the differential of a function, $F(x,t)$, is $dF = \frac{\partial F}{\partial t}dt + \frac{\partial F}{\partial x}dx + \frac{1}{2}\frac{\partial^2 F}{\partial x^2}(dx)^2$ (ref. [38]).

differential equation and it is solved by standard techniques. The value of the investment option, *F(P)*, and the optimal price level, *P**, is then determined by specifying a set of boundary conditions[18] and ruling out infeasible solutions. The results are shown in (4-5) and (4-6).

$$\frac{1}{2}\sigma^2 \cdot P^2 \cdot \frac{d^2F}{dP^2} + \alpha \cdot P \cdot \frac{dF}{dP} - \rho \cdot F = 0 \tag{4-4}$$

$$F(P) = \left(\frac{k}{\beta}\right)^{\beta} \cdot \left(\frac{\beta - 1}{I}\right)^{\beta - 1} \cdot P^{\beta} \tag{4-5}$$

$$P^* = \frac{\beta \cdot I}{k(\beta - 1)}, \quad \beta = \tfrac{1}{2} - \alpha / \sigma^2 + \sqrt{\left(\alpha / \sigma^2 - \tfrac{1}{2}\right)^2 + 2\rho / \sigma^2} \tag{4-6}$$

Having developed the closed-form solutions in (4-5) and (4-6) we can now investigate the optimal investment for a set of assumptions (Table 4.1). First, we assume that there is no expected growth in the price ($\alpha = 0$). The resulting values of the investment option for three different levels of uncertainty are shown in Figure 4.2. When there is no uncertainty about future price ($\sigma = 0$) there is no option value in waiting. The value of holding the investment option is therefore zero until the price reaches the level where the NPV of the project becomes positive. In this case the optimal investment price, *P**, is the same as in the static NPV analysis. The figure also shows that uncertainty in the price adds value to the investment option, so that optimal investments are triggered at higher prices. When a growth rate is added to the price process ($\alpha = 0.03$), we see a similar picture (Figure 4.3). However, the optimal investment prices are higher, and now there is a value in having the investment opportunity, even if there is no uncertainty. Hence, both the underlying growth and uncertainty in the price give rise to the value of the investment option.

Table 4.1 Input parameters for investment in a new hydropower plant.

Parameter	Description	Value	Unit
ic	Installed capacity new plant	100	MW
af	Capacity factor	4000	hours/year
I	Inv. cost (@10000NOK/kW)	1000	MNOK
T	Life time	30	years
ρ	Risk adjusted discount rate	0.08	per year
α	Expected price growth rate	0 or 0.03	per year
σ	Standard deviation in price	0, 0.1 or 0.2	per year

[18] Three boundary conditions are used: $F(0) = 0$, $F(P^*) = V(P^*) - I$, and $F'(P^*) = V'(P^*)$. See [38], Chapter 5 and 6, for a more detailed description of similar investment problems.

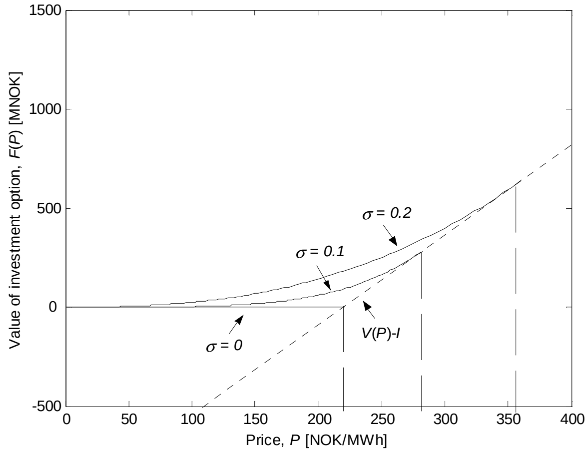

Figure 4.2 The value of the investment option, F(P), with no expected growth in price (α = 0), and three levels of price uncertainty (σ = 0, σ = 0.1 and σ = 0.2). The net present value of the project, V(P)-I, is also shown.

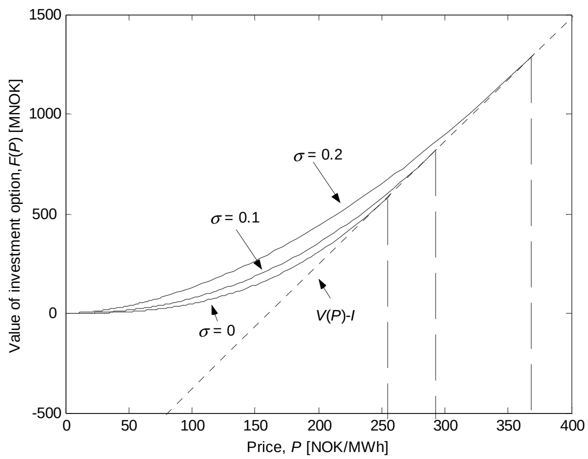

Figure 4.3 The value of the investment option, F(P), with expected growth in price (α = 0.3) and three levels of price uncertainty (σ = 0, σ = 0.1 and σ = 0.2). The net present value of the project, V(P)-I, is also shown.

The example presented above serves to illustrate how real options theory can be applied to identify optimal investment thresholds as a function of the underlying state variable(s). The central idea in real options analysis is illustrated, namely that the optimal investment criterion can deviate considerably from what the static NPV analysis suggests. Our problem formulation is very simplistic, as we have assumed that the value of the hydropower plant is a function of one state variable only, the electricity price. At the same time the price is modelled as a simple stochastic process. This is of course a very aggregate representation of the electricity price, as the price in reality is a function of more fundamental variables, such as electricity demand, fuel prices, installed generation capacity and the rules and regulations of the electricity market. The electricity market also contains a high degree of seasonality, which should be taken into consideration. Later in the chapter we will return to the problem and develop a more fundamental model for optimal investments in power generation assets, where a wider range of uncertainties can be taken into account. Another problem with the DP approach presented above is that it requires the specification of an explicit risk-adjusted discount rate, ρ, for the investment project. As already mentioned, it can be difficult to derive an appropriate discount rate for the project under consideration. An alternative method has therefore evolved for valuation of real options, which better takes into account the risk and return characteristics for the investment project. This alternative method, called contingent claims analysis, is briefly outlined in the following section.

4.1.4 Contingent Claims Analysis and Risk-Neutral Valuation

The use of contingent claims analysis (CCA) for evaluation of investment projects is closely linked to financial option pricing, which was first developed by Black and Scholes [43], and Merton [44] in the early 1970s. The idea behind CCA is to create an artificial portfolio of assets that are traded in the financial market, so that the portfolio exactly replicates the uncertain net cash flow from the investment project. A riskless position can then be obtained by holding the option to invest in the project and an offsetting short position in the replicating portfolio. The return on the riskless position must equal the risk-free interest rate, in order to avoid arbitrage opportunities. By setting the return on the riskless portfolio equal to the risk-free interest rate, and expanding the change in the value of the investment option (dF) using Ito's lemma, a differential equation can be derived for the problem. The value of the replicating portfolio can be assessed relative to the total financial market portfolio, for instance by using the Capital Asset Pricing Model (CAPM) model[19]. Consequently, the investment project is evaluated according to the total financial market's pricing of risk, and the market value of the project is maximised. The value of the investment opportunity can now be expressed without using a specific risk-adjusted interest rate for the project. Instead, the risk-free interest rate and the market's required rate of return for the replicating portfolio are used to evaluate the investment option. For the investment example presented

[19] The Capital Asset Pricing Model (CAPM) is described by Brealey and Myers in [45]. The CAPM provides an expression which relates the expected return on an asset, r_x, to its systematic risk, β. CAPM states that: $r_x = r_f + \beta^*(r_m - r_f)$, where r_f is the risk-free interest rate, r_m is the return on the total financial market portfolio and $\beta = \sigma_{xm}/\sigma_m^2$ is a measure for the asset's systematic (non-diversifiable) risk.

above, the differential equation resulting from CCA valuation is shown in (4-7). We see that (4-7) bears close resemblance to (4-4). The only differences are that the risk-free interest rate, r, is used in place of the risk-adjusted discount rate, ρ, and the growth rate of the price process, α, is replaced by the risk-free interest rate adjusted for dividend, r-δ. Furthermore, by comparing (4-4) and (4-7) we see that the investment option could be evaluated by discounting with the risk-free interest rate and letting the price follow a stochastic process with an alternative growth rate (r-δ), as shown in (4-8). This illustrates the principle of ***risk-neutral valuation***[20], which gives the same result as the no-arbitrage arguments behind CCA.

$$\frac{1}{2}\sigma^2 \cdot P^2 \cdot \frac{d^2F}{dP^2} + (r-\delta) \cdot P \cdot \frac{dF}{dP} - r \cdot F = 0 \tag{4-7}$$

$$dP' = (r-\delta) \cdot P' \cdot dt + \sigma \cdot P' \cdot dz \tag{4-8}$$

where

r	the risk-free interest rate
δ	dividend (or convenience yield) on the replicating portfolio (i.e. $\delta = r_p - \alpha$, where r_p is the expected return on the replicating portfolio according to CAPM)

The use of CCA for valuation of real assets relies on the assumption that a portfolio can be established in the financial markets, which exactly replicates the uncertainty in the underlying stochastic processes. This is an appropriate assumption if the state variable is the price of a commodity that is traded in futures markets with high liquidity. However, unless one can assume the existence of complete financial markets, there would sometimes be situations where the underlying state variables have characteristics that are not similar to any portfolio of traded financial assets. In this case the use of CCA would not yield correct results. However, the DP algorithm with an exogenous discount rate would still apply.

4.1.5 Limitations of the Continuous DP and CCA Approaches

If the investment problem is specified in an appropriate way, it is possible to find closed-form solutions for the differential equation resulting from either the dynamic programming or the contingent claims analysis approaches. However, in order to find an analytical solution to the investment problem, the state variables have to follow a specific group of stochastic processes. Ito and Poisson processes are the only stochastic processes that are suitable

[20] In the risk neutral valuation paradigm one uses risk-neutral stochastic processes to describe the dynamics of the underlying state variables, and discounts all cash flows at a risk-free rate. See Hull [46] for a description of risk neutral valuation and derivatives pricing.

for solving the problem analytically, according to Dixit and Pindyck [38]. In most applications from finance theory it is assumed that the underlying stochastic variable(s) can be described either by geometric Brownian motion or by a mean-reverting process (both belong to the group of Ito processes). The number of state variables is also normally limited to one or two in real options applications from finance theory, as analytical solutions rarely exist for two or more state variables. To release the strong assumptions for finding analytical solutions, it is sometimes better to formulate the investment problem in discrete time and also discretise the state variables. This allows for a more flexible, detailed and therefore more realistic problem formulation. With discrete representation of time it is also possible to represent delays, for instance due to the construction time for a project. The disadvantage is of course that it is not possible to derive closed-form solutions that can be applied directly for decision support. One of the more advanced models from finance theory with application in the energy industry is proposed by Schwartz and Smith [47]. They develop a stochastic model based on two underlying Ito processes to analyse short-term variations and long-term dynamics in oil prices. Kalman filtering is applied to estimate the parameters in the continuous time model from price data of oil futures contracts. Potential use of the model is illustrated with an example where they use real options theory to evaluate two different oil production projects. In order to find a solution to the real options problem they have to formulate it using discrete time SDP. The two underlying state variables are also discretised. This serves to illustrate that only under very strict assumptions can an analytical solution be derived when there is more than one state variable in the model. In addition, the difficulty of estimating model parameters also increases rapidly with the complexity of the model.

4.1.6 Real Options and Competitive Markets

In the above presentation of real options theory we assume that the company has an exclusive opportunity to investment in a new project. In competitive markets the option to invest is usually not limited to one firm only. Consequently, there is always a risk concerned with postponing an investment project, since it gives other investors the possibility to enter the market. It is likely that the possibility of investments from other firms will influence on the optimal investment criteria. The direct validity of the above analysis is therefore limited to a monopoly situation.

So far we have not taken into account the effect on the future price and project value from other participants' investments, unless we can assume that other participants' actions are already included in the underlying stochastic processes. In the real options literature there are proposals for how this can be done. Dixit and Pindyck [38] start with an investment model similar to the one in the hydropower example above, and assume that other participants in the market will invest if the price rises sufficiently high. Now there is no longer an option value in postponing the investment, since this would result in competitors investing instead. In a fully competitive and open market, with homogenous participants where everyone faces the same uncertainties, there will be one single optimal investment price for all participants. Since there is no option value in postponing a project, investments would be made as soon as the net value of the project exceeds the investment cost. This optimal price puts an upper barrier on the price distribution, so that the expected value of the project is lowered. This is illustrated in Figure 4.4. With this simple investment model it turns out that the optimal investment price under competition is the same as in the monopoly case. However, now it is not the option value in the investment that raises the optimal price level above the original static NPV criterion. Instead it is the lowered expected value of the project itself, due to the barrier in the price distribution created by the competitors, which give a higher optimal investment price.

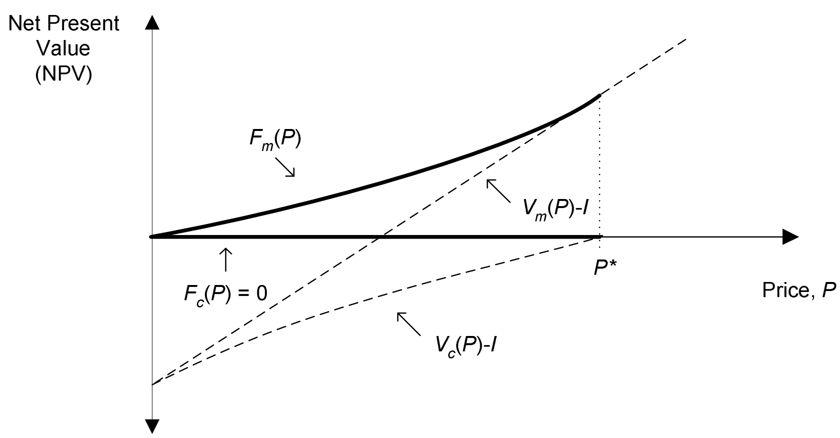

Figure 4.4 The value of an investment option and the corresponding investment project as function of price in monopoly (m) and perfect competition (c). The optimal investment price, P, is the same in both cases. Source [38].*

Smit and Ankum [48] include game-theoretic considerations into the valuation of investment opportunities. The net operating cash flow from a project is defined as the sum of the opportunity cost of capital and the expected economic rent. Economic rents occur when a company has a competitive advantage and are naturally permanent in a monopoly situation. However, the rent will only exist temporarily in competitive markets characterised by costless entry and exit of competitors. This is represented with exponentially declining economic rents. A duopoly situation is also studied, where two firms are operating so that the behaviour of each competitor directly influences the value of the project. In this situation an early investment can contribute to pre-empt the competitor. A two-step binomial decision-tree is constructed to evaluate an investment option under duopoly. The Nash equilibrium from game theory is applied to identify investment strategies and corresponding project and option values at each decision node under both symmetric and asymmetric market power. In this situation the values depend on the strategy of the other firm, particularly if an early investment pre-empts the competitor or results in a competitive advantage. The degree of market power for the leading firm and the amount of information shared between the firms influence on the optimal investment. The level of cooperation between the firms is also important when the investment decision is modelled as a game.

Dixit and Pindyck [38] also model a duopoly within their continuous time framework. A dynamic game with two players is formulated, and the value of an investment project and the corresponding optimal investment criterion is derived for both. The result depends on whether the firm is a leader, i.e. the firm which invests first, or a follower. The investment threshold is lower for the leader, because the option value of waiting is limited due to the risk of the other participant investing first instead. However, the option values and investment thresholds naturally depend on whether the roles as leader and follower are preassigned or not.

4.1.7 Literature Survey: Real Options in Power System Planning

The restructuring of the electric power industry has increased the uncertainty concerning the profits from investments in new power generation. However, the electric utilities were also faced with many of the same uncertainties under traditional regulation, although the focus was on cost minimisation and not profit maximisation. Models for optimisation of investments under uncertainty were therefore also applied within the regulated industry. Hobbs [3] gives a good overview of optimisation methods for electric utility resource planning under cost minimisation, i.e. the selection of power generation and energy efficiency resources to meet customer demands for electricity. According to Hobbs most utility planners use deterministic methods, such as deterministic equivalents and scenario analysis, to assess different expansion plans under uncertainty. More advanced methods for stochastic optimisation under uncertainty are rarely used, due to the complexity and also the computational requirement involved. Still, there are a few proposals for how to better deal with uncertainty and flexibility for the regulated industry. Mo et al. [16] use stochastic dynamic programming to identify optimal investment strategies to meet future heat demand. Heat demand and oil price are represented as stochastic variables using Markov chains. The effect of different construction times for the candidate technologies is also represented in the model. The model minimises the expected sum of investment and operating costs within a DP framework, and therefore takes into account flexibility and timing in a similar way as the real options theory. Gorenstin et al. [49] also applies stochastic optimisation over long-term uncertainties for expansion planning. Load growth is represented as a binomial tree, and decomposition techniques are used to couple the operation and investment sub problems. A minimax regret criterion is used in the objective function, as it is argued that the minimisation of expected cost is not adequate for "low frequency" phenomena such as the load level in expanding systems.

Gardner [50] looks at the value of flexibility for different technologies under uncertain demand. He defines a technology's flexibility benefit as the difference between its value under certainty and uncertainty. A set of features that are important for a technology's flexibility benefit are identified, such as lead time, life time and the ratio between investment and operating costs. A decision tree, where the uncertain demand can follow three different growth paths between each time period, is used to calculate the flexibility benefit. A case study from Canada shows that capital-intensive long lead-time technologies, such as nuclear generation, have a smaller flexibility benefit than low capital cost, short lead-time technologies. Gardner and Rogers [51] analyse the electric utility's problem of finding the optimal mix of technologies to meet uncertain demand in a specific target year. The traditional approach is to use technology screening curves combined with the load duration curve to select supply technologies in merit order (i.e. according to increasing operating cost). These traditional screening curves can be directly applied when the technologies are described by operating and capital cost only. However, Gardner and Rogers use a two-stage stochastic program to show that the lead time is also an important technology parameter that could change the optimal selection of technologies when future demand is uncertain. A numerical example shows that some short lead time technologies screened out by standard screening methods may enter the optimal solution when differences in lead time are considered, while some long lead time technologies may leave. Teisberg [52] uses option valuation directly to look at investment in a power plant for a regulated utility. This approach does not take into consideration technical constraints in the power system, but focuses on the effect of different regulatory incentives. The value of the plant is modelled as a stochastic process[21] where the growth rate is adjusted for different regulative regimes for cost allowance. The effect of construction time and sequential cost

[21] Teisberg uses a geometric Brownian motion similar to (4-8) to describe the value of the project and applies contingent claims analysis to find the value of the investment option. Different regulating regimes are represented by letting δ be a function of the stochastic variable.

outlays are represented and analysed using a simplified binomial option model, as the corresponding differential equation does not have a closed-form solution in this case.

New models for evaluation of investments in generation facilities under competitive regulation have naturally emerged over the last few years. Some of these approaches are linked more directly to the options theory from finance. Closed-form analytical solutions for the option value of generation assets, assuming that electricity and fuel prices follow either a geometric Brownian motion or a mean-reverting process are derived by Deng et al. [53]. Futures contracts for electricity and fuel are used to establish a risk-free portfolio based on the principles for risk-neutral valuation. The same logic is used to obtain the value of locational spread options for valuation of transmission assets. Dobbe et al. [54] also uses futures based replication for real options analysis of new generation assets. Forward prices for gas and electricity are used for the valuation of a new gas power plant in Norway, under different regulatory regimes for CO_2 emissions. Oren [55] looks at demand side management, and suggests that customers' flexibility to curtail load can be considered as a real option and evaluated accordingly. The value of a "double-call" option[22] is derived based on the principles of the Black-Scholes formulas, with the underlying assumption that the forward price of electricity can be described as a geometric Brownian motion. A discrete binomial lattice model for real option valuation of two inter-related generation units is derived by Min and Wang [56], again assuming that the value of the projects evolve over time according to geometric Brownian motions. The model is used to evaluate capacity expansion and reduction. Venetsanos et al. [57] compares the use of discounted cash flow and real option evaluation of investments in wind power plants. The benefits of modularity and short lead-time under load growth uncertainty are taken into consideration by adjusting the expected investment cost, and the value of the investment option is calculated using the standard Black-Scholes formulas. The results show that the benefits from modularity and short lead-time can be substantial for wind power projects, but the option valuation still tend to encourage postponement of investment due to the value of waiting for future uncertainties to unfold. Short-term operational constraints are added to the real option valuation of generation assets by Tseng and Barz [58]. A combination of forward moving Monte Carlo simulation and backward dynamic programming is used to find a more realistic short-term

[22] A "double-call" option is defined as a call option with one strike price if executed before delivery and another strike price if executed at delivery. It is shown that a forward contract bundled with an appropriate double-call option provides a "perfect hedge" for customers that can curtail load in response to high spot prices. The curtailment loss is assumed to be lower if the decision is made with sufficient lead time.

value of generation assets. Here it is assumed that electricity and fuel prices follow lognormal mean-reverting processes corrected for hourly patters over the week. It is shown that failure to consider physical unit commitment constraints may significantly overvalue a power plant.

The literature survey shows that the stochastic planning models for the regulated industry tried to include the main technical constraints in the power system. However, the objective was to identify optimal strategies to meet future load growth, usually in terms of minimising cost, so that the price dynamics in the electricity market was of less concern. The more recent planning models recognise that it is the uncertain future price, and not the load growth by it itself, that triggers new investments in the power system. Still, in most of the models it is assumed that the electricity price, or the value of a new investment, can be described by fairly simple stochastic Ito processes. The advantage is of course that these processes usually can be dealt with analytically. However, when it comes to representing the price dynamics in the current and future power markets, which is a function of both technical constraints and market regulations, the assumptions behind these option pricing calculations are probably to simplistic. Our aim is still to use the principles behind the dynamic real option valuation to analyse investments under uncertainty in new generation assets. By developing a model framework that is capable of including more fundamental modelling of the price dynamics in the power market, we are better equipped for analysing the long-term consequences of power market restructuring.

4.2 Uncertainties and Real Options in Restructured Power Systems

After the introduction to real options theory we now look more directly into the conditions in the restructured electric power sector. As we have seen, future uncertainties give rise to the option value of an investment opportunity. Therefore, we first give an overview of the most important uncertainties that an investor in a new power generation facility is facing, and how these uncertainties can be represented mathematically. A differentiation is made between long- and short-term uncertainties. It is the long-term uncertainties that are most important for real options valuation, because they are correlated from year to year and therefore contribute to the option value of an investment opportunity. However, the short-term uncertainties can also play a role for the investment decision, particularly if the investor is risk-averse and sensitive to fluctuations in income from year to year. These uncertainties are also important when looking at the system consequences, for instance in terms of price stability and system reliability, following from optimal investment behaviour.

4.2.1 Long-Term Uncertainties and the Value of an Investment Option

From the real options theory presented above we know that long-term uncertainties give rise to the option value of an investment opportunity. The most important fundamental uncertainties for investments in new power generation facilities are listed below. These long-term uncertainties can influence the profitability of a project, either directly as an uncertain cost element or indirectly through the market price of electricity, or sometimes in both ways.

- Future *electricity demand* is a major uncertainty that is very important also in the restructured power market, as demand naturally is a major price driver in the system. Total demand over the year as well as peak demand is changing with time and influence the price and profitability of new investments. Hence, there could be a value in postponing an investment decision to await more information. There are different underlying factors, such as growth in population and economy, which in turn cause changes in electricity demand. However, in a stochastic investment optimisation model it would lead to far to model demand in great detail, due to computational complexity.

- Changes in *fuel prices* can influence directly the operating costs of a new investment if it is a thermal unit. It also affects the operating costs of existing units and therefore the price level in the electricity market. Historical data show that the prices of petroleum products tend to return to an equilibrium level in the long run [38]. The value of postponing an investment to wait for lower fuel prices might therefore be limited if the level of mean reversion is high.

- *Climate* is another factor that is uncertain in a long-term perspective. Climate changes can result in higher or lower demand than expected, and it can also influence the availability of energy sources such as hydropower. Although there are several forecasts available for long-term climate changes the randomness is still high, so that there might be a value in waiting, for instance to see if and how the inflow to a prospective hydro reservoir changes.

- *Investment costs* are also to an extent uncertain. This is particularly the case for emerging technologies such as solar panels, wind mills and other renewable technologies where cost reductions are likely, but still uncertain. The uncertainty about future currency rates might also make an impact on the actual investment cost, and in such situations it should be taken into account in the project appraisal.

- Uncertain changes in *capital costs*, due to future variations in the interest rates, can also contribute to the value of a real option to invest in a new generation plant.

For the investor there are also other long-term uncertainties, which are not really stochastic elements, but rather results of the decisions taken by other participants in the power system. These decisions also contribute to the value of the investment opportunity, and for the investor they can sometimes appear as random. Therefore, in certain situations it would make sense to model them as stochastic variables. Such exogenous decisions could be:

- *Transmission constraints* influence the electricity price. The prices in deficit areas tend to be higher than in surplus areas, if locational pricing is used. However, this can change if new transmission lines are built. Even if transmission and distribution is still under regulation, long-term plans for investments in new gridlines are rarely present. If investors in new generation are exposed to risks concerning future network constraints and their impact on the price of electricity at the location of the new plant, an option value of postponing investment decisions will arise.

- In a newly liberalised electricity system the *market design and system regulations* are likely to change several times before a stable long-term solution settles. The profitability of an investment in a specific technology can be highly dependent on the prevailing market design. For instance, the mechanisms that are being used for the provision of short-term ancillary services and long-term system adequacy will affect generator income. Direct economic incentives, in terms of taxes and subsidies, are also important factors that can be crucial for the viability of different technological alternatives. When there is substantial uncertainty about some of these factors it makes sense to postpone investment decisions until more certain information about future regulations is available.

- The system's *capacity balance* and electricity price is dependent on the change in system load and on the investor's own investment decisions. However, investments in new generation from other participants in the market also contribute to improve the capacity balance and lower the price. These investments could be considered as random variables and thereby treated in a similar way as other long-term uncertainties. In a competitive industry it is probably a better approach to assume that these investments are linked to the price level in the system, and that investments from others are being made if sufficiently high prices are reached. The last approach is taken in the model presented later in this chapter. Decisions to retire capacity are partly given by the vintage of the existing plants in the system, but also by the market conditions. The random element is even lower for plant decommissions, and they could be treated either as exogenous deterministic inputs or in a similar way as capacity additions.

The list of long-term uncertainties could have been made longer. Although the qualitative interpretation of the real options theory applies to most of these uncertainties, it is only possible to take a limited number of them into account in a mathematical model. A decision maker that wants to quantify the value of a real option would therefore have to select the uncertainties that are considered as most important, and then use a stochastic description of them in the optimisation model. The effect of the remaining uncertainties will have to be assessed through qualitative judgements or scenario analysis.

In this thesis we propose using a discrete investment model, in order to accommodate more details in the problem formulation than what would be possible with a continuous model. If more than one stochastic variable is added to the problem, the correlations between the variables have to be taken into account. In a discrete model this can be done by defining states that are combinations of the underlying stochastic variables and assign appropriate state transition probabilities. However, a consequence is that the size of the state space grows exponentially, so that the computation time increases very quickly with the number of stochastic state variables. The fast growing size of the problem is therefore the main analytical challenge with a discrete model.

In the process of selecting appropriate stochastic variables for the problem one must also consider how to best describe the underlying uncertainty in mathematical terms. From the standard real options models we know that the fairly simple Ito processes are the ones which are best suited for finding analytical solutions. When applying stochastic dynamic programming in discrete time the stochastic variables must have Markov properties. However, this is still more flexible than the typical Brownian and mean-reverting continuous time stochastic processes, whose stochastic behaviour is strictly described by the normal distribution. Figure 4.5 shows a binomial tree for stochastic changes in load. There are no constraints on the transition probabilities, other than the Markov property, i.e. the probabilities at each time step are independent of earlier state transitions[23]. Hence, no assumption of normality is required. Another advantage of using a discrete time

[23] This assumption could also be relaxed by extending the state space, so that it includes the states for more than one step ahead in time. This is equivalent to adding additional stochastic variables to the model, and the computational burden therefore increases accordingly (i.e. exponentially).

optimisation is that the transition probabilities do not need to be defined exogenously. They can be functions of other states in the system, such as capacity balance or electricity price. When modelling electric load one could for instance include price elasticity of demand by adjusting the transition probabilities for load according to the electricity price. In this way the stochastic process can be an endogenous part of the optimisation problem.

For the uncertainties that result from decisions made by other participants in the power system, the possible outcomes (or states) are sometimes very limited. In such situations the required state space expansion is much smaller, and the increase in computational burden is therefore less severe. Figure 4.6 shows how an economic incentive, in terms of an uncertain CO_2-tax, could be represented in a discrete model.

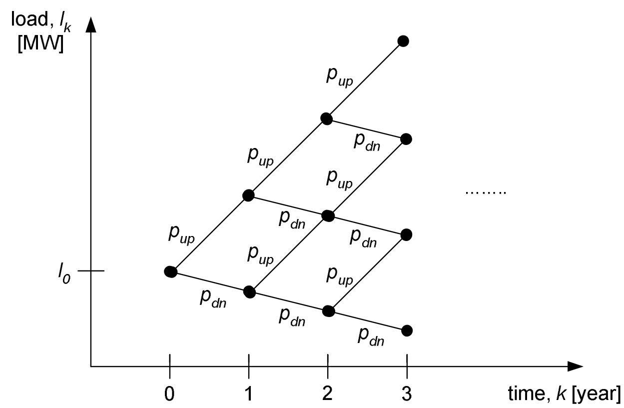

Figure 4.5 Illustration of discrete binomial representation of load level, l_k. p_{up} and p_{dn} are transition probabilities.

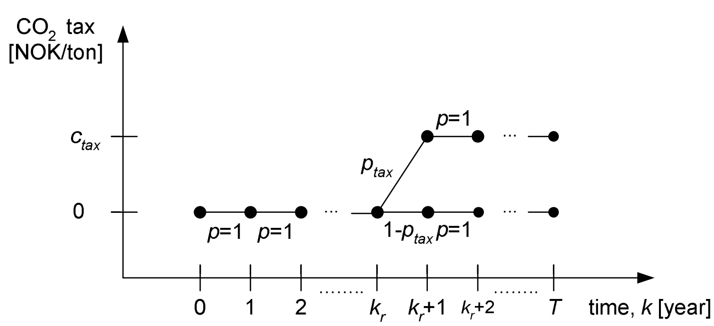

Figure 4.6 Illustration of how an uncertain introduction of a future CO_2-tax could be represented as a stochastic variable with two possible outcomes (0 and c_{tax}). p_{tax} is the probability that a CO_2-tax is introduced after time step k_r.

4.2.2 Short-Term Uncertainties

In this thesis we define short-term uncertainties as stochastic elements that are not correlated from year to year. Hence, the short-term uncertainties can affect the profits for a power plant from season to season and year to year. However, since investments in generation capacity have a long life-time (20-40 years), the positive and negative effects from short-term uncertainties on profits should level out in the long run. Consequently, there is no value in waiting for more information about these uncertainties. The most important short-term uncertainties for the generation expansion problem in a system with a high amount of renewable resources are factors like precipitation and wind. Incidental outages in the system are also important in the short-run, as well as deviations in load which again could be caused by unexpected temperature conditions.

Although the short-term uncertainties do not contribute to the option value of an investment opportunity, it can still be advantageous to represent the most important of them in an expansion model. The reason is that the operating profits for a power plant, and therefore the expected value of an investment project, will depend on the distribution of short-term uncertainties. With the presence of a futures market the investor can hedge his investment against price fluctuations caused by the short-term uncertainties, by selling the power in the futures market instead of the spot market. If there is no risk premium in the futures market the investor would then earn the expected spot price. Another reason for including the short-term uncertainties in the model is that it gives us the opportunity to study system consequences of optimal investments in the system. From a reliability point of view the system will be at its most critical state under certain realisations of the short-term uncertainties.

4.3 A Stochastic Dynamic Model for Optimal Investments

In this section we describe a stochastic dynamic optimisation model for optimal investments in new generation assets in a deregulated power market. The main purpose of the model is to analyse the optimal investment timing for an investor who has the license to construct a new power plant. Although the model only considers one technology at a time, we can compare different technological alternatives by changing the input data for the new technology. In addition to analyse optimal timing and technology choice, we also want to use the model to study the effect on the power system if investors behave according to the model's results.

The optimisation model builds on general stochastic dynamic programming theory and could be applied to power systems with various physical characteristics. Still, the market description and representation of short-term uncertainties have been chosen in order to fit the conditions in Scandinavia, where hydropower makes up a large share of the existing capacity. As discussed in Chapter 2 stochastic dynamic programming has also been used for generation planning within the regulated industry (Mo et al. [16]). However, the investor's objective is now to maximise the sum of expected profits over the planning horizon, and the profits are a function of the prices in the electricity market. Therefore, we need to pay particular attention to how the prices are represented. We include the influence of both short- and long-term uncertainties on the electricity price. The inclusion of the price dynamics adds a new level of complexity compared to the cost minimisation problem for the regulated industry. Another important issue, which can substantially influence the investment decisions, is the investor's risk preference. These topics are further discussed in this section as the model concept is presented.

4.3.1 Main Assumptions in the Model

The model builds on a set of simplifying assumptions. The most important assumptions are listed below.

- The investor is assumed to have a permit to construct a new plant which does not expire. It is the value of this permit (which can be regarded as an investment opportunity) that we want to calculate and compare to the value of owning the project itself.

- The investor's objective is to maximise the expected profits from new investments. Income is earned by selling power into the spot market for electricity. Additional income could also come from investment incentives, such as subsidies or capacity payments.

- The investor's risk preference is represented by using a risk-adjusted discount rate.

- The investor does not take into account the possible negative price effect on existing generation assets when new investments are considered. Hence, the investor acts as a new entrant to the market and does not exercise any market power, neither in investment decisions nor in operating strategy.

- Two different assumptions about the market conditions can be represented in the model: 1) the investor has an exclusive right to invest in the system (monopoly situation, but the investor still acts as a new entrant).

2) investments from competitors are triggered when the electricity price exceeds a certain threshold.

- Load is the only long-term stochastic variable represented in the model. The effect of other long-term uncertainties will therefore only be considered in quantitative terms. Furthermore, we assume that there is a constant relation between peak load and average load over the year.

- Investment costs are adjusted according to the length of the planning period. Furthermore, it is assumed that the investment cost is spread out evenly over the construction period, so that the cash flow can be represented by one single outlay half way into the construction period.

- New technologies are assumed to have the ability to switch off their production whenever the spot price is below the variable operating cost. Hence, unit commitment constraints are disregarded.

- Investment decisions can be made once a year, i.e. the time resolution of the optimisation model is one year.

- No decommissioning of existing capacity within the planning horizon.

The assumptions in the model are further discussed in the outline of the model below.

4.3.2 Mathematical Description of the Investment Problem

The overall problem for an investor considering investing in a new generation plant can be stated as a stochastic dynamic optimisation problem over a planning horizon of T years, as shown in (4-9)-(4-13). The investor's objective is to maximise the sum of discounted profits over the planning horizon. We use a one year time resolution and assume that investments can only take place at the beginning of each year. Furthermore, we adjust the investment costs according to the length of the planning period, so that the termination payoff, g_T in (4-12), is simply the expected profit in the last period under the condition that no new investment is made. In the basic formulation we assume that the investor has an exclusive right to invest in new power generation. How to represent the effect of other participant's investment decisions is discussed in section 4.3.7.

$$J_0(x_0,l_0)=\max_{u_0,\ldots,u_{T-1}} \underset{\omega_l}{E}\left\{\sum_{k=0}^{T-1}\left[(1+r)^{-k}\cdot g_k(x_k,l_k,u_k,\omega_s)\right] + (1+r)^{-T}\cdot g_T(x_T,l_T,\omega_s)\right\} \tag{4-9}$$

$$x_{k+1}=x_k+u_{k-lt+1} \tag{4-10}$$

$$l_{k+1}=l_k+\omega_{l,k} \tag{4-11}$$

$$g_T(x_T,l_T,\omega_s)=g_T(x_T,l_T,\omega_s\,|\,u_T=0) \tag{4-12}$$

$$x_k\in\Omega_{x,k}\quad l_k\in\Omega_{l,k}\quad u_k\in\Omega_{u,k}\quad \omega_s\in\Omega_{\omega_s}\quad \omega_{l,k}\in\Omega_{\omega_l,k} \tag{4-13}$$

where

$J_0(x_0,l_0)$	max. expected total profits over planning period at initial states	[MNOK]
$g_k(x_k,l_k,u_k,\omega_s)$	expected net profit function, time step k	[MNOK/ year]
$g_T(x_T,l_T,\omega_s)$	termination payoff, i.e. expected net profit in period T	[MNOK/ year]
x_k	investor's total new installed capacity (state variable)	[MW]
l_k	average load level (state variable)	[MW]
u_k	new capacity (decision/control variable)	[MW]
ω_s	short-term uncertainties	
$\omega_{l,k}$	stochastic change in load level	
r	risk adjusted discount rate	
lt	construction lead time	
$\Omega_{x,l,u,\omega_s,\omega_l}$	discrete feasible sets for x, l, u, ω_s, ω_l	

The investor's new installed capacity (x_k) and average load over the year (l_k) are the two state variables in this dynamic optimisation problem. In the state transition for new installed capacity we take into account that there is a construction delay (4-10). This is done by adding construction states for installed capacity (Figure 4.7). However, in order to avoid too much increase in the state space we assume that new investment decisions can not be taken in these construction states. Hence, the investor can never have more than one new plant under construction at the same time.

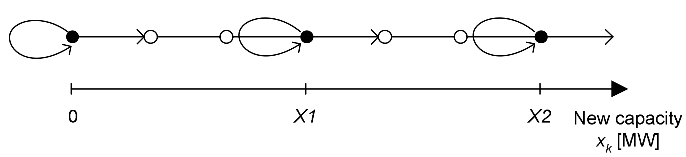

Figure 4.7 Representation of construction delay in the investment model. The black circles are decision states, while the white circles are construction states. All state transitions take one year. X1 and X2 are discrete feasible levels of new installed capacity.

The initial values of the state variables are specified by the model user and should be set equal to the current conditions in the system, if the aim is to assess an investment project for the near future. The model will indicate whether or not it is optimal to undertake an investment today. However, since one of the state variables is stochastic, the model can not calculate optimal timing for future investments, as the optimal investment strategy depends on the realisation of the stochastic variable. Still, by varying the initial values of the state variables one can identify state variable threshold levels, for which it becomes optimal to investment. This is illustrated when we present results from case studies in section 4.4.

The short- and long-term uncertainties differ in respect to how they influence the optimal investment decision, as outlined above. Load growth is the only long-term uncertainty that is included in the formulation in (4-9)-(4-13). The load growth is modelled as a binomial Markov tree (see Figure 4.5). One could easily extend the model to also include other long-term uncertainties. Change in fuel prices is another important uncertainty that could be treated in a similar way as the load growth by adding an additional state variable. However, as mentioned above one should consider mean reverting probabilities to better represent the stochastic character of the fuel prices. The other category of long-term uncertainties may be revealed at a certain time in the future, and can be modelled with only two outcomes, as shown in Figure 4.6. Regulatory risks, such as the possible introduction of a CO_2-tax or a capacity payment, are examples of such risks. Other decisions taken outside the model boundary, such as a possible decision to increase transmission capacity to surrounding areas, would also fall into this category. The increase in the discrete state space by adding this category of uncertainties is much lower since there are maximum two possible states in each time step. All the long-term uncertainties have to be represented as Markov trees in order to apply the SDP formulation.

The short-term uncertainties are represented with one aggregate variable in the model. If the investors are sensitive to short-term fluctuations in income, the short-term risk might influence the investment strategy, as different technologies are exposed to different levels of short-term risks. However, the market design has an important impact on the effect of short-term uncertainties. Futures or forward markets makes it possible to fix the electricity price ahead of delivery, and can therefore reduce the short-term risk exposure considerably. In our model we maximise the sum of expected net profits over the planning horizon. The short-term uncertainties (ω_s) only have an effect on the net expected profit within the periods (g_k), while the long-term uncertainties (ω_l) influence the state transitions. The short- and long-term uncertainties are assumed to be uncorrelated.

Since the long-term uncertainty in load is represented as a discrete Markov tree, and the annual expected profits are additive we can solve the investment problem using stochastic dynamic programming. We use a backward SDP algorithm with discrete time and states, as described by Bertsekas in [59], to find a solution to the problem. (4-14) shows the Bellman equation for the investment problem.

$$J_k(x_k,l_k) = \max_{u_k \in \Omega_{u_k}} \Big\{ g_k(x_k,l_k,u_k,\omega_s) + (1+r)^{-1} \cdot \mathop{E}_{\omega_{l,k}}[J_{k+1}(f(x_k,l_k,u_k,\omega_{l,k}))] \Big\} \tag{4-14}$$

The net expected profit function in time step k (g_k) is shown in (4-15). It consists of the discounted sum of profits from energy sales in the electricity market and income from a possible capacity payment ($\Pi_{energy,k}$ and $\Pi_{capacity,k}$), minus the cost of investment ($C_{inv,k}$). The income from energy sales depends on the short-term stochastic variable ω_s, so we therefore have to take the expectation over ω_s. The other two components are treated in a deterministic way for each combination of state variables.

$$g_k(x_k,l_k,u_k,\omega_s) = \mathop{E}_{\omega_s}\left[\Pi_{energy,k}(x_k,l_k,\omega_s)\right] + \Pi_{capacity,k}(x_k,l_k) - C_{inv,k}(u_k) \tag{4-15}$$

A further description of the three parts in the net profit function in (4-15) is given in the sections below.

4.3.3 Profits from Energy Sales in the Electricity Spot Market

A good representation of the price for electricity is important in order to achieve reasonable results in the market based model. There are several price models available that simulates the electricity spot price, including bottom-up production cost based models[24], bid-based stochastic models[25] and many others. In theory, any of these models could be used to represent the price in each combination of states in our optimisation model. However, computational efficiency is very important since we have to calculate the price for all combinations of states. Therefore, we use an aggregate and

[24] The EMPS model was originally developed as a hydropower production planning model for the regulated Scandinavian power system. It is still the most used model for price forecasting in the restructured Scandinavian power market. The EMPS model is described by Haugstad and Rismark in [60].

[25] Skantze and Ilic [21] develops a bid-based stochastic model for the electricity spot price, where load and supply are modelled as stochastic processes.

simplified description of the electricity spot market. The model still captures some of the main causal relations in the spot market for electricity, such as:

- The relation between available generation capacity and load level on the one hand compared to the electricity price and its volatility on the other.
- The relation between short term uncertainties, such as availability of hydropower, and electricity price.

We assume that the average electricity price over the year, P_{av}, is a function of the load factor LF, i.e. the fraction of average load to average power generation over the year. However, in systems with high amounts of renewable resources, the average power generation will vary extensively from year to year. The availability of thermal resources can also vary, due to maintenance and unplanned outages. Thus, we represent the initial average power generation in the system with a discrete probability distribution, described by the short-term uncertainty, ω_s. Consequently, we also end up with a discrete probability distribution for the load factor, $LF(x_k,l_k,\omega_s)$, and for the average price over the year, $P_{av}(LF)$. The relationship between ω_s, LF and P_{av} is illustrated in Figure 4.8. We also assume that there is a functional relationship between the average price and the volatility in the spot price. The volatility is usually higher in years with high prices, since the system is operating closer to its capacity constraints. Hence, the standard deviation in spot price, $\sigma_s(P_{av})$, is an increasing function of average price. The functions $P_{av}(LF)$ and $\sigma_s(P_{av})$, as well as the probability distribution for ω_s are to a high degree dependent on the existing conditions in the system, such as the total initial installed capacity (x_{tot_init}). The parameters describing the functions can be estimated from historical data or by simulations with more detailed price models where new investments can also be included.

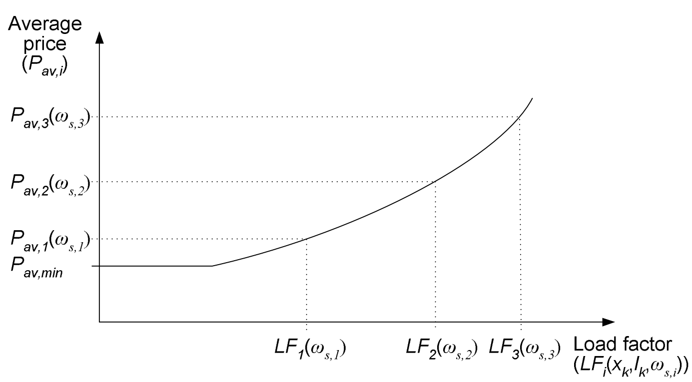

Figure 4.8 Illustration of the average price over the year, P_{av}, as a function of load factor, LF. LF is a function of the state variables x_k and l_k (which are assumed constant here), *and of the short-term uncertainty, ω_s. $\omega_{s,1}$, $\omega_{s,2}$ and $\omega_{s,3}$ represent high, medium and low availability of initial installed power generation.*

By combining the estimates of average prices and volatilities in the spot market for one combination of state variables, we end up with a number of different spot price distributions over the year. The lognormal distribution is chosen to represent the spot price distribution over the year, due to its non-negativity and its asymmetric shape that can partially capture the occurrences of high peak-load prices in years when the load factor is high. The spot price, $P_{s,i}$, is modelled as shown in (4-16), where i refers to the discrete value of the short-term stochastic variable $\omega_{s,i}$.

$$P_{s,i}(x_k, l_k) \sim \boldsymbol{\log} N(P_{av,i}(x_k, l_k), \sigma_{s,i}(P_{av,i})) \tag{4-16}$$

Figure 4.9 shows an illustration of probability distributions for the spot price for one combination of state variables. If an investment in a new generation plant is made, the load factors in Figure 4.8 would shift towards the left, so that the average prices over the year would decrease accordingly. Consequently, the spot price distributions in Figure 4.9 would also shift towards lower prices.

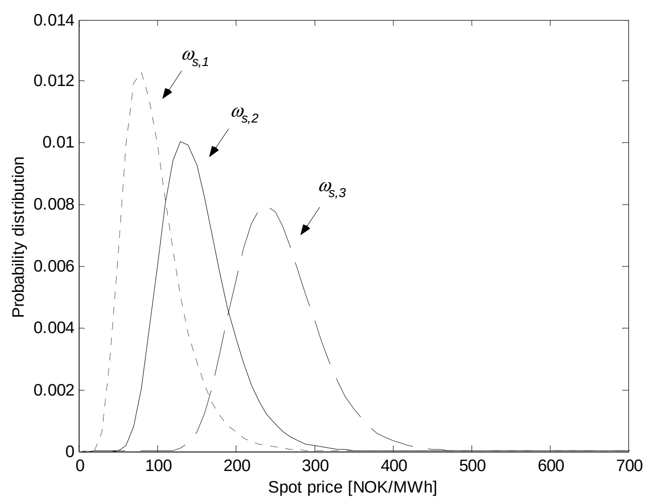

Figure 4.9 Probability distribution functions for spot price with three different realisations of the short-term stochastic variable ω_s.

Having developed the formulas for the electricity spot price, it is straightforward to calculate the profit from energy sales in the spot market. We assume that the new technology has the flexibility to easily stop the generation when the spot price is below operating costs. Short-term unit commitment constraints are ignored. (4-17) expresses the resulting profit formula for one realisation of the short-term uncertainty, $\omega_{s,i}$, while (4-18) shows the expected profit over all realisations at time step k.

$$\Pi_{energy,k,i}(x_k, l_k, \omega_{s,i}) = 8760 \cdot af \cdot x_k \int_{p=CV}^{\infty} (p - VC) \cdot f_{P_{s,i}}(p)dp \tag{4-17}$$

$$\underset{\omega_s}{E}\left[\Pi_{energy,k}(x_k, l_k, \omega_s)\right] = \sum_{i=1}^{n_{\omega_s}} p_{\Omega_{\omega_s}}(\omega_s = \omega_{s,i}) \cdot \Pi_{energy,k,i}(x_k, l_k, \omega_{s,i}) \tag{4-18}$$

where

af	expected availability of the new technology	
VC	variable costs for the new technology	[NOK/MWh]
$f_{P_{s,i}}(p)$	continuous probability distribution for $P_{s,i}$	
$p_{\Omega_{\omega_s}}(\omega_s)$	discrete probability distribution for ω_s	
n_{ω_s}	number of possible realisations of ω_s	

The probability distributions for the spot price, and therefore also the expected profits from energy sales, are completely determined by the state variables (x_k and l_k), the short term uncertainty ω_s and initial parameters. Hence, the profits can be calculated for all combinations of states prior to the stochastic dynamic programming algorithm.

4.3.4 Profits from Capacity Payment

The introduction of a capacity payment is one possible regulatory market intervention that could be used as a means of encouraging earlier investments in new power generation capacity. By including a capacity payment in the model we can study the resulting effect on the optimal investment strategy. We represent a capacity payment by assuming that a regulatory body, e.g. the system operator, determines a capacity payment (*CP*) which is a function of the expected peak load (l_{max}) within the year and the maximum available capacity (x_{max}) in the system. This is illustrated in Figure 4.10. The capacity price is only being paid in years when the capacity factor, i.e. the ratio of available capacity to peak load, is below a certain threshold (CF_{limit}). We assume that the payment is settled once a year, and that it increases as the capacity factor decreases, so that an incentive to invest in more capacity is given when the capacity balance is low. Note that the capacity payment for a new plant is not known when an investment decision is made, since the load growth is stochastic. The annual profits from the capacity payment are therefore uncertain, just like the profits from energy sales in the electricity spot market. This is in contrast to a direct investment subsidy, which would be known at the time of the investment decision. The mathematical description of the capacity payment and the corresponding profits to the owner of new generation capacity is shown in (4-19) and (4-20).

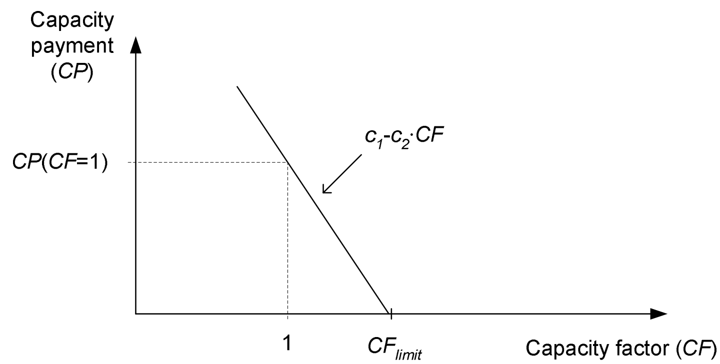

Figure 4.10 Illustration of how a capacity payment is represented in the investment optimisation model.

$$CP(x_k,l_k)=\begin{cases} c_1-c_2\cdot CF(x_k,l_k) & ,CF<CF_{limit} \\ 0 & ,CF\geq CF_{limit}\end{cases} \tag{4-19}$$

$$\Pi_{capacity,k}(x_k,l_k)=af\cdot x_k\cdot CP(x_k,l_k) \tag{4-20}$$

where

$CP(x_k,l_k)$	annual capacity payment	[NOK/MW]
$CF(x_k,l_k)=\frac{x_{max}(x_k)}{l_{max}(l_k)}$	system capacity factor	
$x_{max}(x_k)=x_{max\_init}+af\cdot x_k$	max available capacity	[MW]
$l_{max}(l_k)=(l_{init}+l_k)\cdot c_{l,max}$	peak load in the system	[MW]
c_1, c_2	constants defining a linear relationship between *CP* and *CF*	
$c_{l,max}$	constant ratio between max and average system load	

4.3.5 Investment Cost

The representation of the investment cost is closely linked to the objective function in (4-9) and the corresponding termination payoff in (4-12). The cost of investment is adjusted according to the proportion of the new plant's lifetime that is within the remaining part of the planning horizon. The discount rate is used for the adjustment, as shown in the last part of (4-21). The resulting adjusted investment cost corresponds to representing the investment cost with a fixed annuity for all time steps in the planning period. Note that we also adjust the investment cost according to the new technology's construction time (*lt*), by assuming that the total investment payment is made half way into the construction period. This is why the adjusted investment cost is discounted with *lt*/2 in the first part of (4-21).

$$C_{inv,k}(u_k) = (1+r)^{-\left(\frac{lt}{2}\right)} \cdot CFI_k \cdot u_k \cdot \frac{\sum_{i=1}^{T-k}(1+r)^{-i}}{\sum_{j=1}^{nt}(1+r)^{-j}} \tag{4-21}$$

where

$C_{inv,k}$	adjusted investment cost at time step k	[NOK]
CFI_k	unit investment cost at time step k	[NOK/MW]
lt	construction time for the new plant	[years]
nt	lifetime for the new plant	[years]

4.3.6 The Investor's Risk Preference and Appropriate Discount Rates

The optimal investment strategy depends on the investor's risk preference. From the theoretical outline above we know that in real options theory the estimation of the correct interest rate can be bypassed by making the stochastic processes in the model risk-neutral, and then use the risk-free interest rate for discounting instead. As we have a fundamental model of price with underlying long-term uncertainty in load growth, we can not assume that a replicating portfolio can be established from the existing market of financial assets. The use of risk-neutral valuation in our model is therefore difficult to justify. However, we could assume that there exists a liquid long-term futures market without any risk premium. The expected output from a new plant throughout its entire lifetime could then be sold in the long-term market as soon as an investment decision is made. Hence, it would be possible to obtain a risk-free position by deciding to construct a new plant and at the same time fix the price for future power generation in the futures market[26]. In this situation it would make sense to discount the project with the risk-free interest rate. However, long-term markets with high liquidity rarely exist in liberalised electricity markets. It is therefore likely that investors would have to pay a risk premium[27] if the output is sold in contracts with very long maturity. The majority of investors would probably choose to sell most of the power generation in shorter-term markets, and therefore expose themselves to fluctuations in the future spot price for electricity. We therefore find it more appropriate to use a constant risk-adjusted discount rate in the dynamic investment model.

[26] In a standard futures market this statement only applies as long as there is no uncertainty about the future generation from the plant. For investments in thermal base load technologies this is a reasonable assumption. However, for renewable technologies with high variability in generation one would also need to hedge variations in output (volume risk).

[27] A discussion of the risk premium in futures markets for electricity is provided in Appendix A. An empirical analysis of Nord Pool's futures market is also presented. The analysis shows that on average there has been a negative risk premium in the long-term market, i.e. futures prices have on average been above the realised spot prices in the period of delivery. However, Nord Pool's futures market only has a time horizon of up to 3-4 years into the future, so it is not possible to hedge investments in new generation assets there.

With a constant discount rate we implicitly assume that investor's assessment of the project's risk level is independent of future realisations of the state variables. This would not be the case unless we can assume that the investor is risk neutral. A possible better approach would be to incorporate risk preferences in terms of maximising the investor's expected utility instead of the expected profits, and then use the risk-free interest rate for discounting. By representing the investor's utility function explicitly we would obtain a more consistent evaluation of the variability in future profits[28]. However, a problem arises when we want to determine the shape of the investor's utility function, as most decision makers would have a very hard time expressing their risk preferences in terms of a utility function. Despite this problem we consider an explicit representation of the investor's utility function as a possible future extension of the model concept presented here.

4.3.7 Representation of Other Investors in the System

So far we have assumed that there is only one investor in the system and that the prices in the electricity market are functions of the long-term uncertainties and the investor's investment decisions only. This represents a monopoly situation. However, in a competitive electricity market the prices will also be influenced by actions from other companies in the same market. The electricity prices are likely to decrease, also when other participants invest in new power plants. This will affect the profitability of new investments in two ways. Firstly, the option value of postponing the investment decision will be reduced, as postponing the decision could result in other participants entering the market prior to the investor. Secondly, the upside of the future profit distribution will be lowered, since investments from other participants also contribute to bringing the prices down. The two effects change the optimal investment decision in opposite directions. Which effect is stronger depends on the characteristics of the price model and also on the entry price level for other investors.

The effects from other investors on the optimal investment decision can be represented by assuming that investments from others are triggered as soon as the average spot price exceeds an exogenously defined entry level. This representation is shown in (4-22)-(4-24). The investments from other participants add to the total amount of new installed capacity in the system, and thereby reduce both the prices in the spot market and the capacity payment. Notice that we assume that there is no construction delays for the

[28] An example of a discrete stochastic dynamic optimisation model that uses utility instead of profits in the objective function is described by Mo et al. in [61]. This is an integrated risk management tool for hydropower producers, and is used for combined optimisation of production planning and contract hedging in long-term futures markets.

investments from others, and that they are not modelled as separate state variables. With this representation of other investments the entry price level in reality becomes an upper limit on the average price in the system. The entry price level for other investors should be based on expectations about the required price for other participants to invest in the market. In a fully competitive market where all participants have access to the same technologies, the entry price should be the same for all investors.

$$v_k(x_k,l_k) = \begin{cases} v_{cap} & ,\overline{P_s}(x_k,l_k) \geq P_{s,entry} \\ 0 & ,\overline{P_s}(x_k,l_k) < P_{s,entry} \end{cases} \tag{4-22}$$

$$x_{k+1}' = x_k' + u_{k-lt+1} + v_{k+1} \tag{4-23}$$

$$\overline{P_s} = \sum_{i=1}^{n_{\omega_s}} p_{\Omega_s}(\omega_{s,i}) \cdot P_{av,i}(x_k,l_k) \tag{4-24}$$

where

x_k'	updated level of new installed capacity after investment from others	[MW]
v_{cap}	new installed capacity of other participants	[MW]
$\overline{P_s}$	average spot price	[NOK/MWh]
$P_{s,entry}$	entry price level for other investors	[NOK/MWh]

The representation of other investors that is outlined above is of course a very simple one. However, it still captures important effects on the value of the investment option and of the project itself. It is similar to the approach taken by Dixit and Pindyck [38] to model a fully competitive market (see Figure 4.4). In order to model a market with several decision makers with separate objective functions one would have to develop an agent-based model, where different investors are represented with separate state variables for installed capacity. However, most applications of agent based modelling in electricity markets so far have been concerned with modelling repetitive bidding strategies in the spot market (see e.g. Visudhipan [13]). A challenge arises when applying agent-based techniques to the investment problem, since the frequency of such large-scale investment decisions is very low. It will therefore be difficult to specify adaptive investment strategies, and also to use historical data to calibrate and test the model. Game theory is another possible tool for developing investment strategies with multiple investors in the system. The stochastic dynamic investment model presented here is limited to include the effect of how a simple and aggregate representation of other investors affects the investment decision for one single decision maker. However, the application of game theory in combination with the stochastic dynamic optimisation framework presented here is an interesting area for future research.

4.4 Illustrative Examples

Potential applications of the investment model are illustrated in this section, where we use the model to analyse a gas power investment project that is similar to projects currently under consideration in the Norwegian power system. The first part of the analysis is concerned with identifying optimal investment criteria for an investor with permission to construct a new gas power plant. We also analyse how certain investment incentives can change the optimal criteria. Then we look into potential consequences for the power system if the market participants make their investment decisions according to the model's recommendations. We also use the model to examine to what extent an investor benefits from using stochastic dynamic optimisation, as opposed to other modelling approaches for investment planning.

The optimisation model allows us to analyse the investment problem along some of the different analytical dimensions discussed in section 2.3. In the analysis we focus on the two dimensions illustrated in Figure 4.11. Although the model is primarily developed for full stochastic dynamic analysis, it can also be used to analyse the problem from a static and deterministic perspective. The model finds both the static and dynamic solution in the same optimisation run, since it always calculates the expected value of investing immediately (i.e. static view) and compares it to the expected value of postponing the investment (i.e. dynamic view). Load growth is represented as a long-term uncertainty in the model. The effect of using deterministic compared to stochastic representations can be analysed by running the model with different input values for standard deviation in load growth. Note that short-term uncertainties are treated identically, i.e. on an expected value basis, in all the four combinations in Figure 4.11.

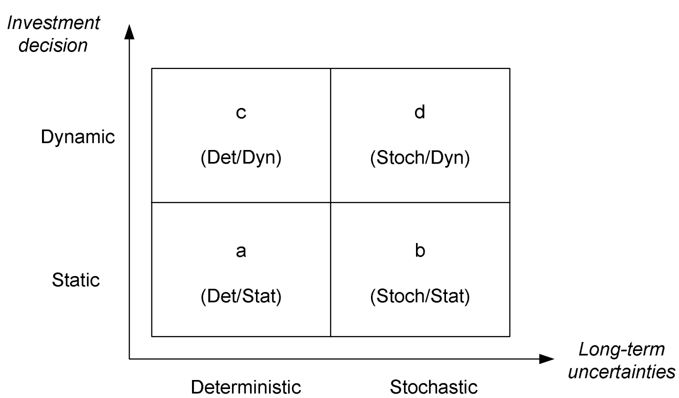

Figure 4.11 Two important analytical dimensions in investment planning. Solutions for all four combinations can be extracted from the stochastic dynamic model. The indices (a, b, c, d) will be referred to as decision rules when results from the model are presented.

The first parts of this section focus on the investor's optimal investment criteria. A number of results can be derived based on the optimal first period decision. However, in order to better assess the long-term dynamics of prices and investments, we develop a simulator which simulates investments in the system for a number of years. The simulator is also used to estimate the investor's improved decision making from using stochastic dynamic optimisation. Monte Carlo simulations, where investment decisions are based on the different decision rules in Figure 4.11 are used for this purpose.

4.4.1 General Input Data

We use the model to look at a gas power project which is relevant in the Norwegian power system. Therefore, we have estimated parameters in the model based on historical data for Norway. Table 4.2 and Table 4.3 show key figures for load and generation of electricity in Norway in the period after restructuring. Table 4.4 shows corresponding input parameters to the model, which are used in all the 4 scenarios presented below.

Table 4.2 Historical data for load in the Norwegian system. Source: Statistics Norway and Nord Pool.

Average annual system load, 90-02	13210 MW	115.7 TWh/year
Max annual system load (in 2001)	14330 MW	125.5 TWh/year
Min annual system load (in 1990)	12090 MW	105.9 TWh/year
Annual load growth, 90-02	142 MW	1.25 TWh/year
Annual std. dev. in load growth, 90-02	297 MW	2.60 TWh/year
Average ratio btw. max and average load, 95-02		1.55
Max ratio btw. max and average load (2000)		1.64
Min ratio btw. max and average load (2001)		1.49

Table 4.3 Historical data for generation in the Norwegian system. Source: Statistics Norway and Nordel.

Average generation, 1990-2002	13680 MW	119.8 TWh/year
Max generation (2001)	16300 MW	142.8 TWh/year
Min generation (1996)	11950 MW	104.7 TWh/year
Max available capacity (2002)		23500 MW

Table 4.4 Initial input parameters for the investment model.

Parameter	Name in model	Value
Average initial generation	x_{tot_init}	13500 MW
Max initial generation	x_{max_init}	23500 MW
Load growth	l_{growth}	140 MW
St. dev. in load growth	l_{std}	0 or 300 MW
Max ratio btw. max and average load	$c_{l,max}$	1.6

The parameters in the spot price model were estimated with regression analysis based on historical load and price data for 1993-2002. Exponential functions were used to express the functional relationships between average spot price and load factor, $P_{av}(LF)$, and between standard deviation in spot price and average spot price, $\sigma_s(P_{av})$. The resulting curves are shown in Figure 4.12 and Figure 4.13. Not surprisingly, the figures show that both of these relationships are increasing. The price tends to be higher when the capacity factor is high, and the standard deviation of price also increases with higher average prices. Note that we used load and generation data for Norway only, while the system price is the unconstrained price for the entire Nord Pool power exchange area. This is partly because the Nord Pool area has been enlarged several times in the period of analysis (1993-2002)[29], and Norway is the only country that has been part of the power exchange area throughout the period. Also, Norway has more than 60 % of the hydropower generation and almost 70 % of the reservoir capacity in the current Nord Pool area. Therefore, the system price will still be very dependent on the availability of hydropower, and implicitly the load factor, in Norway[30].

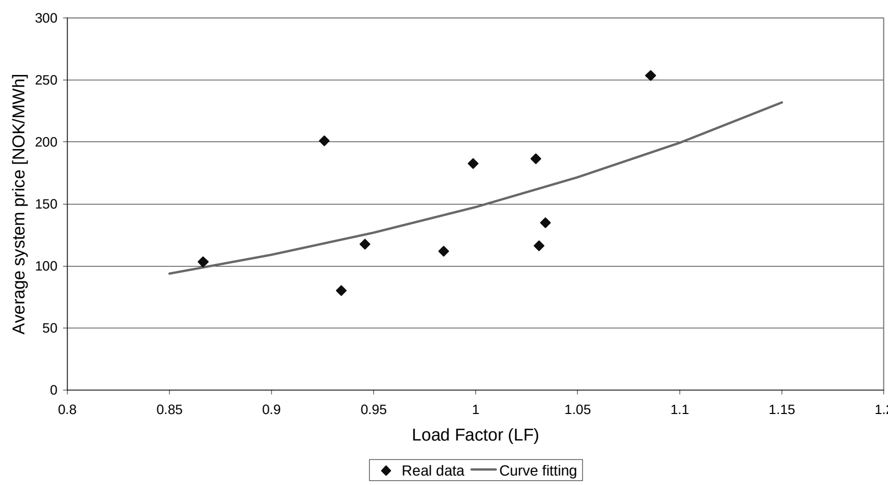

Figure 4.12 Estimated and real data for relationship between load factor in Norway, LF (i.e. load/ generation), and Nord Pool's average system price, 1993-2002. Equation for estimated curve: $P_{av}(LF) = 80.8 \cdot (20.3)$^LF. Lower limit: $P_{av,min} = 70$ NOK/MWh.

[29] A short description of the historical development of Nord Pool, including data for prices, loads and generation is given in Appendix A.

[30] There has been extensive exchange of power between the Scandinavian countries, both prior to and during the stepwise restructuring of the power markets. The system price has therefore been influenced by the energy balance in all four countries throughout the reference period (1993-2002). An alternative to using the Norwegian system load in the calibration of the spot price model would be to use the total load in the current Nord Pool area instead. However, this has not been prioritized in this thesis, and is left for future work. Another interesting extension would be to use monthly or even weekly instead of annual data, in order to also capture seasonal variations in price and load.

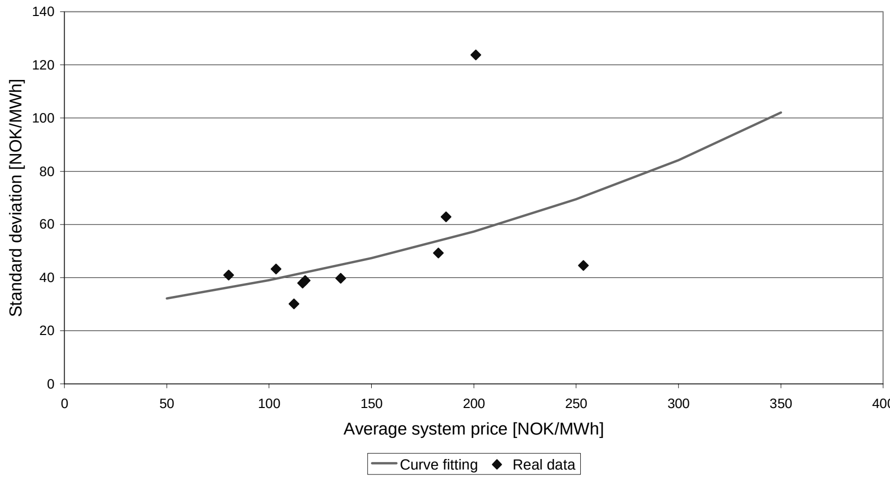

Figure 4.13 Estimated and real data for relationship between standard deviation in Nord Pool's system price and average system price, 1993-2002. Equation for estimated curve: $\sigma_s(P_{av}) = 26.6 \cdot (1.004)^{\wedge} P_{av}$.

The availability of hydropower is the most important short-term uncertainty in the Norwegian power system, and is the only one we take into account in the analysis. We use historical data for inflow from the period 1961-1990 to estimate the probability distribution for relative availability of hydropower generation in the system (RHG_i). The inflow data is used as input to the EMPS model[31], which simulates total hydropower generation in Norway for all the 30 inflow scenarios. The results are aggregated into 5 discrete hydropower availability levels, and the resulting probability distribution is shown in Table 4.5. With this representation of short-term uncertainties, ω_s, the load factor for different realisations of $\omega_{s,i}$ can be expressed as in (4-25). The load factor will in turn affect the spot price distributions, as described in section 4.1.3.

$$LF_i(x_k, l_k, \omega_{s,i}) = \frac{l_k}{af \cdot x_k + RHG_i \cdot x_{tot\_init}} \tag{4-25}$$

Table 4.5 Discrete probability distribution for relative availability of hydro generation (RHG_i) in the initial Norwegian system. The values are based on simulations with the EMPS model, using inflow data for 1961-1990.

Realisation, i	1	2	3	4	5
$p_{\Omega_{\omega_s}}(\omega_s = \omega_{s,i})$	0.1	0.2	0.4	0.2	0.1
RHG_i	1.174	1.063	0.986	0.939	0.878

[31] The EMPS model is described by Haugstad and Rismark in [60].

Although the investment project that is analysed below is similar to projects that are currently under consideration in the Norwegian power system, it is important to emphasise that the purpose of presenting these results is to illustrate potential use of the model. A more comprehensive job on input data and model calibration would be required to use the model for decision making in the real world. Investments and decommissioning of current capacity in other parts of the Nord Pool system, which would also affect the system price, are for instance not considered here. Transmission constraints at the specific site for a new plant are also disregarded in the analysis. However, many of these aspects could easily be incorporated into the model, by using more comprehensive input data and extending the scope and detail of the spot price model.

4.4.2 Gas Power in Norway

We use the model to analyse an investment in a new large-scale gas power plant. It is assumed that the investor has obtained permission from the regulators to build the plant, and wants to optimise the timing of his investment decision. Technical specifications for the new gas power plant are presented in Table 4.6. Furthermore, a planning horizon of 10 years (T = 10 years) is used in the calculations, and we assume that the investor can only construct one plant within this time period, so that the state space for the investor's new capacity consists of two states (0 and 800MW). Four different scenarios are considered as described below.

Table 4.6 Technical specification for the new combined cycle gas power plant (CCGT).

Parameter	Symbol in model	Value	Unit
Installed capacity	u_k	800	MW
Investment costs	CFI_k, $k = 1..T$	6000	NOK/MW
O&M and fuel costs	VC	110	NOK/MWh
Average availability	af	0.9	
Construction time	lt	3	years
Life time	nt	30	years
Risk-adjusted discount rate	r	8	% pa

Scenario 1: Base Scenario

In the base scenario we assume that the new gas power plant's profit is earned entirely from sales in the spot market for electricity. The effect of other investors entering the market is disregarded. In order to identify optimal investment thresholds we run the investment model repeatedly, increasing the initial load with a small interval between each run, and storing the expected profit from investing and waiting. Results are shown in Figure 4.14 and Figure 4.15.

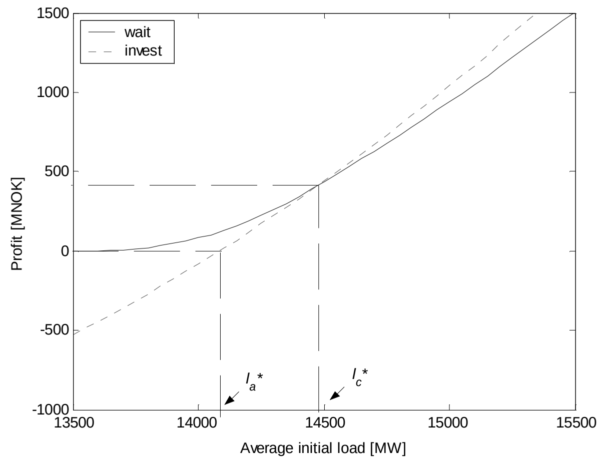

Figure 4.14 Profit over planning horizon from investing now and waiting in base scenario. l_a and l_c* are average load levels for which immediate investment becomes optimal under deterministic static (a) and deterministic dynamic (c) optimisation. $l_{sdv} = 0$.*

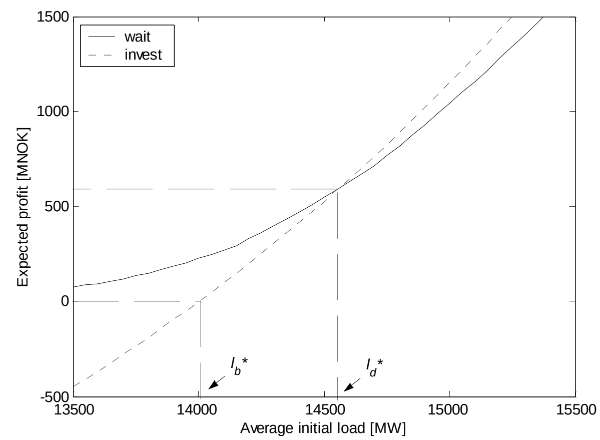

Figure 4.15 Expected profit over planning horizon from investing now and waiting in base scenario. l_b and l_d* are average load levels for which immediate investment becomes optimal under stochastic static (b) and stochastic dynamic (d) optimisation. l_{sdv}=300.*

The results for the base scenario with deterministic (l_{sdv} = 0) and stochastic optimisation (l_{sdv} = 300) are shown in Figure 4.14 and Figure 4.15 respectively. The dotted line in Figure 4.14 shows the investor's profit from investing in the new gas power plant immediately. If we use a static assessment of the project we know that the investor should invest as soon as the NPV is positive, i.e. when the average load level over the year reaches l_a*. However, by not investing the investor keeps the opportunity to invest open, and the value of this option is equal to the line labelled "wait" in Figure 4.14. If we apply a dynamic assessment of the gas power plant we therefore conclude that in order to achieve maximum profit the investor should not invest until the average load level reaches l_c*. This is when the profit from investing immediately exceeds the profit from postponing the investment. We see that even in the deterministic case there is a significant difference in the optimal investment criterion depending on whether a static or dynamic assessment is applied. The reason is that there is an underlying load growth in the system, which gives rise to an option value of waiting for higher future prices and thereby increased profits for the power plant. It is not optimal to invest until the profit gain from waiting for higher future loads and prices is exceeded by the loss from not having the gas power plant available as soon as possible. This is what happens at l_c*.

In the stochastic case we must compare the *expected* profit from investing and waiting. Figure 4.15 shows that the static investment criterion (l_b*) is lower, while the dynamic criterion (l_d*) is higher than in the deterministic analysis. The reason for the lower static criterion is that there is a convex relationship between load and profits, so that expected profits from the project is increased when uncertainty is added in load growth, although the growth rate is the same. The increased dynamic criterion is due to the uncertainty, which adds on to the option value of postponing the investment. The expected profit from waiting and investing can also be expressed as functions of the average initial price. The corresponding average prices for which investment is optimal in the stochastic case are shown in Figure 4.16. Average prices refer to a situation where the short-term uncertainty is represented by its mean value. In this analysis, where short-term uncertainties are based on inflow statistics, the average price refers to a year with average inflow to the hydro reservoirs in Norway.

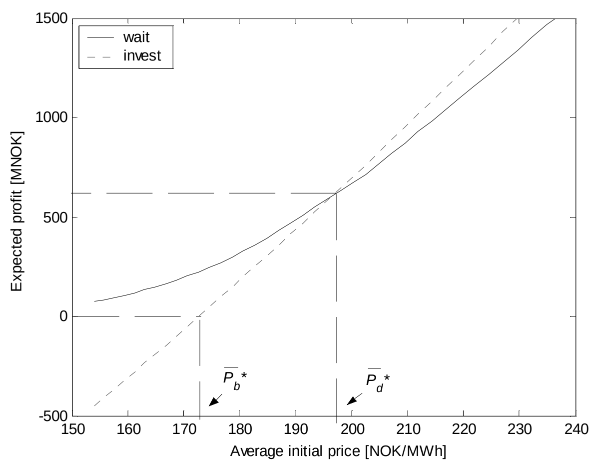

Figure 4.16 Expected profit over planning horizon from investing now and waiting in base scenario. $\bar{P}_b^*$ and $\bar{P}_d^*$ are average price levels for which immediate investment becomes optimal under stochastic static (b) and stochastic dynamic (d) optimisation. l_{sdv}=300.

Key figures for the base scenario are summarised in table Table 4.7. Note that with the input assumptions used in this analysis, the total unit cost for the new gas power plant, using annualised investment costs and taking into account the construction delay, adds up to 180 NOK/MWh. Not surprisingly, since there is load growth in the planning horizon, the static optimal investment prices are below the unit cost. However, the dynamic criteria are considerably above the unit cost, and this is due to the option value of postponing the investment decision.

Table 4.7 Average load, price and expected profits at investment threshold under different analytical project appraisals (a – det/stat, b – stoch/stat, c – det/dyn ,d – stoch/dyn).

	a	b	c	d	
Average load	14080	14000	14470	14560	[MW]
Average price	176	173	192	196	[NOK/MWh]
Expected profits	0	0	407	590	[MNOK]

From Table 4.7 we see that there is a distinct difference between the results for static and dynamic analyses (a vs. c and b vs. d). However, the change in results when going from a deterministic to a stochastic analysis (a vs. b and c vs. d) seems to be less significant. In order to look further into how the uncertainty influences the results we run the model for different levels of standard deviation in load growth. The result is shown in Figure 4.17. As can be seen from the graph the investment threshold increases with higher uncertainty, but the effect seems to level off as the standard deviation increases. From the graph we also see that the expected profit from investing in the project rises with increasing standard deviation.

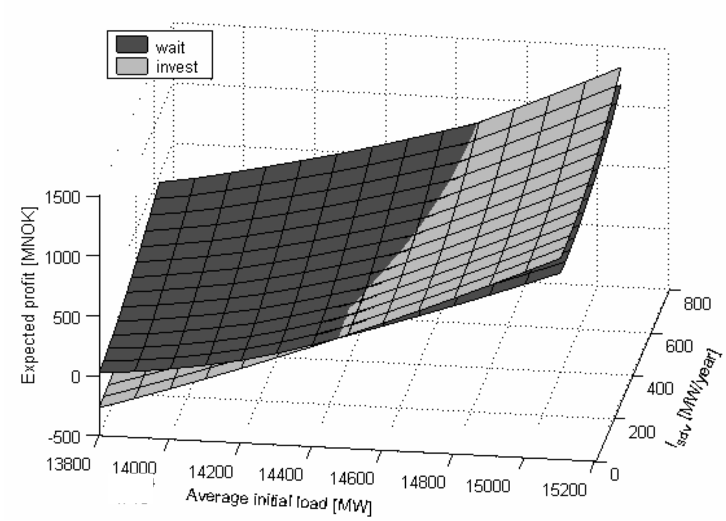

Figure 4.17 Expected profit from investing now and waiting as function of average load and standard deviation in load growth.

Scenario 2: Other Investors
In scenario 2 we introduce the effect of other investor's decisions into the analysis using the aggregate model representation outlined in section 4.3.7. We now concentrate on the stochastic analysis (i.e. decision rule b and d in Figure 4.11), with a standard deviation in load growth of 300 MW/year. First, we assume that investments from others are triggered when the average price exceeds 210 NOK/MWh, and that the unit size of these investments is 200 MW (i.e. $P_{s,entry}$ = 210 NOK/MWh and v_{cap} = 200 MW in (4-22)). Apparently, our investor then has a competitive advantage since we know from scenario 1 that it is optimal for him to invest at a lower price level (Table 4.7). Still, the possible entry of other investors affects the future expected profits of investing in the new gas power plant, and possibly also the investment criteria for our investor. Expected profit from investing and waiting when other investors are represented in the model is shown in Figure 4.18.

By comparing Figure 4.18 and Figure 4.15 we see that as average initial load grows, the expected profit from the gas power project is increasing much less than in the basis scenario. This is because the investments from others effectively cap the average price in the market at 210 NOK/MWh. The static investment criterion (l_b*) is increased due to the lower expected value of the gas power plant. The lower expected profit from the project also contribute to increase the dynamic criterion (l_d*). However, at the same time the option value is now lower due to the possible entry of other investors. The lower option value has an opposite effect on the investment criterion, so that in total the optimal investment threshold is close to the one in the base scenario (l_d*(scenario 1) = 14570 MW, l_d*(scenario 2) = 14600 MW).

To further investigate how the representation of other investors influence the decision, we have plotted the optimal investment threshold, l_d*, and the investor's expected profit, as function of the entry price level for other investors (Figure 4.19). We see that the investment criterion is only affected for rather low entry prices, as l_d* first starts to increase when $P_{s,entry}$ reaches below 220 NOK/MWh. In contrast, the expected profit is significantly decreased, also for higher entry prices. The lower expected profit is due to the increased competition, which is represented in the lower entry price for others investors. The expected profit in Figure 4.19 approaches zero for low entry prices for others. This is in accordance with the discussion in section 4.1.6, where we showed that according to the real options theory there should be no expected surplus profit at the optimal investment threshold in a fully competitive market (Figure 4.4).

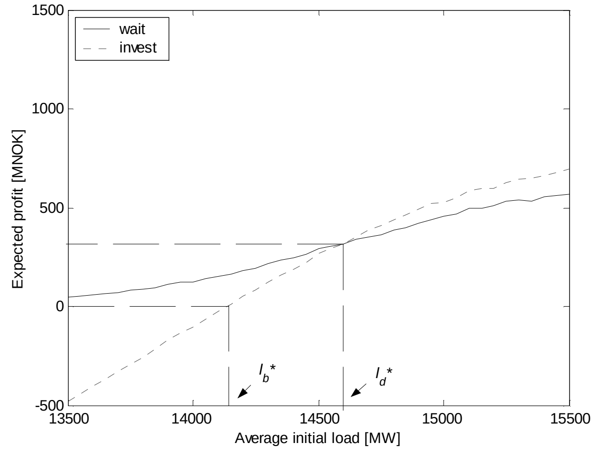

Figure 4.18 Expected profit over planning horizon from investing now and waiting in scenario 2. l_b and l_d* are average initial load levels for which immediate investment becomes optimal under stochastic static (b) and stochastic dynamic (d) optimisation. l_{sdv}=300. $P_{s,entry}$ = 210 NOK/MWh.*

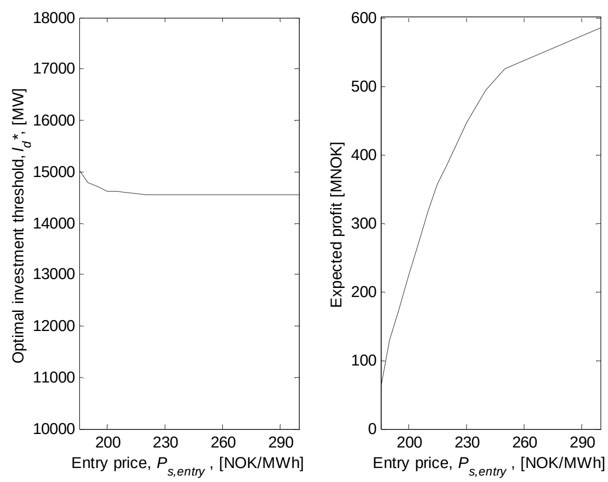

Figure 4.19 Investor's optimal investment threshold, l_d, and corresponding expected profit as function of other investor's entry price level, $P_{s,entry}$. $P_{s,entry} \in$ [185,300]. l_{sdv}=300.*

Scenario 3: Capacity Payment

We now extend the analysis from scenario 2 to also include the effect of introducing a capacity payment as an incentive for earlier investments in new power generation. The capacity payment is modelled as explained in section 4.3.4, with a constant relationship between average and maximal load in the system ($c_{l,max}$ = 1.6). First, in scenario 3a, we assume that there is a capacity payment in years when the capacity factor, i.e. the fraction of available capacity to peak load, is below 1.05 (CF_{limit} = 1.05). The magnitude of the capacity payment is a linear function of the capacity factor, as shown in Figure 4.10. In order to analyse how the capacity payment influence the optimal investment threshold, we run the model for different levels of capacity payment. Figure 4.20 shows that the optimal investment threshold is lowered as the capacity payment is increased. This is what we would expect, as the total profit for the investor now is higher due to the additional capacity payment. However, it turns out that the investor's expected profit at the optimal investment threshold also increases. The reason behind this observation is less intuitive, but it is due to the change in the expected payoff for the new plant. The expected profit function from investing immediately becomes steeper when the capacity payment is added. At the same time the capacity payment is an uncertain income. Together, these two factors increase the option value of postponing the investment. Hence, the required profit for investing also increases.

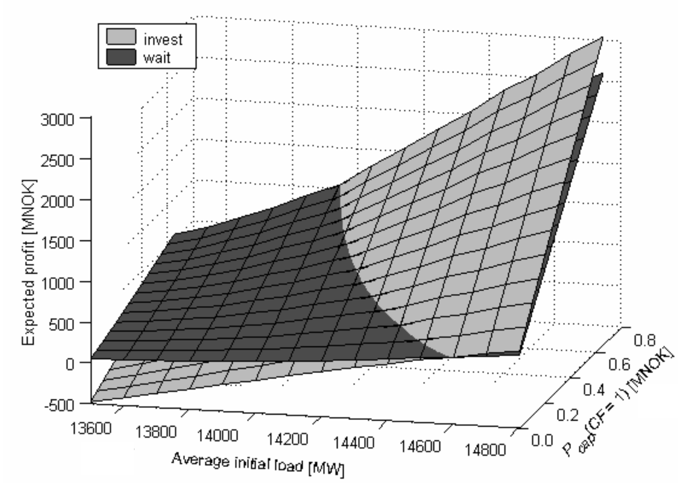

Figure 4.20 Expected profit from investing and waiting as function of average load and different levels of capacity payment in scenario 3a. CP(CF=1) is the capacity payment when the capacity factor is equal to 1. CF_{limit} = 1.05. l_{sdv}=300. $P_{s,entry}$ = 210 NOK/MWh.

The effect of the capacity payment is also dependent on the capacity factor limit (CF_{limit}), at which the payment is introduced. So far we have set CF_{limit} to 1.05, which gives a rather steep capacity payment function and in turn, a steeper total profit function for the new plant. In scenario 3b we do the same analysis with CF_{limit} equal to 1.15 instead. In practice, this means that there is a higher incentive to invest, since there is a capacity payment also when the system is further away from a critical capacity balance. This is reflected in the results (Figure 4.21), which shows that the investment threshold is reduced quicker than in scenario 3a. At the same time the increase in expected profit is also lower as the level of the capacity payment is increased. This is because the capacity payment function is now less steep, so that the option value of postponing the investment is also reduced compared to scenario 3a.

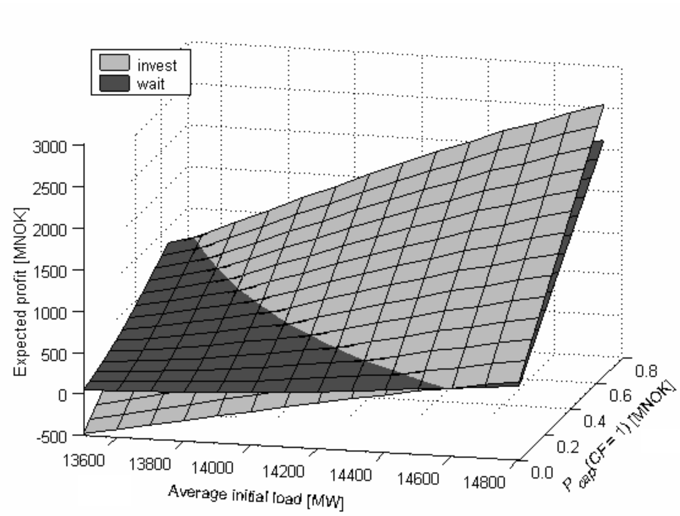

Figure 4.21 Expected profit from investing and waiting as function of average load and different levels of capacity payment in scenario 3b. CP(CF=1) is the capacity payment when the capacity factor is equal to 1. CF_{limit} = 1.15. l_{sdv}=300. $P_{s,entry}$ = 210 NOK/MWh.

Scenario 4: Investment Subsidy

A direct investment subsidy is an alternative incentive, which would also trigger earlier investments in new generation facilities. A subsidy is a certain payment to the investor, and it would increase the expected profitability from the new plant independent of the load in the system. In the model we represent an investment subsidy, simply by reducing the investment cost of the new plant. The effect of subsidising the gas power plant with 20 % of the investment cost is shown in Figure 4.22.

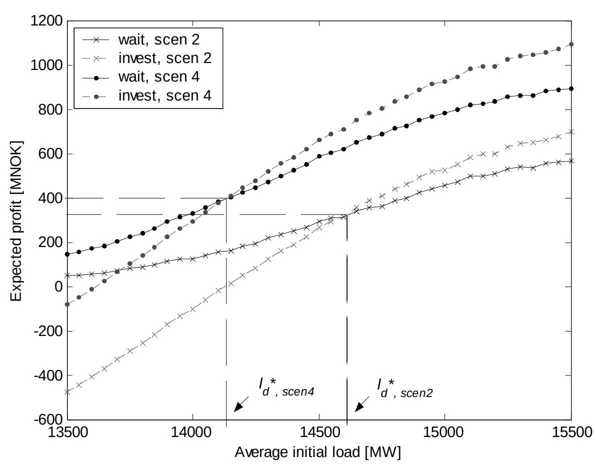

Figure 4.22 Expected profit over planning horizon from investing now and waiting, without (scenario 2) and with (scenario 4) 20% investment subsidy. $l_d^*{}_{,scen2}$ and $l_d^*{}_{,scen4}$ are average initial load levels for which immediate investment becomes optimal. l_{sdv}=300. $P_{s,entry}$ = 210 NOK/MWh.

From Figure 4.22 we see that effect of the investment subsidy on the expected profit from investing in the project immediately is a parallel shift upwards, compared to the situation without a subsidy (scenario 2). The expected profit from waiting and thereby keeping the option to invest open also shifts upwards. However, the shift in the option value is not parallel, and for low load levels there is only a small increase. Consequently, the resulting optimal investment criterion is reduced with almost 500 MW, while the increase in expected profit at the investment threshold is only modestly increased.

Centralised investment incentives should only be introduced if there are externalities present in the power market. According to economic theory, an externality arises if the actions of one economic agent affect the interests of another agent other than by affecting prices. One externality in the power market could for instance be that the market does not price reliability properly, so that the market prices alone do not provide adequate investment incentives. The result could be that an externality cost is imposed on the end-users, in terms of low reliability and too high frequency of outages[32]. In general, the use of specific investment incentives can only be justified if the cost of the incentives is lower than the cost of the externality. Therefore, it is important to design an incentive scheme that achieves the desired result with as low extra cost as possible.

We have looked at the effect of capacity payments and direct investment subsidies on the optimal investment criterion. The investor's extra profit from these investment incentives must be covered by some other part in the system. It is likely that the extra cost is transferred to the end-users through a system of tariffs or taxation. We can now use the stochastic dynamic analysis to compare the extra cost of using these two alternatives to trigger investments at a specific load level. Assume that the optimal investment level for the system ($l_d{}^{*}{}_{,optimal}$) is at an average load of 14130 MW. This is the same level as the optimal investment criterion in scenario 4, with 20 % investment subsidies ($l_d{}^{*}{}_{,scen4}$). The same effect on the investment threshold can be achieved by choosing appropriate parameters for the capacity payment in scenarios 3a and 3b. Table 4.8 summarises the cost of the investment incentive and the expected profit for the investor with the different incentives, also including the situation with no incentive (scenario 2). The expected profit from sales in the spot market is calculated from scenario 2, and is slightly negative (-5 MNOK) at the desired optimal investment level. However, when the additional income from a capacity

[32] Common problems in restructured electricity markets, which could result in long-term imbalance between supply and demand, and thereby possible externality costs, are further discussed in Chapter 5.

payment or an investment subsidy is taken into account, it becomes optimal to invest in the new plant. As we can see from Table 4.8 and Figure 4.23, the required incentive to trigger investment is higher with a capacity payment (scenario 3a and 3b) than with a direct investment subsidy (scenario 4). The reason for this is that the capacity payment is uncertain, and also increasing as function of the load, and therefore gives rise to a higher option value of waiting than the constant investment subsidy. This is also why scenario 3a, with the steepest capacity payment function, gives the highest expected incentive cost.

Although the analysis presented here is by no means sufficient to make a decision about whether to use capacity payments or investment subsidies in the case of an externality that requires investment incentives, it still shows some interesting consequences for the system's cost. A more comprehensive assessment of the two incentives would have to include more details in the analysis of demand side effects. A capacity payment would for instance give an incentive to end-users to reduce their peak load, since the payment is a function of installed capacity and peak load in the system, whereas the constant investment subsidy does no have the same feedback to the end-user[33]. Another advantage for the capacity payment, when it comes to the implementation of the incentives, is that it is spread out through the new plant's lifetime. The investment subsidy, on the other hand, requires a huge capital outlay up front, and can therefore be more difficult to get public accept for. These are some of the factors that would have to be considered in an extended analysis of the different alternatives for investment incentives.

Table 4.8 Investment threshold, cost of investment incentive and investor's expected profit over planning horizon with no incentive (scenario 2), capacity payment (scenario 3a and 3b) and investment subsidy (scenario 4). Scenario 3a: CF_{limit} =1.05, CP(CF=1) = 386000. Scenario 3b: CF_{limit} =1.15, CP(CF=1) = 188000. Scenario 4: CFI_k = 4800 NOK/MW.

Scen-ario	Investment threshold		Cost of incentive		Expected profit	
	Average load [MW]	Average spot price [NOK/ MWh]	Investment subsidy [MNOK]	Expected cap. payment [MNOK]	In spot market [MNOK]	Total [MNOK]
2	14600	198	0	0	315	315
3a	14130	178	0	947	-5	942
3b	14130	178	0	523	-5	518
4	14130	178	396	0	-5	391

[33] An investment subsidy could also be a function of the capacity balance in the system, in the same way as the proposed capacity payment. The same feedback to the end-users would then be achieved, but an option value of postponing the investment would also arise, since the future level of the investment subsidy would now be uncertain. This alternative is not explored further here.

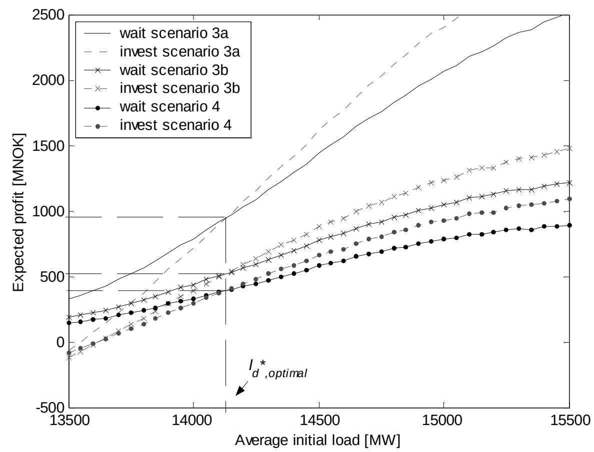

Figure 4.23 Expected profit over planning horizon from investing now and waiting, in scenario 3a, 3b and 4. All scenarios give the same desired investment criterion $l_d{}^*{}_{,optimal}$. Scenario 3a: CF_{limit} =1.05, CP(CF=1) = 386000. Scenario 3b: CF_{limit} =1.15, CP(CF=1) = 188000. Scenario 4: CFI_k = 4800 NOK/MW. l_{sdv} = 300. $P_{s,entry}$ = 210 NOK/MWh.

In the end it is interesting to note that the cost analysis presented here with the stochastic dynamic investment model, could not be carried out with a static model. With a static assessment all the investment decision would be triggered at a zero NPV. Consequently, the expected cost of the incentive would always be equal to the expected loss in a scenario with no incentive, whether a capacity payment or an investment subsidy is being introduced. Hence, a static analysis would not be able to differentiate the cost of the alternatives, since it does not take into account the difference in the value of postponing the investment in the two incentive scenarios.

4.4.3 System Consequences of Optimal Investments

An advantage of modelling physical state variables (such as installed capacity and load) as opposed to non-physical variables (such as the price directly) is that the consequences on the physical system can be analysed in greater detail. After having identified optimal investment criteria, we can now analyse the reliability of the system under various operating conditions. We assume that the investors in the system make their investment decisions according to the recommendations from the model, and that gas power is the most competitive technology that will be chosen ahead of other, more expensive, technologies. For the gas power plant, the investment decision has to be taken 3 years before the new plant is available online. The most critical situation for the energy and capacity balance in the system is in the last year before new capacity is added, i.e. two years after the investment decision is made. Table 4.9 shows the state of the system at this point in time if the growth in average load follows the expected trend, i.e. 140

MW/year. We see that without an investment incentive the capacity balance is negative before the new plant is available. The energy balances are also negative, not only with low inflow, but also in a normal inflow scenario. This means that we usually will have to rely on considerable amounts of import in order to meet the energy demand over the year, and also to meet the peak load in the system. In the scenarios with investment incentives we see improved supply reliability, and the capacity balance is now positive. The energy deficits are also reduced, although still negative with normal precipitation. Table 4.9 also shows that the investment incentive reduces the average price over the year in the low inflow situation with 36 NOK/MWh.

Table 4.9 Capacity balance, energy balances and average electricity price over the year in Norway 2 years after investment decision is taken. Normal and low inflow refers to average and the lowest ($\omega_{s,5}$) realisations of inflow in short-term uncertainties.

Scenario	Capacity balance [MW]	Energy balance (normal inflow) [TWh]	Energy balance (low inflow) [TWh]	Average price (low inflow) [NOK/MWh]
No incentive (scenario 1, 2)	-308	-12.1	-26.5	318
Inv. incentive (scenario 3, 4)	+444	-8.0	-22.4	282

We can also use the results from the model to analyse the long-term price and investment dynamics in the system, resulting from optimal investment behaviour. A simulator is therefore implemented, which uses the optimisation model to simulate optimal investments over time, by updating initial model parameters (i.e. load and installed capacity) for each simulated time step, as shown in Figure 4.24. We can now simulate investments in the system under different investment rules and market designs, and for various realisations of the uncertain load growth ($\omega_{l,k}$).

Here, we look at the development of prices and investments when the average load grows according to its mean value (i.e. $\omega_{l,k}$ = l_{growth} = 140 MW/year). We use an initial average load of 14100 MW, which is equal to the real average load in 2000. Investments in new gas power plants in the Norwegian system are simulated over a time period of 30 years, while investments in other technologies are disregarded. A constant planning horizon of 10 years is used in the optimisations. We assume that there are always participants in the power market that are willing to invest as soon as the conditions are favourable for new entrants. Figure 4.25 shows simulated investments in new capacity for scenario 2 and 4, when the stochastic dynamic decision rule (d) is applied. It is apparent that the investment subsidy in scenario 4 contributes to trigger earlier investments in the system.

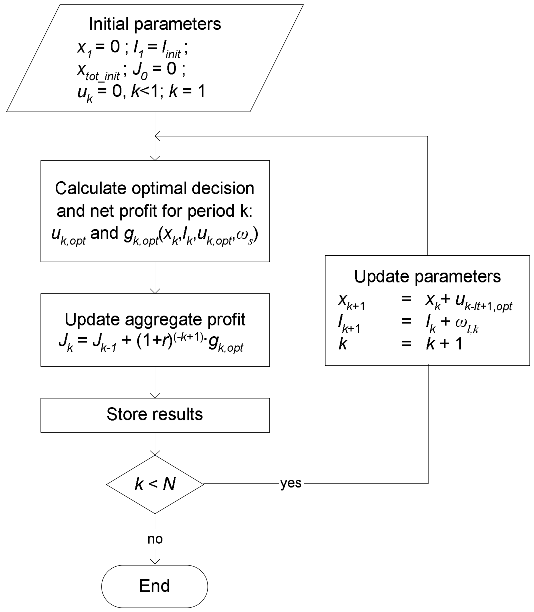

Figure 4.24 Flow chart for simulator which uses the investment model to simulate optimal investment decisions ($u_{k,opt}$) and corresponding profit ($g_{k,opt}$) with feedback from the realisation of the load growth ($\omega_{l,k}$) for each time step k.

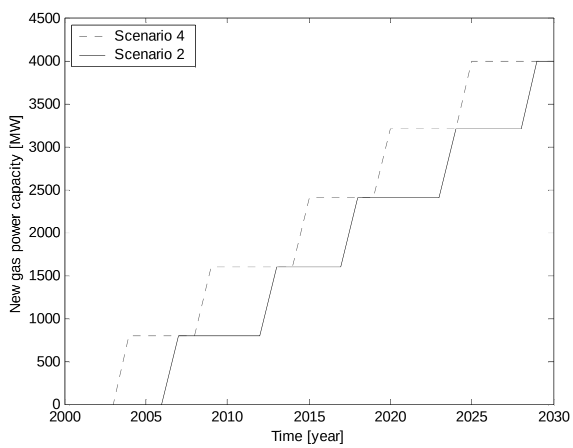

Figure 4.25 Additions of new gas power capacity in the Norwegian power system in scenario 2 (no investment incentive) and 4 (investment subsidy). Investment decisions are based on stochastic dynamic optimisation. l_{2000} = 14100MW, l_{growth} = 140 MW/year.

The difference in investment timing is also reflected in the prices (Figure 4.26), with lower prices in scenario 4 due to earlier investments. An interesting observation in scenario 2, without investment incentives, is that the average price is always above the total unit cost for the new gas power plant, even right after a new plant becomes available. The total unit cost can be considered as the long-run marginal cost (LRMC) of system expansion, and with a static analysis investments would be made so that prices are kept near or below LRMC[34]. However, we see that when investment decisions are based on stochastic dynamic optimisation, the investor's optimal investment policy is to delay investments so that the average price level exceeds LRMC. This is the case even if we have assumed in the model that no market power is exercised. In scenario 4, when an investment subsidy is introduced, we see that the price level is brought down and fluctuates around LRMC. In both scenarios we see that the difference between prices in low and high inflow situations is reduced by time. This is due to the increasing proportion of gas power in the system, for which the generation over the year is not dependent on the short-term uncertainties in the model.

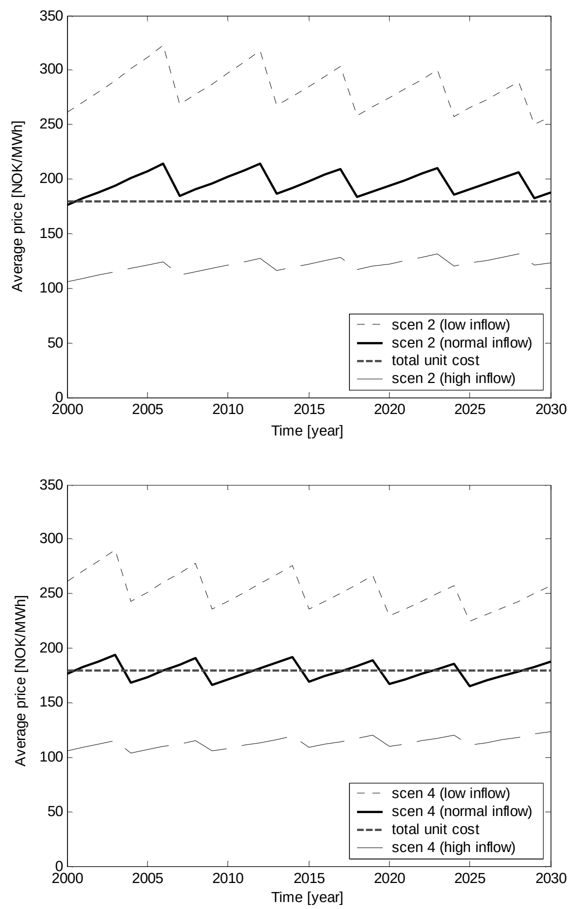

Figure 4.26 Simulated prices in the Norwegian power system in scenario 2 and 4, and total unit cost for new gas power. High, normal and low inflow refers to high, average and low realisations of inflow in short-term uncertainties (ω_s).

[34] A more comprehensive discussion of the long-run marginal cost in power generation expansion planning is provided in the next chapter.

Table 4.10 summarises the simulated investment schedule for scenario 2 under all four possible decision rules, and compares them to the result for rule d in scenario 4. We see that with static decisions for scenario 2 (i.e. 2a and 2b), the simulated investment schedule is very close to scenario 4. This means that with a static investment analysis the conclusion might be that there is no need for an investment incentive to keep the average prices close to LRMC. However, with decision rules based on dynamic optimisation, the investments are delayed considerably, both under deterministic (2c) and stochastic (2d) optimisation. When comparing decision rule 2c and 2d, we see that when uncertainties are taken into account, all investments are delayed one year if the load growth is constant at 140 MW/year. However, also in these simulations it turns out that the difference between static and dynamic investment optimisation is more significant than the difference in results between deterministic and stochastic optimisation. This is of course due to the relatively small differences in investment criteria that we have already seen between deterministic and stochastic dynamic optimisation.

Table 4.10 Simulated capacity additions for different investment decision rules (a, b, c, d) in scenario 2 and for stochastic dynamic optimisation (rule d) in scenario 4. Investment decisions are made 3 years prior to the capacity addition, due to construction delay.

Plant no.	Scenario 2				Scenario 4
	a	b	c	d	d
1	2003	2004	2006	2007	2004
2	2009	2009	2012	2013	2009
3	2015	2015	2017	2018	2015
4	2020	2020	2023	2024	2020
5	2026	2026	2028	2029	2025

In the end, we also look at the simulated energy balance for scenario 2 and 4 (Figure 4.27). Not surprisingly, the energy balance is less negative in scenario 4, with investment subsidies. However, in both scenarios the Norwegian system needs to rely on imports in order to meet the total demand in years with average inflow. This result is due to the parameters in the spot price model, which are based on historic price and load data from a period with an energy surplus in the neighbouring countries (1993-2002). Consequently, since the parameters in the price model are constant throughout the simulation period, it will not be profitable to invest until parts of the import capacity is utilised. However, if the energy surplus in neighbouring countries is reduced, the prices would increase quicker in Norway and therefore also trigger earlier investments. This is a likely development in the future, but is not included in the results presented here. Still, the effect of changing import availability could easily be added into the investment analysis, for instance by letting the parameters in the price model be dependent on the time.

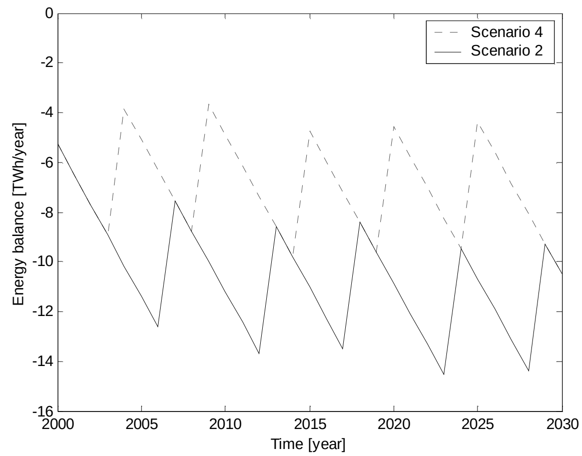

Figure 4.27 Simulated energy balance for the Norwegian system in scenario 2 and 4.

The analysis of system consequences that is provided here is of course very simplified, as we confine the study to the Norwegian power system and only look at investments in one large-scale technology. Furthermore, we have only simulated the assumed average realisation of the underlying load growth in the system. In reality, there are several decision makers, both inside and outside Norway, investing in various technologies, and thereby influencing the system's development. At the same time the real load growth is stochastic. Investment patterns will therefore be less regular than the graphs show. Still, it is likely that several investors, particularly in smaller scale technologies, decide to invest at more or less the same time, when the conditions are advantageous. Cyclical patterns, although less regular, are therefore still likely to occur. This is also supported by the results from the multi-technology deterministic system dynamics model presented in Chapter 3. The effect of uncertainty on the simulated investment decisions is further discussed in section 4.4.4.

4.4.4 The Investor's Value of Using a Stochastic Dynamic Model

So far we have used the model to look at how the inclusion of uncertainty in the optimisation problem contributes to change the optimal investment criterion, and thereby the development of the system in a long-term perspective for a given load growth. As we have seen, the model also calculates the investor's expected profit at the beginning of the planning horizon, which is the objective function in the optimisation problem. In a real situation a prudent investor would reconsider investment alternatives regularly, and always use all available updated information in these assessments. However, the model only takes the value of the feedback from updated information into account when a stochastic dynamic decision rule (d) is applied. For the static and deterministic dynamic decision rules (a, b,

c) the model only calculates the expected profit from an investment strategy which is fixed for the entire planning horizon. The value of the feedback from new information to future decisions is therefore not taken into account in the model's profit estimates with these decision rules.

The value of using a stochastic solution method for dynamic optimisation problems is discussed by Mo in [62]. It is stated that the difference between the optimal value of the objective function for a deterministic (DP) and a stochastic (SDP) model applied to the same problem, is an upper limit for the true value of using stochastic dynamic optimisation, when information feedback is included. It is straightforward to use this result to calculate an upper bound to the value of using the SDP instead of the DP methodology (i.e. decision rule d instead of c). For instance, in the gas power base scenario the difference in the calculated value of the objective function for an initial load of 14100 MW is: $J_{tot,opt,d}(l_{init}=14100)$ - $J_{tot,opt,c}(l_{init}=14100)$ = 267 - 130 = 137 MNOK. This would then be an upper bound for the value of using SDP instead of DP optimisation when the average initial load is 14100MW. However, this comparison does not take into account that future investment decision can be based on updated information, also when the deterministic decision rule is applied.

A more accurate comparison of the value of using the different decision rules, when the information feedback is included, can be carried out by running Monte Carlo simulations with the simulator in Figure 4.24. In order to do that we draw the stochastic load growth ($\omega_{l,k}$) from a normal distribution, and run the simulator repeatedly with different realisations of $\omega_{l,k}$. The simulator can then be used to run Monte Carlo simulations in order to test how well the different decision rules perform, when the realisation of the stochastic variable is taken into account in the investment optimisations for each consecutive time step.

The time horizon (T) in the investment optimisation problem is now set equal to the remaining length of the simulation period (N-k+1) in each time step. This is in contrast to the constant T that was used in the simulations in section 4.4.3. Consequently, only uncertainties within the simulation period are now taken into account in the optimisation. Simulated investment decisions are therefore not affected by uncertainty in possible profit after the end of the simulation period. At the same time the simulated investment cost is also adjusted according to the remaining length of the simulation period, in the same way as explained in section 4.3.5. By adjusting the investment cost and time horizon we can perform consistent testing of the various decision strategies, without having to take into account the value of the investment option and the power plant itself at the end of the simulation period. However, this also means that the difference between the stochastic and deterministic investment criterion diminishes throughout the simulation period, as less uncertainty is considered in the investment decisions as the end of the simulation period comes closer. The simulated decisions do therefore not fully replicate real-world decisions, as investors will usually consider uncertainties throughout the lifetime of the investment. However, the simulations still give an indication of the value of using the stochastic dynamic investment strategy compared to the deterministic and static ones.

Here we use the simulator to analyse investment decisions and profits in the gas power base scenario (scenario 1) only, where the effect of other investors are disregarded. We simulate a period of 10 years, and the investor is only allowed to invest once in this period. Hence, the simulator uses the investment model to find the optimal timing of the investment under the different decision rules, when the information feedback is also taken into account. The long-term uncertainty, $\omega_{l,k}$, is drawn from a normal distribution with mean and standard deviation of 140 MW and 300MW respectively. These values are also used as input to the stochastic dynamic investment optimisation. In the results presented below the number of Monte Carlo simulations is 5000, and the same set of random realisations of load growth are used for the different investment decision rules.

First, we assume that the average load at the beginning of the simulation is 14100 MW. This is the same as we used in the analysis of system consequences in section 4.4.3, and also equal to the Norwegian load in 2000. At this initial load level both static first period decisions (a and b) turn out to be immediate investment, while the dynamic assessments (c and d) would suggest to postpone the investment (this can be seen from the investment criteria in Table 4.7). The distribution of simulated capacity additions for the different decision rules are shown in Figure 4.28. With the static assessments (a and b) we see that the investor would always invest in the first time period (k=1), so that the capacity is added to the system three years later (k=4), after the construction delay. For the dynamic decision rules (c and d) the decisions are made at different time steps, depending on the realisation of load growth. We see that with the stochastic decision rule (d) the investments tend to be postponed more than for deterministic decisions (c). This is due to the higher option value of waiting. The difference is most significant for decisions taken in the second time period. For the remaining periods the number of simulated investments is at the same level or higher for decision rule d, so that there is only a small difference in the number of scenarios where investments are not made at all.

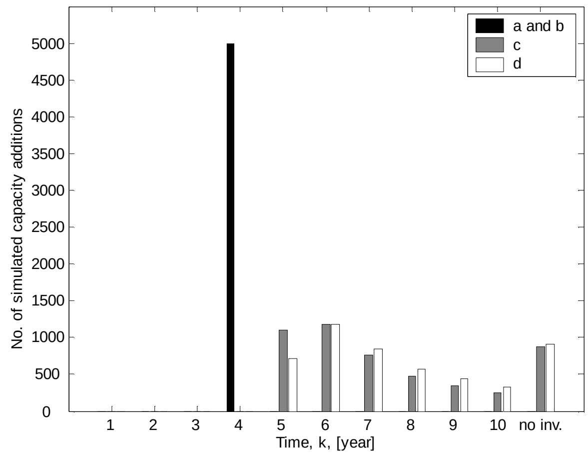

Figure 4.28 Frequency distribution for capacity additions in the Monte Carlo simulations for different investment decision rules (a and b, c, d). Investment decisions are taken three years prior to capacity additions, because of investment delay. l_{init} *= 14100 MW.*

The corresponding distributions of simulated total profit over the simulation period are shown in Figure 4.29. With the static decision rules we see that negative and positive profits are rather evenly distributed. This is because there is no flexibility in the investment strategy, so that the investor is equally exposed to positive and negative shifts in the underlying load growth. With decision rule c and d the investor postpones the investment decision and is therefore able to avoid investing in many of the scenarios where load and price grow less than expected. This is why the profit distributions are much more biased towards positive profits in c and d. The more flexible investment strategy also explains the high frequency of zero profit in c and d, which is due to the high number of simulations where no investment at all is undertaken.

From Figure 4.29 we also see that the difference in profit distributions between c and d appears to be very small. This is due to the limited difference in investment criteria between SDP and DP optimisation. The resulting variations in simulated investments are further reduced since the investment opportunity is reassessed for each simulated time step based on the simulated realisation of load growth. The summary of results in Table 4.11 shows that the average simulated result for decision rule c is actually slightly higher than for d. However, the difference between c and d seem to be insignificant in this scenario. When looking at the static decision rules, Table 4.11 confirms that the average profit is much lower, while the standard deviation is higher for rule a and b. Another interesting observation is that the expected total profit from the first period investment optimisation is close to the simulated result for the SDP used in rule d, while the DP optimisation in rule c gives a far too low estimate of the expected profit. This is because the calculated total profit with DP does not take into account the flexibility in adjusting the investment plan according to the realisation of future uncertainties.

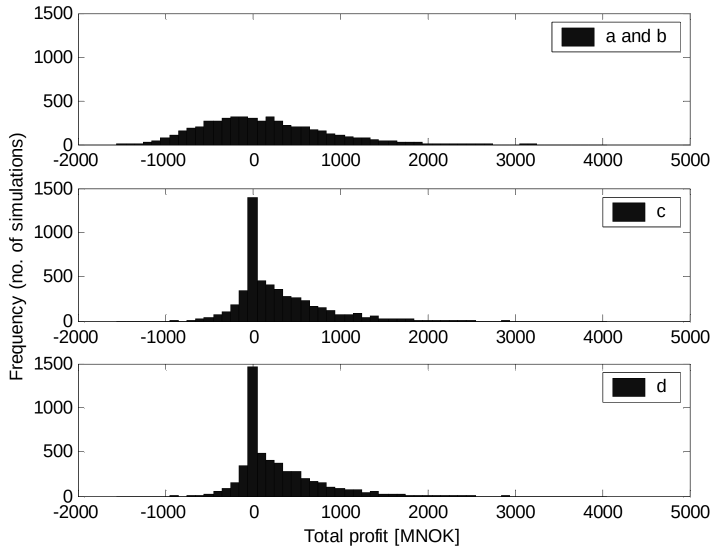

Figure 4.29 Frequency distribution for total profit in Monte Carlo simulations for different investment decision rules (a and b, c, d). l_{init} = 14100 MW.

Table 4.11 Summary statistics for total profits in Monte Carlo simulations with investment decision rules a, b, c and d. Expected total profit from first period investment optimisation is also shown for c and d. All numbers in MNOK. l_{init} = 14100MW.

	a and b	c	d
Average total profit (MC simulations)	100.3	270.3	269.6
St.dev. in total profit (MC simulations)	663.1	447.6	429.4
First period expected profit, $J_{0,opt}$	-	129.6	266.7

We now repeat the analysis above for a different average load level in the first time period, using l_{init} = 14500 MW. With this initial load rule c and d give different first period decisions. The first period DP strategy in c is now to invest immediately, while the SDP assessment in d still finds it optimal to postpone the investment decision. From Figure 4.30 we see that the investment strategies for decision rules a, b and c are now the same, with immediate investment in all simulations. For decision rule d the investments are distributed throughout the simulation period, and there are still some realisations of the load growth for which no investment is undertaken. However, with an initial load level of 14500MW the majority of the investment decisions are made in the second time step for rule d, with corresponding capacity additions in time step 5.

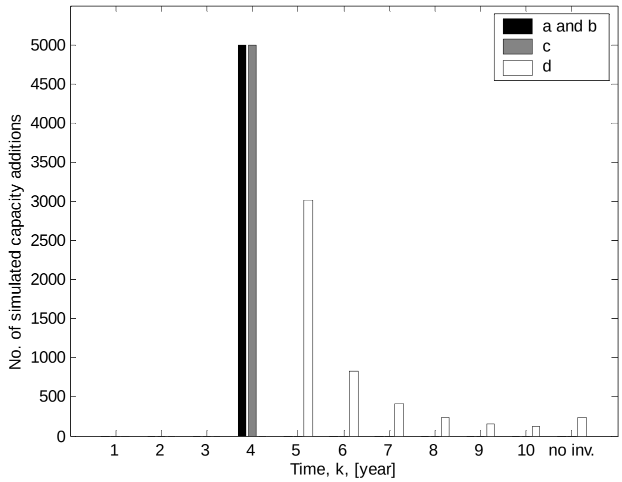

Figure 4.30 Frequency distribution for capacity additions in the Monte Carlo simulations for different investment decision rules (a and b, c, d). Investment decisions are taken three years prior to capacity addition, due to investment delay. l_{init} *= 14500 MW.*

The distributions of simulated total profits are now the same for decision rules a, b and c, since they result in identical investment schemes. From Figure 4.31 we see that the more flexible investment strategy for rule d is still able to avoid some of the outcomes with negative profit that result from the inflexible strategies (a, b and c), although the difference is now less significant than for the lower initial load level in Figure 4.29.

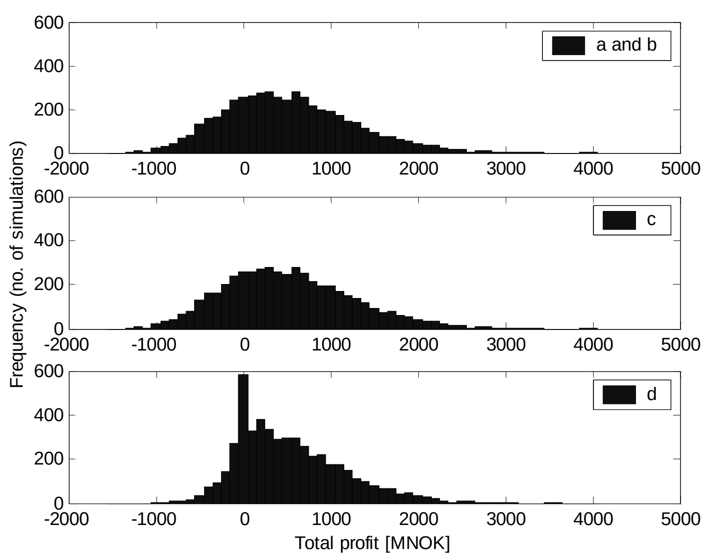

Figure 4.31 Frequency distribution for total profit in Monte Carlo simulations for different investment decision rules (a and b, c, d). l_{init} *= 14500 MW.*

Table 4.12 shows that the average simulated profit for rule d is now higher than for the other decision rules. Hence, in this situation, where the initial investment optimisations give different decisions for rule c and d in the first time step, SDP seems to also outperform DP as a tool for investment decision support. However, the difference in the average simulated total profit is still rather small. Table 4.12 also shows that the SDP rule in d gives the smallest standard deviation. Most investors would look at this as an advantage, since it implies a lower risk. However, the reduced standard deviation should not be used as an indicator for the SDP model's performance, since the objective function in the model formulation does not take the standard deviation explicitly into account. In the end, we see again that the expected first period total profit for the DP optimisation is lower than the simulated average for decision rule c. At the same time, the first period expected profit for SDP is still close to the average from the Monte Carlo simulations.

Table 4.12 Summary statistics for total profits in Monte Carlo simulations with investment decision rules a, b, c and d. Expected total profit from first period investment optimisation is also shown for c and d. All numbers in MNOK. l_{init} = 14500MW.

	a and b	c	d
Average total profit (MC simulations)	526.7	526.7	538.3
St.dev. in total profit (MC simulations)	743.4	743.4	612.5
First period expected profit, $J_{0,opt}$	-	441.0	542.4

The results of the Monte Carlo simulations presented here build up under the conclusions from the analyses of the initial investment criteria. There is a substantial change in simulated investments, which causes a large increase in the investor's average profit, when going from a static to a dynamic project appraisal. However, the increase in average profit when going from a deterministic dynamic to a stochastic dynamic evaluation is less significant. It is somewhat surprising that the SDP investment rule only seems to outperform the DP rule for one of the two initial load levels in the stochastic simulations. One possible explanation to this observation is the simulation procedure itself, which does not fully represent the influence of uncertainty on investment decisions throughout the entire simulation period. Another reason could be the approximations in the investment optimisation model, particularly the discrete binomial representation of load growth in the model. A more comprehensive analysis of the value of using stochastic optimisation could be carried out by running Monte Carlo simulations also for other scenarios. A different simulator, which uses an extended planning horizon and at the same time takes into account the value of the investor's position at the end of the simulation period, could also give more insight. However, further investigation of this topic is left for future work.

4.4.5 Investments in Other Technologies

In this chapter we have used the model to analyse new investments in only one technology, a combined cycle gas power plant. However, the model can of course also be applied to assess investments in other technologies. The main adjustment required is simply to change the model parameters that are describing the technology in question (see Table 4.6 for the list of parameters for the CCGT project). The specific version of the investment model that is presented here is probably best suited for investment analysis of base load technologies. However, by adding more details to the price model it would be possible to apply the same methodology also for medium and peak load technologies. The framework can also be adjusted to technologies which rely on energy resources with more variation in availability, which is typically the case for many renewable resources. For such technologies it is more important to take into account the correlation between the short-term uncertainties in the existing system and the availability of the technology itself. Again, this can be done by adjusting the price model and the way it is used in the calculation of profits.

We do not go further into these issues here. The theoretical representation of long-term uncertainties and its influence on the optimal investment strategy applies to all investment problems in new generation assets. Most of the qualitative results that we have seen in the gas power example are therefore likely to be valid also for investments in other technologies, although technology specific variations will occur.

4.4.6 Computational Issues

The stochastic dynamic investment optimisation model presented in this chapter is implemented in Matlab. The dimension of the state space in the optimisation problem depends on the length of the planning period and the number of capacity states. The computation time is in turn dependent on the size of the state space. Besides, the inclusion of other investors into the model also increases the computation time. In the illustrative examples the computation time for calculating the expected income of waiting and investing for one load level is below 1 second in all the scenarios in section 4.4.2 on a 1.2 GHz/256 MB RAM computer. However, running the Monte Carlo simulations in section 4.4.4 took several hours.

4.5 Chapter Summary and Concluding Remarks

In this chapter we have introduced a new stochastic dynamic model for optimisation of investments in power generation assets under uncertainty. The model builds upon real options theory, which is specifically developed to better take into account how uncertainty and dynamics affect optimal investment decisions. Our model framework gives a better opportunity for analysing system consequences than the traditional real option models, since physical factors are directly represented as state variables in the model. The inclusion of physical state variables also makes it possible to capture more of the specific price dynamics in the power market, which is different from what is observed in most other commodity markets. The model optimises the investment strategy for an individual profit maximising investor, and can also take into account how the strategy is influenced by the actions of other participants in the market. In total, the model framework and the underlying theory offers a new tool, which is capable of analysing optimal strategies for investment in power generation assets under uncertainty. The work can contribute to increase the understanding of the long-term performance of competitive power markets under different regulations and market designs.

We argue in this chapter that different growth trends and long-term uncertainties in the power system add to the value of an investment opportunity, and thereby influence the optimal timing of an investment decision. The stochastic dynamic optimisation model takes into account the expected growth and uncertainty in system load. Results from the model show that both factors contribute to postpone the optimal investment decision compared to project appraisals based on static and deterministic analyses. However, the change in optimal investment criterion is more significant when going from a static to a dynamic analysis, than the difference in criteria between deterministic and stochastic analysis. For the investor it is therefore very important to take the dynamic aspect of load growth into account when assessing investments in new power generation. Adding the uncertainty in load growth into the investment optimisation also contributes to increase the investor’s expected profit, but to a less extent. These results are confirmed by Monte Carlo simulations, where an investor’s total profit is simulated under different investment strategies. The representation of other investors in the model gives a lower expected profit on new investments. However, the results from the case study show that the optimal investment criteria are only to a very limited extent changed as competition from others are taken into account.

The model results also illustrate that the optimal investment criteria which follow from stochastic dynamic optimisation do not necessarily result in a long-term price level equal to LRMC, which would be the conclusion from a static assessment. In the case study of gas power in Norway the price in the long run fluctuates above the LRMC in years with average precipitation to the hydro stations. Various investment incentives can contribute to trigger earlier investments if the prices in the power market do not give adequate investment signals. Our analysis indicates that a fixed investment subsidy would achieve the desired result at a lower cost than a capacity payment. This is because the direct subsidy does not give rise to any additional option value of postponing the investment decision. However, a more detailed analysis of how the incentives influence the demand side in the power system would be needed in a comprehensive study of investment incentives.

In the end it is important to emphasise that the stochastic dynamic investment optimisation model presented in this chapter contains a general framework that could be extended in several directions. The model can therefore serve as a starting point for more comprehensive analyses of investments in the power system. A more detailed description of power system operations could for instance be implemented. Several long-term uncertainties could also be taken into account, by increasing the number of stochastic state variables. In the next chapter we extend the model framework to include investments in two technologies. At the same time we also introduce an alternative description of the electricity market, which is more similar to the market representation in Chapter 3.

Chapter 5 OPTIMAL INVESTMENTS UNDER CENTRALISED AND DECENTRALISED DECISION MAKING

In this chapter we look at optimal investment policies under centralised and decentralised planning. We use the same model framework for optimal investments under uncertainty as developed in the previous chapter. However, we now describe the power market in terms of a supply and demand curve, in order to quantify socio-economic figures such as social welfare, total system costs, consumer and producer surpluses under different planning regimes and market structures. We also introduce two technologies with different cost characteristics into the optimisation model. A market simulator is also here developed and can now be used for simulations of not only investments and price, but also total social welfare in different scenarios. The simulator bears resemblance to the system dynamics model in Chapter 3, and a similar market description is used in the investment optimisation. However, investment decisions are now based on the stochastic dynamic optimisation model instead of the static net present value assessment, so that long-term uncertainties and the flexibility of investment timing can be taken into account. An outline of theories for pricing of electricity and investments in new generation capacity, for the regulated and liberalised power industry, is given before the model is presented.

5.1 Optimal Investments and the Price of Electricity

Optimal investments in new power generation are closely related to the price paid by the end users for electricity. An extensive literature exists on pricing policies and optimal investments in new power generation for regulated utilities. Parts of this theory are also relevant for the restructured industry, although some of the underlying assumptions are obviously changed. A brief outline of the main theoretical directions for pricing under regulation is first presented. In the light of this theory we look into some of the challenges facing a restructured power system, where market prices are supposed to give the correct investment incentives. The discussion is limited to the price of electricity generation, as transmission and distribution are still regulated monopolies in most systems. The theory presented in this section serves as a background for the modelling and analyses of investment under uncertainty that follow later in this chapter.

5.1.1 Pricing and Investments under Regulation

In a regulated system the price for electricity is controlled by a regulating authority, either directly through a specified price or indirectly through a limit on the profits for the utility (e.g. rate of return regulation). In both cases a tariff will have to be determined in order to charge the customers for their use of electricity. The objective under regulation is usually to obtain a system where the sum of benefits to all participants in the system is optimised. For modelling purposes this can be done by maximising the social welfare function in the system.

A possible approach is to base the regulated tariffs on the marginal costs in the system. According to standard economic theory the tariffs should be set equal to the system's short-run marginal costs (SRMC) to ensure short-term economic equilibrium. In a system which is optimally dimensioned the long-run marginal cost (LRMC) of expanding the system would equal the SRMC of operating the existing system. Investments should be made in time to avoid that SRMC exceeds LRMC so that long-term economic equilibrium is maintained [2]. Prior to restructuring of the Norwegian power system in 1990, the parliament determined the price that Statkraft, the large state owned power generation company, charged for its power generation. This price penetrated the wholesale market for electricity and was kept close to LRMC for the Norwegian system (Figure 5.1). By keeping the price close to the LRMC the regulator ensured sufficient investments in new capacity.

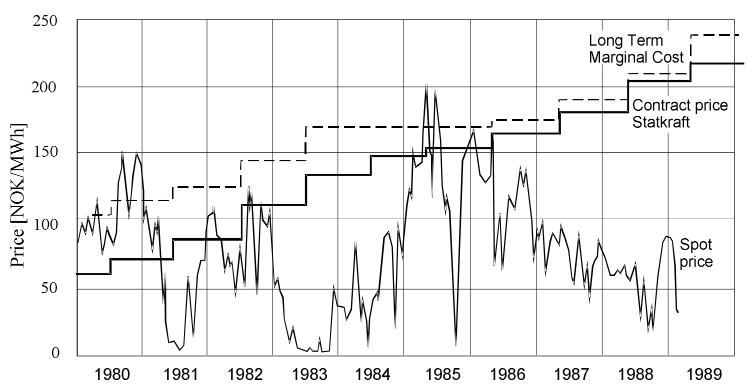

Figure 5.1 Wholesale prices in Norway before restructuring. The spot market could only be used after contract obligations were met, and had a relatively low turnover. Source: [2].

The advantage of an annual uniform tariff based on marginal costs is that it is easy to implement in terms of metering and billing. However, it does not take into account that demand varies over the day, week and season. With a uniform price over the year these demand fluctuations are not in any way dampened by the price. The theory of peak-load pricing[35] was developed to specifically deal with the non-storability and periodic and stochastic demand fluctuations for electric power. By using time-of-use tariffs the price elasticity of demand contributes to dampen demand fluctuations and thereby lower the need for investments in peaking capacity. The use of dynamic pricing therefore has advantageous effects for both consumers and the supplier of electricity. Boiteux was the first to propose peak-load pricing of electricity [65]. He uses a simple deterministic two-period model with one generation technology to derive optimal pricing formulas during the off-peak and peak load period. The results show that the operating cost should be charged in the off-peak period, while the price in the peak load period should include the sum of operating and capital costs. In this way the utility recovers its capital cost expenditure during peak load hours, while capacity is at its limit.

The theory of peak-load pricing has been extended in several directions. Crew and Kleindorfer expand the basic deterministic model of Boiteux to include several technologies [66]. The objective is to maximise the social welfare in the system, given that demand is met in each time period and generation is below capacity limits. The effect of introducing a variety of technologies with different operating and investment costs is in general to lower peak period prices and increase off-peak period prices. In turn, this means that the demand fluctuations are less dampened with a diverse mix of technologies. The prices within each period are still set equal to the long-run incremental cost of meeting an additional unit of demand, so that capital costs are recovered. Criteria for optimal mix of technologies are also derived. The basic rule states that capacity should be installed and operated in order of increasing operating costs (i.e. merit order), but both capital and operating costs determines whether or not a technology is part of the optimal mix of technologies. In traditional power system expansion planning the same rule is used to plot so called screening curves for available generation technologies. The system's load duration curve can then be utilised to determine optimal installed capacities of the different technologies[36].

[35] Crew and Kleindorfer give a comprehensive survey of the general theory of peak load pricing in [63], while a more verbal discussion with emphasis on the electrical power system is presented by Doorman in [64].

[36] The use of technology screening curves to determine the optimal mix of generation technologies in the power system is explained by Wangensteen [2] and Stoft [67].

A stochastic model for the peak-load pricing problem is also developed in [66]. When demand, and possibly also supply, is uncertain, one might end up in situations with demand unexpectedly exceeding available supply. In this situation parts of the system load has to be rationed. Therefore, the cost of rationing has to be taken into account in the objective function. Ideally, rationing should take place according to increasing willingness to pay for electricity, so that the loss in consumer surplus is minimised. However, this requires that the system operator can actually curtail load according to customer's willingness to pay, which is a very strong assumption in most power systems. Firstly, there is usually substantial uncertainty concerning what customers are actually willing to pay for electricity. This is illustrated by the inherent difficulties in estimating the value of lost load. Secondly, even if information about different customer's value of lost load were available, the system operator would still have a technological problem in shedding load according to a pre-specified schedule based on increasing willingness to pay. Random rationing would therefore be less costly for the system operator, although the loss in consumer surplus is obviously higher[37]. The results from the stochastic peak-load pricing model shows that social welfare optimisation under uncertainty entails marginal cost pricing rules similar to those obtaining for deterministic peak-load pricing. However, determining and quantifying the appropriate marginal costs under uncertainty requires that rationing and excess demand conditions must be considered explicitly. Note that the uncertainties represented in these models are what we referred to as short-term uncertainties in the previous chapter. It means that they do not affect the investment plan other than in terms of changing the expected values within each time step.

The implementation of peak-load pricing requires that the customers are billed according to their actual temporal load profile. Despite more complex metering and billing procedures dynamic time of use rates have been implemented in parts of Europe, e.g. in Germany, France and England. In general, the price periods could be based on seasonal, weekly, daily, or even more frequent load variations. Real-time pricing, or spot pricing of electricity, was first introduced by Schweppe et al. [68]. With spot pricing the price is set as close to real time as possible. A major advantage with real-time pricing is that uncertainties concerning load and supply interruptions are minimised, so that the flexibility in supply and demand is exploited to its limits. With sufficient price elasticity of demand the need for rationing schemes disappears under real-time pricing. The spot price is determined by a centralised entity, and the price can also take into account other factors than the costs of electricity generation. These other factors

[37] Doorman [64] gives a comprehensive discussion of customers' willingness to pay for electricity and the quality of supply.

could be maintenance, quality of supply and possibly also revenue reconciliation for the utility. The proposed spot prices are also capable of reflecting the cost associated with transmission losses and network constraints, and can therefore help facilitate the unbundling of generation and transmission in a restructured setting. At the same time, Caramanis [69] argues that correct investment incentives from a social welfare point of view are given to both suppliers and consumers under spot pricing of electricity, also when the parties act as independent profit maximising firms. The requirement is that social and private interest rates are the same. The spot pricing theory therefore has had a substantial impact on the trend towards liberalisation and restructuring of power markets, although the main aim of the theory originally was to improve the pricing efficiency within the regulated electric power industry.

5.1.2 Prices and Investments in a Restructured Market

In a restructured power market with decentralised decision making the price of electricity is determined by the bids from the suppliers and consumers in the system. If we disregard inter-temporal constraints and assume perfect competition, a rational supplier would bid the marginal cost of generation into the market while consumers would bid their marginal willingness to pay. The spot price is settled at the intersection of the aggregate supply and demand curves. In most situations the price would equal the marginal cost of the last generation unit needed to meet demand. However, in situations with high demand and scarcity of supply the price would be given by the consumer's marginal willingness to pay. The two situations are illustrated in Figure 5.2, and this is just the traditional picture of market based trade of a commodity. The electricity market will be in short-term equilibrium as long as the time resolution of the market is high, and the market clearing is carried out close to real time[38]. According to traditional economic theory the long-term equilibrium is ensured by investors who are willing to invest as soon as they anticipate prices that are high enough to cover the total costs of their investments. The total discounted unit costs of the most competitive new generation technologies available should therefore represent an upper limit for the average prices in different load segments. The desired effect of restructuring is therefore to obtain both short- and long-term equilibrium in the system based on market mechanisms, which again ensures that social welfare optimum is established through efficient market incentives. The spot price is obviously more fluctuating than the tariffs in a traditional regulated setting, but this has positive welfare effects. Besides, a complete

[38] In Scandinavia the spot market has an hourly time resolution, and the market is cleared on a daily basis. Some uncertainties therefore arise between market clearing and physical delivery. These uncertainties are taken care of by market based and automated feedback mechanisms closer to real time.

market design would also have long-term markets where risk-averse participants can lock in the price for future deliveries and thereby reduce their exposure to price variability.

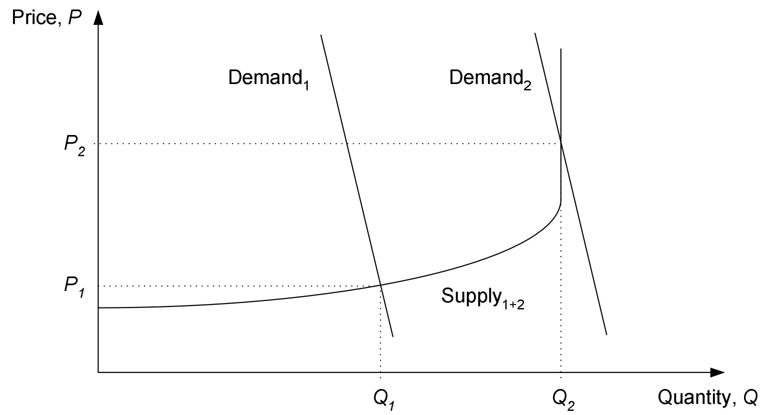

Figure 5.2 Illustration of market clearing during base (1) and peak (2) demand periods, based on aggregate bid curves for supply and demand in the spot market.

Some of the special characteristics of the power system can, however, distort the long-term equilibrium of the power market. Vazquez et al. [70] discuss three difficulties in real power markets that can contribute to prevent optimal investments in new generation. The first is related to the limited price elasticity of demand in current systems. If there is limited or no short-term price flexibility on the demand side one can end up in situations where the market fails to define a price (i.e. the supply and demand curves in Figure 5.2 do not intersect). In such situations the regulator would have to define a price that caps the market. However, unless the price cap is set equal to the real value of energy not served, this will give wrong investment signals. There is a tendency that regulators define price caps that are too low, and this will clearly reduce profit expectations and discourage new investments. Even in markets with no defined price cap there is always the risk of regulatory intervention if the prices rise to very high levels[39]. The second problem arises due to risk aversion among investors. The risk involved in investing in new power generation is particularly high for peak load plants. Unless there are liquid long-term markets where the investor can efficiently hedge these risks, it is likely that potential capacity expansions are postponed or cancelled. The third difficulty that is mentioned

[39] The Scandinavian spot market for electricity does not have a clearly defined price cap, although there is an upper technical limit on the bid prices that are allowed to be submitted to the market. This limit has been adjusted according to the market situation and does not represent a regulatory price cap. Still, the political debate in Norway following the high prices during the winter of 2002/2003 illustrates the risk of regulatory intervention and price control if electricity prices remain high over an extended period of time. This risk of regulatory intervention can be conceived by some participants as a price cap in the long run.

is caused by potential exercise of market power by large producers in the system. Under-investment in order to increase prices may result, unless the barriers to entry are low for new investors in the market.

Also from the consumer's point of view there are problems that can distort the long-term functioning of the power market. Stoft [67] refers to two demand-side flaws in deregulated power markets. The first flaw is the lack of metering and real-time billing. This results in the limited short-term price elasticity of demand that has already been mentioned. The large majority of customers in restructured power systems today are still being billed based on some sort of average price measure. Hence, there is an absence of real-time feedback from price to demand, so that customers can not adjust their load according to short-term price fluctuations. The second flaw is the lack of real-time control of power flow to specific customers. This prevents the physical enforcement of bilateral contracts, and therefore in practice the system operator becomes the default supplier in real time. Under these conditions the incentive for customers to sign long-term contracts to protect themselves against higher prices and service interruptions are therefore low. As a consequence, efficient long-term markets for sharing of investment risks, particularly in peaking capacity, are absent in most restructured power markets[40].

Three types of regulatory approaches have been employed or proposed to deal with the problem of adequate investments in the power system[41]: 1) In the "energy only" model it is left to the market forces to secure optimal investments. This solution is based on the assumption that consumers after a learning period will increase their price flexibility and also efficiently participate in long-term markets. The restructuring of the power markets in Scandinavia, California and Australia are based on this model. 2) In a "capacity obligation" model an obligation is imposed on the buyers, forcing them to buy their peak capacity in a long-term capacity market, so that a prescribed level of generation capacity is ensured. This solution has been implemented in the north east of the US (PJM, NYPP, NEPOOL). A similar system was also implemented in the Norwegian power system prior to restructuring[42]. 3) In a "capacity payment" model, a regulatory mechanism for a payment to generators, in addition to income from the energy market, is established. This capacity payment encourages investments by increasing

[40] See Doorman [64] for a comprehensive discussion on peaking capacity in restructured power systems.
[41] The pros and cons of the three market models are elaborated by Vázquez et al. in [70] and by the organisation for Nordic system operators, NORDEL, in [71].
[42] Participants taking part in the coordinating inter-regional exchange scheme, called "Samkjøringen", were obliged to maintain a neutral capacity and energy balance through long-term contracts.

and stabilising the volatile income of generators. Spain, Argentina, Colombia and Chile have included a capacity payment in their market designs.

With the investment model that is presented later in this chapter we can analyse market designs based on the “energy only” and “capacity payment” market designs. The capacity obligation model is of less interest from a capacity and reliability point of view, since the minimum level of installed capacity is predetermined by the regulator.

5.1.3 Long-Term Uncertainties, Flexibility and Investment Dynamics

The theoretical considerations behind most of the results presented above, both for the regulated and competitive industry, are usually of a static nature. This is reflected in the mathematical models that are used to support the results. The investment problems are typically solved as static optimisation problems, where optimal investments are determined for the system in a “snapshot” of time. In this way Lagrangian techniques can typically be applied to find optimal prices and investments from the shadow prices of the system’s energy and capacity constraints. Short-term uncertainties due to unexpected load variations and generator outages are sometimes added to the static models. This is for instance the case in the peak-load pricing problem formulated by Crew and Kleindorfer [63], and also in the model for spot-pricing of electricity proposed by Scwheppe et al. [68]. However, the gradual development of long-term trends and uncertainties are not represented, so that the dynamic option values inherited in flexible investment strategies are not taken into account.

In the theory for time of use rates and peak load pricing there are rare occasions of dynamic formulations of the investment problem under social welfare maximisation. A dynamic one-technology model is solved by Crew and Kleindorfer [66] (chapter 7). The results show that whatever the level of installed capacity, the price should be set to maximise instantaneous welfare returns subject to the given capital restriction, i.e. price should equal SRMC. At optimum, capital stock is adjusted so that SRMC equals LRMC. The static and dynamic cases are the same in optimum, except that in the static case the time path of adjustment of installed capacity is not considered. Kaya and Asano [72] extend this model to a situation with multiple generation technologies. The same pricing rule is still valid in this situation, and the pricing policy in steady-state is equal to the static case. The static technology screening rule, with capacity installed and operated in order of increasing operating costs, also applies in the dynamic setting, according to [72]. The dynamic models referred to here are both deterministic, so that the impact of long-term uncertainties on optimal investment decisions is not included. Another factor that can play an important role in real world investment decision, namely the effect of different technology lead times, is also omitted.

The main principles behind real options theory was outlined in the previous chapter. Although most of the literature on real options is devoted to investment decisions of individual firms, the theory is also extended to look at competitive industry equilibrium and optimal investments from a social welfare point of view. Dixit and Pindyck [38] formulate a dynamic model for a competitive industry. Optimal exit and entry thresholds are determined using a version of the standard continuous time real options framework. Not surprisingly, it turns out that the optimal thresholds under uncertainty differ substantially from the static NPV criteria. Depending on the level of uncertainty, the optimal price threshold for entry of new investors can be much higher than in a static analysis. An aggregate industry model is also formulated, where the objective is to maximise total social welfare. It is shown that social optimum coincides with the competitive equilibrium, also in the dynamic framework. Hence, also under centralised planning with a social welfare criterion there is an option value in having a flexible investment strategy. Dixit and Pindyck therefore claim that policy intervention is only justifiable if there is some kind of market failure in the system. A common problem in this respect is the failure of markets to efficiently share risks. From the discussion above we see that this can be a severe problem in restructured power markets. However, it is also shown in [38] that policy interventions to reduce risk, for instance in terms of a price cap, can in fact increase prices in the long run.

Dixit and Pindyck's models of industry equilibrium and socially optimal investments are based on the standard real options framework with one stochastic state variable, which could represent either price directly or a shift in demand. Although there are many advantages in applying a continuous time model which can be solve analytically, there are also limitations, as discussed in section 4.1.5. The models do for instance not take into account the time variability of demand that is studied in the literature on peak load pricing. The impact of different technology lead times and the lumpiness of investments are also disregarded. These factors are usually important in electrical power systems, where demand is time-variant by nature and investments often are large scale with long lead times.

The dynamic investment model presented in this chapter combines elements from the traditional peak load pricing models with real options theory for investments under uncertainty. Our objective is to analyse optimal investments in new power generation assets under different assumptions about market design and power system structure. With a simplistic representation of the power market we can look at optimal investments for a decentralised profit maximising investor as well as from a centralised social welfare point of view.

5.2 A Simple Economic Model of the Power Market

In this version of the investment optimisation model we use a simplistic representation of the power market, based on marginal production cost and consumer's willingness to pay. A simple power market description gives us the possibility to study macro economic effects of investments in a long-term perspective. The model is based on a set of simplifying assumptions that are important to keep in mind from the beginning. The most important assumptions in the model are therefore listed below:

- The time step in the investment optimisation model is one year, but each year is split into base, medium and peak demand sub periods. Demands within sub periods are interdependent and grow proportionally.

- Demand is split into a fixed and a price responsive part, and is represented with linear demand curves within each demand sub period. The demand curves are bid into the spot market and represent customers' willingness to pay for electricity.

- Growth in demand is the only long-term uncertainty represented in the model. Deviations in load due to temperature etc. can be represented as short-term uncertainties.

- End-users are billed according to dynamic prices. They therefore face different prices in the different demand sub period.

- Two technology groups are represented in the supply side of model, i.e. base and peak load plants. Decommissioning of existing plants is not taken into account.

- The inter-temporal dynamics of storage (for instance storage in hydro dams) are not represented in the model. Other inter-temporal constraints, such as start-up/shut-down costs and ramp rates, are also omitted.

- The capacity variables in the model represent available capacity. Availability factors are therefore not represented explicitly for the supply technologies in the model.

- There is no revenue reconciliation for old units, so that existing plants compete in the spot market on equal basis with new investments.

- There is no exercise of market power in the spot market for electricity. Suppliers bid their marginal costs in the market, and aggregate bids are represented with piecewise linear curves.

- Operating reserves (OR) during peak demand are provided by existing plants with low efficiencies and high operating costs. The OR requirement is kept as a constant capacity, and the plants that provide OR during peak demand are not represented in the spot market supply curves.

- A real discount rate is used in the model, and we can therefore assume no inflation in the planning period.

- The electrical power system is modelled as an isolated one-area system, i.e. exchange with neighbouring areas is not considered. In addition, transmission constraints and losses within the area are not explicitly represented in the model.

More details about the assumptions and the mathematical formulation of the model are presented in the sections below.

5.2.1 Representation of Electricity Demand

The representation of electricity demand in the model is illustrated in Figure 5.3. By using three demand sub-periods (i.e. base demand (1), medium demand (2) and peak demand (3)) we can capture parts of the temporal variations in electricity demand. The demand within each sub period is modelled with a fixed and a price flexible part. The fraction of price flexible demand is not only dependent on the characteristics of the load itself and the service that it provides, but also on how much of the load that is exposed to real-time prices and how actively the end-users take part in the electricity markets. With a one year time resolution it is likely that there is some feedback from sub-period prices to sub-period demands, although the effect might be delayed if there is no real-time billing in the system. Still, in a recently restructured electricity market it will take time before end-users adapt to the new situation and act rationally in the markets according to their willingness to pay for electricity. The proportion of price flexible load in current power markets can therefore be very limited.

In the model we assume that if the electricity price reaches a sufficiently high level ($P_{flex,max}$), the regulator will intervene in the market with load shedding. The use of load shedding could be needed because of limited price elasticity of demand, which can result in a failure of the market to clear in peak demand situations. It could also reflect a regulatory policy where there is a limit on the bid prices allowed from the demand side of the market. During load shedding the electricity price is set equal to a load shedding price, P_{cap}, which caps the price in the spot market. P_{cap} is assumed to penetrate the entire spot market. The price levels for $P_{flex,max}$ and P_{cap} could be part of the market design and therefore predetermined values transparent for the market participants. However, they could also reflect investors' expectations about the regulator's behaviour in situations with very tight capacity margins. The effect on optimal investment criteria would be similar. The importance of these parameters is dependent on the amount of price responsive demand in the power system. With a sufficiently high price elasticity of demand the regulator will never need to use load shedding in order to balance supply and demand in the system.

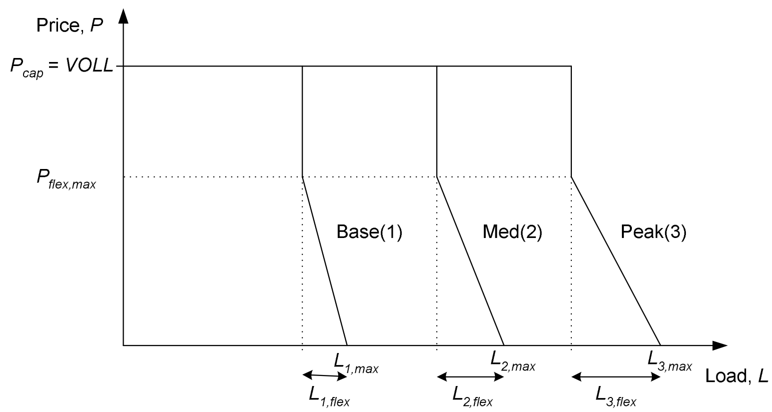

Figure 5.3 Representation of fixed and flexible parts of base, medium and peak demand in the investment optimisation model.

In Figure 5.3 we have assumed that P_{cap} is equal to the value of lost load (*VOLL*)[43] for the customers affected by the load shedding. As pointed out in section 5.1.1 it can be very difficult for the system operator to shed load according to customer's willingness to pay. Consequently, we assume that there is a high degree of randomness in the selection of customers for load shedding. *VOLL* therefore represents the average value of lost load for the fixed part of the demand, and this is considerably higher than the maximum marginal willingness to pay for the price flexible part of the demand ($P_{flex,max}$). A load shedding price equal to *VOLL* would give correct price signals into the market when load shedding is required under this rationing scheme. However, P_{cap} is not necessarily set equal to *VOLL*, either because

[43] Note that we assume that *VOLL* is the same in all sub periods in the model. This is clearly a simplification, as the implications for end-users of interruptions in the power supply can be highly dependent on the time of the day and also the time of the year that it occurs. We also assume that P_{cap} and $P_{flex,max}$ are constant and the same in all the sub periods.

VOLL is not known or because the regulator wants to protect the end-users from very high prices with a lower price cap. Later in this chapter we will present results for different assumptions about P_{cap}, and look at the consequences for optimal investment criteria, prices and system reliability.

The sub-period demands are assumed to be inter-dependent, with a constant proportional relation between the maximum loads ($\boldsymbol{L}_{max}$) in the three segments. This is expressed in (5-1). At the same time, the price flexible parts ($\boldsymbol{L}_{flex}$) are constant fractions of the maximum loads, as shown in (5-2). Consequently, the price elastic demand curves for all three load segments can be described by one state variable only (i.e. l_k) in addition to a set of parameters for prices (P_{cap}, $P_{flex,max}$) and loads ($\boldsymbol{c}_{L,max}$, $c_{L,flex}$). Growth in l_k is the only long-term uncertainty that is included into the model. l_k is represented as a stochastic state variable with a mathematical description similar to the representation of average load in Chapter 4.

$$\boldsymbol{L}_{max,k} = \begin{bmatrix} L_{1,max,k} \\ L_{2,max,k} \\ L_{3,max,k} \end{bmatrix} = \boldsymbol{c}_{L,max} \cdot l_k = \begin{bmatrix} c_{L1,max} \\ c_{L2,max} \\ c_{L3,max} \end{bmatrix} \cdot l_k \tag{5-1}$$

$$\boldsymbol{L}_{flex,k} = \begin{bmatrix} L_{1,flex,k} \\ L_{2,flex,k} \\ L_{3,flex,k} \end{bmatrix} = c_{L,flex} \cdot \boldsymbol{L}_{max,k} \tag{5-2}$$

where

$\boldsymbol{L}_{max,k}$	vector of maximum sub period loads, time step k	[MW]
$\boldsymbol{c}_{L,max}$	vector of maximum load constants	
l_k	state variable for demand, time step k	[MW]
$\boldsymbol{L}_{flex,k}$	vector of flexible sub period loads, time step k	[MW]
$c_{L,flex}$	flexible load constant	

It is also possible to represent short-term uncertainties in demand in the model. The short-term uncertainties (ω_s) could for instance be caused by temperature variations, and are taken into account using a discrete probability distribution. Short-term uncertainties in demand are treated on an expected value basis in the investment optimisation, similar to the representation in Chapter 4. The exact representation which is used for ω_s in the illustrative examples is further described in section 5.3.1.

5.2.2 Representation of Electricity Supply

The representation of electricity supply in the model is illustrated in Figure 5.4. We assume that the initial load is served by existing base and peak load plants[44]. Both groups are assumed to have linearly increasing marginal cost curves. The increasing marginal cost curves reflect that the groups consist of plants based on various technologies and vintages, and therefore have different efficiencies and operating costs. It is possible to invest in two new technologies in the model: new base load and new peak load plants. The new plants are assumed to have lower operating costs than the existing technology groups, due to technology improvements. The installed capacity of the new technologies, $x_{1,new}$ and $x_{2,new}$, are represented as discrete state variables in the model. The new technologies are described by parameters for installed capacity, investment cost, marginal operating cost, life time and also construction time. Figure 5.4 shows a supply curve with all four technology groups represented. No uncertainties are included in the supply side of the model, and we assume constant availability for all the technology groups. In addition, the deterministic supply curve is also constant for all demand sub-periods. Changes in the supply curve only occur when new investments are made.

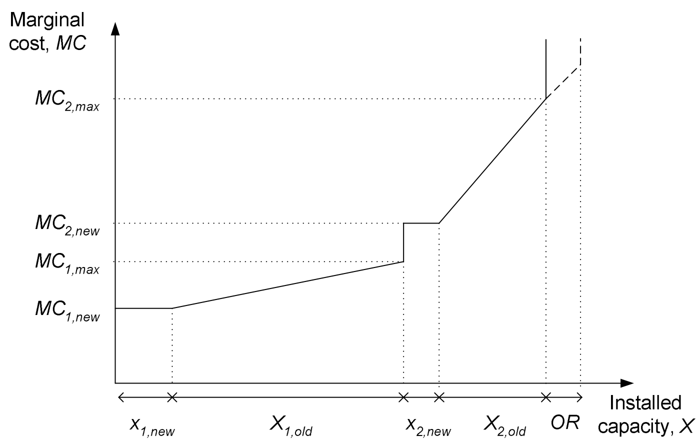

Figure 5.4 Representation of old ($X_{1,old}$ and $X_{2,old}$) and new ($x_{1,new}$ and $x_{2,new}$) generation technologies in an aggregate supply curve for one combination of state variables. OR is the operating reserve requirement.

We assume that operating reserves during peak hours (*OR* in Figure 5.4) are provided by the technologies with highest marginal cost in the system, i.e. from the group of old peaking plants. The *OR* requirement is assumed to be determined by the regulator, and this part of the supply curve is always withheld from the spot market for electricity. However, it still affects the spot prices in peak demand situations, since it determines how much of the old capacity that is available in the spot market. Stoft [73] discusses how the relationship between the *OR* requirement and a price cap in the *OR* market

[44] In this chapter we use the notation peak load technologies to describe all plants that are not pure base load plants. Hence, the group of plants referred to as peak load plants include both medium and peak load technologies.

determine the equilibrium level of installed capacity in the power system. It is assumed that the price cap is paid when the *OR* requirement is violated. At the same time, there must be a relationship between prices in spot and reserve markets, so that arbitrage opportunities do not occur between the two markets. Hence, if the regulator determines a price cap for operating reserves it will also indirectly affect prices in the spot market. In fact, the price cap in the *OR* market will effectively cap the price in the spot market too, due to the arbitrage argument. It is argued in [73] that optimal installed capacity can be achieved with any of a continuum of different policy options ranging from extremely high price caps and low *OR* requirements, to very low price caps and high *OR* requirements. The first alternative would give high price spikes with low frequency while the second alternative would result in low price spikes with higher frequency. In both situations a new peaking unit would exactly recover its fixed costs during peak load hours, and a static equilibrium for installed capacity is achieved. However, the outline in [73] does not take into account how uncertainty and price dynamics can affect installed capacity over time.

Finding an optimal *OR* requirement is a complex problem which is beyond the scope of the analysis presented in this chapter. In the model we simply assume that the regulator determines the *OR* requirement according to short-term system operation and reliability considerations. Furthermore, the regulator pays a price for *OR* which reflects the expected profits foregone for marginal generators by providing *OR* instead of selling the corresponding energy into the spot market[45]. Hence, the *OR* price is not directly determined by the regulator, but is a function of the prices in the spot market. We still assume that the regulator determines a price cap directly in the spot market (P_{cap}), as illustrated in Figure 5.3. The interaction between the spot and reserve markets rules out arbitrage opportunities.

One of the problems we want to analyse with the model is how the level of the price cap in the spot market affects the expected profitability of new investments, and thereby the optimal investment criteria. The level of P_{cap} is determined by the regulator and will also affect the *OR* payment. Marginal generators should be indifferent between participating in the spot or reserve markets, but new generators have low marginal costs and are therefore better off if they sell their generation in the spot market. Under these assumptions it is therefore sufficient to represent the spot price in the model to find optimal investment criteria for new technologies. The resulting

[45] In Norway the system operator buys *OR* in long-term contracts through an auction mechanism. Generators and end-users can bid production capacity and load reduction into the reserve market and thereby gain a premium for providing *OR*. The resulting *OR* capacity must be withheld from the spot market.

investment behaviour determines how often the *OR* requirement is violated. In order to obtain a consistent representation of supply and demand in the model, we assume that the *VOLL* in the demand description reflects the true cost for end-users when the specified *OR* requirement can not be met. This is of course a simplistic description, as the system operator in many situations would be willing to reduce *OR* before load shedding is introduced, and the cost of lower reliability due to reduced *OR* might be lower than *VOLL*. However, the simple description of supply and demand is still sufficient to gain useful insight into the dynamics of investments, prices and reliability under uncertainty in a long-term perspective.

5.2.3 Representation of the Spot Market for Electricity

The representation of the spot market for electricity is illustrated in Figure 5.5. The prices in the spot market are found at the intersection between supply and demand curves in each of the sub-periods for all combinations of states (i.e. load level, l_k, and installed capacity of new technologies, $x_{1,new,k}$ and $x_{2,new,k}$). Note that the operating reserves are now omitted from the supply curve. Prices, loads, operating costs and macroeconomic figures such as social welfare, consumer and producers surplus are calculated for base, medium and peak demand based on the supply and demand curves. With this market description it is possible to maximise social welfare over the planning horizon, instead of maximising the profits for an investor in the market. The optimisation is carried out in the same way as in the investment optimisation model from the previous chapter. However, with the current market description we now have the possibility of using two different objectives in the optimisation. At the same time we have extended the state space to include two new technologies, as opposed to the model in Chapter 4 which only includes one new technology.

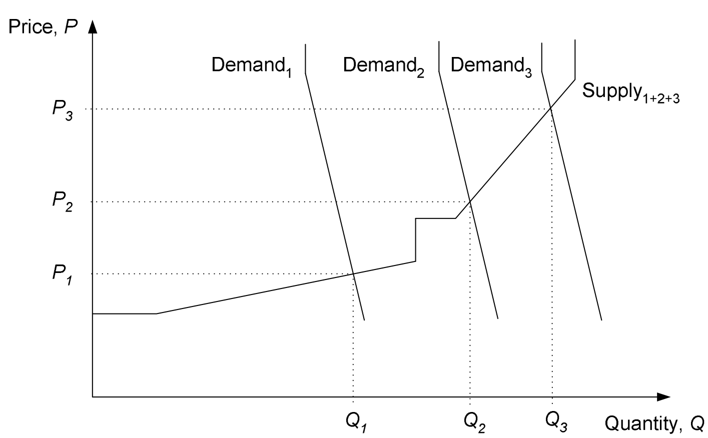

Figure 5.5 Illustration of short-term market equilibrium during base (1), medium (2) and peak (3) demand.

5.2.4 The Optimal Investment Problem

The same mathematical framework as developed in Chapter 4 is applied to find optimal investment strategies for new power generation plants with the new market description. The general investment optimisation problem for two technologies can be described as a stochastic dynamic optimisation problem, using the same structure as in (4-9)-(4-13). The problem now has three state variables and two control variables, as shown in (5-3)-(5-7).

$$J_0(\boldsymbol{x}_0, l_0) = \max_{\boldsymbol{u}_0,..,\boldsymbol{u}_{T-1}} \underset{\omega_l}{E} \left\{ \sum_{k=0}^{T-1} \left[(1+r)^{-k} \cdot g_k(\boldsymbol{x}_k, l_k, \boldsymbol{u}_k, \omega_s) \right] + (1+r)^{-T} \cdot g_T(\boldsymbol{x}_T, l_T, \omega_s) \right\} \tag{5-3}$$

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \boldsymbol{u}_{k+1-\boldsymbol{lt}} \tag{5-4}$$

$$l_{k+1} = l_k + \omega_{l,k} \tag{5-5}$$

$$g_T(\boldsymbol{x}_T, l_T, \omega_s) = g_T(\boldsymbol{x}_T, l_T, \omega_s \mid \boldsymbol{u}_T = 0) \tag{5-6}$$

$$\boldsymbol{x}_k \in \Omega_{x_k}, l_k \in \Omega_{l_k}, \boldsymbol{u}_k \in \Omega_{\boldsymbol{u}_k}, \omega_{l,k} \in \Omega_{\omega_{l,k}}, \omega_s \in \Omega_{\omega_s} \tag{5-7}$$

where

$J_0(\boldsymbol{x}_0, l_0)$	objective function, i.e. max expected payoff over the planning horizon T	[MNOK]
$g_k(\boldsymbol{x}_k, l_k, \boldsymbol{u}_k, \omega_s)$	payoff for time step k	[MNOK]
$g_T(\boldsymbol{x}_T, l_T, \omega_s)$	termination payoff in period T	[MNOK]
$\boldsymbol{x}_k = \begin{bmatrix} x_{1,new,k} \\ x_{2,new,k} \end{bmatrix}$	available installed capacity for techn. 1 and 2 (state variables), time step k	[MW]
l_k	demand (state variable), time step k	[MW]
$\boldsymbol{u}_k = \begin{bmatrix} u_{1,new,k} \\ u_{2,new,k} \end{bmatrix}$	capacity additions of technology 1 and 2 (control variables), time step k	[MW]
$\omega_{l,k}$	stoch. change in demand, time step k	[MW]
ω_s	short-term uncertainties in demand	
r	risk adjusted discount rate	
$\boldsymbol{lt} = \begin{bmatrix} lt_1 \\ lt_2 \end{bmatrix}$	construction lead time for technology 1 and 2	[years]
$\Omega_{\boldsymbol{x},l,\boldsymbol{u},\omega_l,\omega_s}$	discrete feasible sets for $\boldsymbol{x}$, l, $\boldsymbol{u}$, ω_l and ω_s	

The discrete state space is expanded by the three state variables and time. The state variable for demand, l_k, is represented as a stochastic variable with a binomial distribution, as shown in Figure 5.6. This is the only long-term uncertainty in the model, and the mathematical representation is exactly the same as for average load in Chapter 4 (Figure 4.5). For the generation states we have to take into account the construction time, as indicated in (5-4). To limit the size of the state space we assume that only one construction plan can be undertaken at the same time. This means that if an investment decision is made, the investor will have to wait until the construction is finalised, before the next investment decision can be made. The representation of capacity states is shown in Figure 5.7, and is again similar to the model in Chapter 4 (Figure 4.7), except that we now have a two-dimensional state space for new capacity.

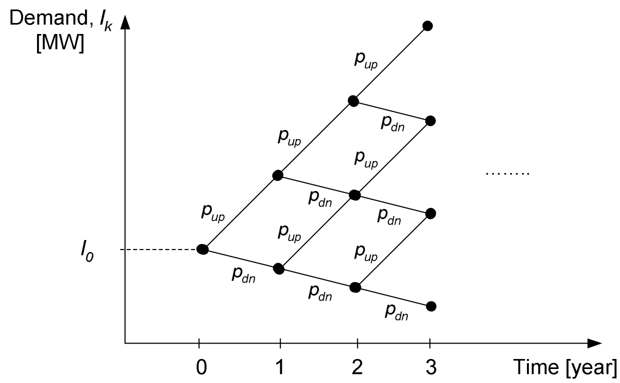

Figure 5.6 Illustration of the state space for demand (l_k) as function of time. l_0 is initial demand (k=0). p_{up} and p_{dn} are transition probabilities.

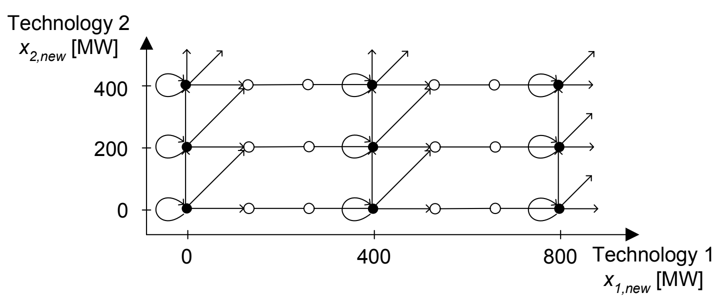

Figure 5.7 Illustration of decision states (black dots) and construction states (circles) for new generation capacity. Transfer between two states has a delay of one year. In this example technology 1 and 2 consist of 400MW and 200 MW plants, with construction times of 3 years and 1 year respectively.

The optimisation problem is solved using backwards stochastic dynamic programming. The corresponding Bellman equation is given in (5-8). We use the same representation of termination payoff and investment cost as in Chapter 4. The termination payoff is set equal to the payoff in the last period, assuming no new investment (equation (5-6)), while the investment cost is adjusted according to the length of the planning period and the technology's construction time. This is explained in section 4.3.5.

$$J_k(\boldsymbol{x}_k, l_k) = \max_{\boldsymbol{u}_k \in \Omega_{\boldsymbol{u},k}} \left\{ g_k(\boldsymbol{x}_k, l_k, \boldsymbol{u}_k, \omega_s) + (1+r)^{-1} \cdot \underset{\omega_{l,k}}{E}[J_{k+1}(f(\boldsymbol{x}_k, l_k, \boldsymbol{u}_k, \omega_{l,k}))] \right\} \tag{5-8}$$

We can now look at optimal investments from a centralised planner's point of view, and compare it to the optimal investment strategy for a decentralised profit maximising investor. The only difference in the mathematical formulation is in the definition of the payoff function, g_k. We assume that the centralised planner wants to maximise the expected social welfare in the system, while the investor wants to maximise expected profits from investing in new plants. The payoff function for the two planning regimes, referred to as *sw*-social welfare and π-profits, are shown in (5-9) and (5-10). Note that we take the expectation over ω_s in the calculation of short-run social welfare and profit in the first parts of (5-9) and (5-10). Under profit maximisation we also add the income from a possible capacity payment in the payoff function. The capacity payment in the model must be a function of the state variables for installed capacity and demand, and can for instance be represented as in section 4.3.4. The investment cost is deterministic and treated identically for the two planning regimes in (5-9) and (5-10).

$$g_{k,sw}(\boldsymbol{x}_k, \boldsymbol{u}_k, l_k, \omega_s) = \sum_{i=1}^{3} \frac{ld_i}{8760} \cdot \underset{\omega_s}{E}\left\{ \int_{q_i=0}^{Q_{i,k}} \left[f_{D_i,l_k}(q_i, \omega_s) - f_{S,\boldsymbol{x}_k}(q_i) \right] dq_i \right\} - \boldsymbol{ic}_k \cdot \boldsymbol{u}_k \tag{5-9}$$

$$g_{k,\pi}(\boldsymbol{x}_k, \boldsymbol{u}_k, l_k, \omega_s) = \sum_{i=1}^{3}\sum_{j=1}^{2} \frac{ld_i}{8760} \cdot x_{j,new,k} \cdot \underset{\omega_s}{E}\left\{ \max\left[(P_{i,k}(\omega_s) - MC_{j,new}), 0 \right] \right\} + CP_k(\boldsymbol{x}_k, l_k) \cdot (x_{1,new,k} + x_{2,new,k}) - \boldsymbol{ic}_k \cdot \boldsymbol{u}_k \tag{5-10}$$

where

$f_{D_i,l_k}(q_i, \omega_s)$	inverse demand curve, sub period i, time step k	
$f_{S,\boldsymbol{x}_k}(q_i)$	aggregate supply curve, time step k	
$P_{i,k}(\omega_s)$	price, sub period i, time step k	[NOK/MWh]
$Q_{i,k}$	load, sub period i, time step k	[MW]
ld_i	load duration, sub period i	[hours]
$MC_{j,new}$	marginal operating cost for new techn. j	[NOK/MWh]
$CP_k(\boldsymbol{x}_k, l_k)$	capacity payment for time step k	[NOK/MW]
$\boldsymbol{ic}_k = \begin{bmatrix} ic_{1,new} \\ ic_{2,new} \end{bmatrix}$	investment costs for new technologies 1 and 2, time step k	[NOK/MW]

A simple algorithm based on merit order loading is implemented to find price and load for each combination of states, where the market is described as illustrated in Figure 5.5. The payoff functions for social welfare and profit maximisation are also calculated in the same algorithm. The values are stored in a set of arrays, before running the SDP loop.

5.2.5 Optimal Investments under Social Welfare and Profit Maximisation

From the theoretical discussion in the beginning of this chapter we know that investment decisions under centralised social welfare maximisation and decentralised profit maximisation in a perfectly competitive market should be the same. Figure 5.8 shows how the objective functions are changed under profit and social welfare maximisation when an investment is made, assuming no capacity payment. While the investor's profit objective only takes into account the increase in producer surplus (area 1), the increase in consumer surplus (area 2) is also included under social welfare maximisation. With a marginal investment in new capacity the effect on price would be negligible and only the producer surplus would increase. In this situation we would expect that the profit and social welfare objectives give exactly the same result. However, when investments are lumpy, so that there is feedback from a new investment to price, we see from Figure 5.8 that the increase in social welfare can be considerably larger than the investor profits. At the same time, the investment cost is the same under both objectives. Therefore, the lumpiness of investments can contribute to give a lower investment threshold under the social welfare criterion. One of the factors that affect the importance of this relation is the price elasticity of demand. The magnitude of the price feedback, and thereby the difference in the changes of the two objectives, decreases as price elasticity increases.

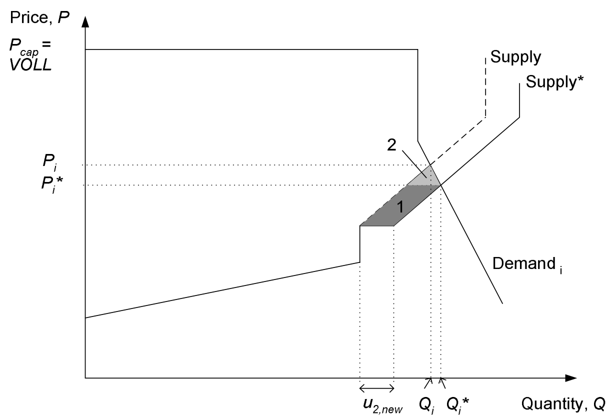

Figure 5.8 Illustration of investor profit (area 1) and social welfare gain (area 1 + 2) in sub period i, from investment in new peak capacity ($u_{2,new}$). Q_i, Q_i, P_i and P_i* are quantities and prices with and without $u_{2,new}$.*

Market externalities, such as the failure of the price in the spot market to reflect the value of reliability, can also cause deviations between investment criteria under social welfare and profit maximisation. The consequence of using a price cap in the spot market (P_{cap}) which is lower than *VOLL* can be analysed with the model. Another important issue in the emerging electricity markets today concerns market power, and how it is likely to affect the participants' dispositions in the market. This model is not designed to analyse the impact of market power on the bidding strategies and thereby short-term changes in electricity spot prices. However, we can look at how the optimal investment strategy changes when an investor owns a part of the initial capacity in the system. If the investor has an exclusive right to invest in the system, the ownership of existing power generation assets can have a strong effect on the optimal investment criterion.

In the end, it is worth noting that while externalities and market power can be attributed to market imperfections, the effect of lumpy investments would also be present in a market without price distortions. Hence, a deviation between investment strategies under social welfare and profit maximisation is not necessarily an indication of price manipulation and market failure. We return to all these effects in the illustrative examples later in this chapter.

5.2.6 Risk, Uncertainty and Discount Rate

The risk preference and appropriate discount rate for an investor that is considering investments in new power generation assets is discussed in section 4.3.6. We argue that risk neutral valuation, which is frequently applied in real options models, is inappropriate in our stochastic dynamic investment model. The reason is that movements in the underlying stochastic variable, demand growth, can not be completely replicated by assets traded in financial markets. At the same time, the liquidity in long-term markets for electricity is usually low, making it difficult to hedge the price for future power generation in long-term markets, without paying a considerable risk premium. We therefore argue that the use of a risk-adjusted discount rate is more appropriate in the model. The same arguments about the appropriate discount rate can be used when the profit maximisation objective is used in this version of the investment model.

A centralised planner, whose dispositions are based on a social welfare criterion, is also likely to consider risk as an important factor when investment projects are assessed. In most circumstances centralised planners have limited resources and can only invest in a small selection of the wide range of investment projects available. Therefore, low risk projects would probably be preferred to projects involving more risk, if the expected gain in social welfare is the same. We do not aim at assessing the level of risk-averseness among centralised and decentralised planners in the power system in this thesis. However, it is likely that the level of risk can play a role for investment decisions under both planning regimes. Consequently, we argue that the use of a risk adjusted discount rate is most appropriate in our stochastic dynamic investment model, also when maximisation of social welfare is the objective in the optimisation.

The discount rate can of course be specified to any number in the investment optimisation model, regardless of which one of the two objective functions that is actually being used. However, in the illustrative examples that follow later in this section we find it convenient to use the same discount rate under profit and social welfare maximisation. The discussion above can serve as an argument for using the same factor for discounting. At the same time, the use of identical discount rates makes it easier to focus on the other factors that can give rise to differences between optimal investment criteria under profit and social welfare maximisation.

5.2.7 Market Simulator

A simulator is also developed for this version of the investment optimisation model. The simulator is similar to the one in Figure 4.24. It starts from an initial state of demand and generation capacity. The investment optimisation model is run, and the resulting investment strategy is used by the simulator to update the investment model's input parameters before a new optimisation for the next time step is carried out. Investor profit, social welfare gain and other results are calculated for each simulated time step. The market simulator can be used to study the investment dynamics in the electricity market over a longer term perspective. In this respect it also bears resemblance to the system dynamics model presented in Chapter 3. The main difference is that the investment decisions are now based on stochastic dynamic optimisation as opposed to the traditional static net present value evaluation underlying investment decisions in the system dynamics model. Moreover, we can now run the simulator under both social welfare and profit maximisation, and thereby compare the results for scenarios with centralised and decentralised decision making.

5.2.8 A Comparison of the Model to the Theory of Peak-Load Pricing

The simple linear market description that we now use in the investment model is in several respects similar to the market descriptions in the traditional peak-load pricing theory, as described by Crew and Kleindorfer in [63]. However, for demand we have assumed that the sub-period loads are proportional and interdependent, and that only parts of the demand is price responsive. This is opposed to the continuous demand functions that are usually applied in the traditional models for peak-load pricing. For generation we take into account the technologies that are already installed in the system, and also that the old technologies can have other cost parameters than the new ones. This is different from the peak-load pricing models in [63], where the objective is to optimise a complete system from the beginning, without taking into consideration existing technologies. Explicit representation of operating reserves is also omitted in the theory for peak load pricing.

An important similarity between the models is the simple representation of supply. Merit order loading of the power plants is assumed and inter-temporal aspects, such as start-up/shut-down costs, ramp rates, and minimum up- and down times, are not taken into account. This corresponds to a market description where the suppliers bid their marginal costs into the power market. Hence, we assume optimal short-term operation of the system, both under centralised and decentralised decision making. Consequently, the model is not suitable for studying effects of strategic behaviour, collusion or gaming in a short-term perspective. Our aim with the model is to study the long-term effects of different planning regimes for the various participants in the power market in a dynamic perspective. The simple market description combined with the stochastic dynamic investment optimisation model facilitates such an analysis. As we have seen above, the dynamic perspective is left out of most peak-load pricing models. Furthermore, the inclusion of long-term uncertainties in our model is also an element which is rarely seen in the theory of peak load pricing. It is therefore of interest to see how our results compare to the results presented in section 5.1.1 from the theory of peak load pricing.

5.3 Illustrative Examples

Having outlined the mathematical description of the model, we now look into a set of illustrative examples where the model is used to compare centralised and decentralised planning under a set of different assumptions. First, we present the main assumptions for the test power system which was used throughout the analysis in this chapter. A static assessment of prices as function of demand for the initially installed generation capacity is also shown, together with an economic evaluation of the new generation technologies. We then use the stochastic dynamic optimisation model to identify optimal investment criteria under social welfare and profit maximisation. We run the model for different fractions of price flexible demand, and we also compare optimal investment criteria for marginal and large-scale investments. In additions, we study the effect of the price cap in the spot market and the impact of ownership in existing generation capacity on private investors' optimal investment decisions. In the end, we use the simulator to investigate the long-term dynamics of investments, prices and reliability in the test power system for a set of different scenarios.

In Chapter 4 we focused on how long-term dynamics and uncertainty affects the optimal investment decision for a decentralised investor in the power market. The results showed that taking the dynamic aspect of investment timing into account is very important for the investor, in order to maximise the expected profit from new investments. The inclusion of long-term uncertainties in load growth into the analysis also contributes to improve decision making, although Monte Carlo simulations show that this effect is less significant. In the examples presented in this chapter we assume that both centralised and decentralised planners use the stochastic dynamic optimisation framework to optimise their investment decisions. The emphasis is now on how the optimal investment criteria and the long-term investment dynamics depends on planning regime, market design and system characteristics such as the fraction of price responsive demand.

5.3.1 Main Assumptions for the Illustrative Examples

The main assumptions for the test power system are summarised in Table 5.1. The test power system is assumed to be a thermal system, and the base load technology group could typically consist of coal and nuclear plants, while the peak technology group could be gas combustion turbines. We assume that only the old generation technologies are present in the system at the initial state. If we compare the initial installed capacity to the demand in the different sub periods, we see that the proportion of total to base generation capacity is slightly lower than the proportion of peak to base demand in the system (1.6 vs. 1.65). Hence, at first sight it may look as if there is a surplus of base load capacity in the system

Table 5.1 Basic assumptions for demand and supply parameters in the test power system.

Demand	Value	Unit	Supply	Value	Unit
VOLL	10000	NOK/MWh	$\boldsymbol{X}_{old}$	[10000 6000]	MW
P_{cap}	1000/10000	NOK/MWh	$\boldsymbol{x}_{new,init}$	[0 0]	MW
$P_{flex,max}$	1000	NOK/MWh	$\boldsymbol{MC}_{new}$	[100 180]	NOK/MWh
$\boldsymbol{c}_{L,max}$	[1.00 1.40 1.65]		$\boldsymbol{MC}_{max}$	[120 400]	NOK/kW
$c_{L,flex}$	0.01-0.20		$\boldsymbol{ic}_{new}$	[12000 6000]	years
$\boldsymbol{ld}$	[5760 2900 100]	hours	$\boldsymbol{\Omega_u}$	[400 200] / [1 1]	years
l_{growth}	100	MW/year	$\boldsymbol{nt}$	[30 20]	NOK/MWh
l_{sdv}	200	MW/year	$\boldsymbol{lt}$	[3 1]	MW
p_u , p_{dn}	0.5		r	6	% pa.

There are two new technologies to choose from. The first new technology represents a base load plant with high investment cost and low operating costs, while the second option is a peak load plant with lower investment cost and higher operating costs. Another difference between the technologies is that the base load plant has a longer life time and construction time than the peak load plant. The fraction of price flexible demand varies between 1 and 20 % in the examples to follow. An expected load growth of 100 MW/year with a standard deviation of 200 MW/year is input to the optimisation model in all scenarios. Note that we use fixed probabilities (p_{up}, p_{dn}) for the entire planning horizon in the binomial tree for load growth (Figure 5.6).

In order to represent short-term uncertainties in demand (ω_s), we introduce a variable for relative demand, rd_m. rd_m reflects deviations from expected demand (e.g. caused by unexpected temperatures). The state variable for demand, l_k, is adjusted according to rd_m, as shown in (5-11). Thus, we end up with a discrete demand distribution in each demand state. The variables for maximum and flexible load, ($\boldsymbol{L}_{max}$) and ($\boldsymbol{L}_{flex}$), in (5-1) and (5-2) are updated accordingly, so that the relative demand has a proportional effect on demand in all sub periods. The payoff functions under social welfare and profit maximisation in (5-9) and (5-10) are calculated by taking the expected value over ω_s, i.e. over all N_m realisations of the relative load, rd_m. rd_m could take on any distribution, but we assume a simple normal distribution as shown in Figure 5.9. Note that short-term and long-term uncertainties are still assumed to be uncorrelated, just as in Chapter 4.

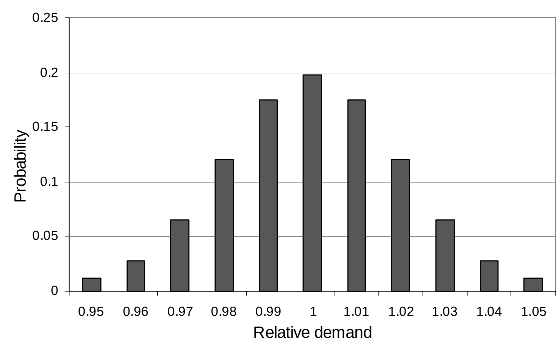

Figure 5.9 Probability distribution for relative demand (rd_m). rd_m has a discrete normal distribution, N ~ (1,0.02), with 11 discrete realisations (N_m = 11).

$$l_{k,m} = l_k \cdot rd_m \qquad , \quad m = 1..N_m \tag{5-11}$$

where

$l_{k,m}$	adjusted demand state, realisation m, m=1.. N_m	[MW]
rd_m	relative demand, realisation m, m=1.. N_m	

When using the stochastic dynamic investment model to calculate optimal first period investment criteria we use a planning horizon of 10 years only (T = 10 years). Furthermore, the state space for capacity extensions in the SDP algorithm is limited to one new plant for each technology (see Figure 5.7 for an illustration of the model's representation capacity states). The model calculates the demand level for which it becomes optimal to invest, and also finds the optimal technology choice, for a given level of installed generation capacity in the system. From Table 5.1 we see that the expected growth in base demand is 100 MW/year while the capacities of the new technologies are 200 MW and 400 MW respectively. The restrictions imposed by the limited number of capacity states might therefore seem very strong and unrealistic. However, sensitivity analyses show that extending the state space in either time or the number of capacity states has a limited effect on the optimal investment criteria calculated by the model[46]. Hence, a formulation with a limited state space appears to capture the main effects influencing the optimal first period investment decisions.

A limited number of capacity states are chosen in the examples, partly because of the reduction in computation time. However, under the profit maximising objective an increase in the number of capacity states would also give the investor an incentive to postpone investment number 2 and 3, in order to earn more on his first investment. By only allowing one investment in each plant we avoid that the first period decision is affected by possible strategic behaviour regarding subsequent investment decisions. Note that the limitation in capacity states only is in effect when the investment criteria are calculated. When we simulate investments in 5.3.4and 5.3.5we assume that there are always participants in the market that are willing to invest when the model indicates that it is favourable.

5.3.2 Static Analysis of Investments and Prices in the Initial System

The static analysis presented in this section serves as a background for the dynamic investment optimisation in later sections of this chapter. First, we do a simple static analysis based on load duration and technology screening curves. This is illustrated in Figure 5.10 and Figure 5.11.

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[46] Sensitivity analyses of the results in section 5.3.3 show that the changes in optimal investment criteria following from an extension in the model's planning horizon to 20 years are negligible in all the scenarios. Extending the number of capacity states to three plants of each technology instead of only one resulted in a limited reduction in the optimal investment criteria under social welfare optimisation, while the changes in investment criteria under the profit objective were still very small. An obvious explanation to the limited impact of state space expansion on investment criteria is the interest rate, which effectively discounts and reduces the impact of cash flows from projects initiated far ahead into the future. In addition, the representation of construction delays in the model limits the number of plants that can be constructed within the planning horizon. This can also reduce the impact on investment criteria from expanding the state space.

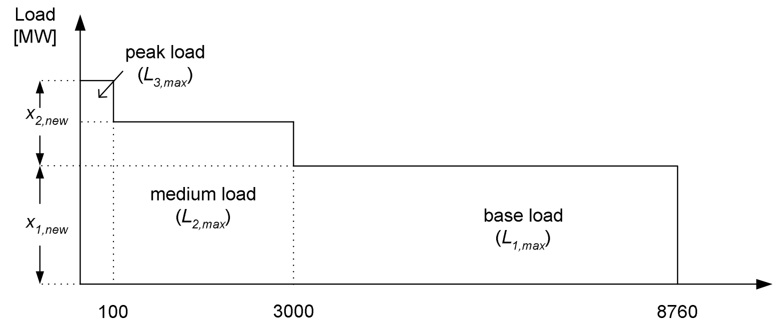

Figure 5.10 Load duration curve in the test power system, with no price flexible demand.

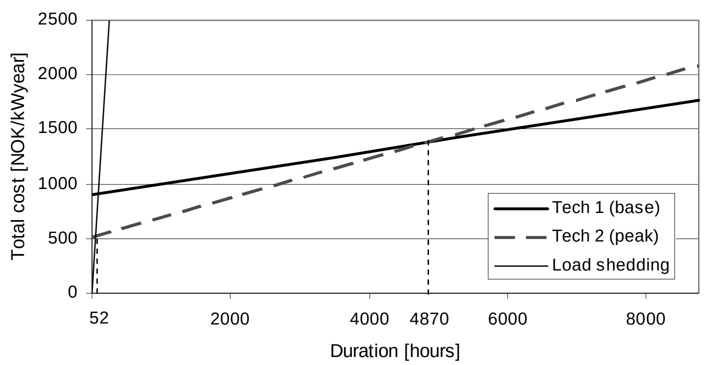

Figure 5.11 Screening curves for the two new power generation technologies and load shedding.

If we disregard the existing power plants in the system, we can use screening curves for the new technologies combined with the system's load duration curve, to determine the optimal mix of new technologies in the system. In order to express the demand in terms of a load duration curve we have to assume that there is no price elasticity of demand. Hence, if we disregard the price flexible part of demand in the model, the demand can be described in terms of a simple load duration curve with linear steps, as shown in Figure 5.10. The length of the base, medium, and peak demand sub periods are 5760, 2900 and 100 hours respectively, and the load levels within each of the sub periods are given by the maximum sub period loads ($\boldsymbol{L}_{max}$) in the demand description. Figure 5.11 illustrates a screening test of the two available new technologies. The results show that for loads with duration higher than 4870 hours, it is optimal to invest in the base load technology. For loads with lower duration the peaking technology is more cost efficient. From the screening curves we can also see that for loads with duration less than 52 hours it is actually cheaper to use load shedding than to invest in additional peaking capacity. This number is of course highly dependent on *VOLL*, which is assumed to be 10000 NOK/MWh. The simple static analysis based on load duration and screening curves shows that base load plants should be constructed to meet base demand, while peaking units are more economic for the medium demand. The capacity of peaking units should also cover the peak load in the system, since the duration of the peak load period in this example is longer than 52 hours. The optimal levels of installed capacity are shown as $x_{1,new}$ and $x_{2,new}$ in Figure 5.10.

In order to analyse how the existing plants in the system and the price flexible demand affect investment decisions in new technologies, we need to take a closer look at how prices in the three sub periods change as function of increasing demand. As explained in the previous section, the demands in different sub periods are interdependent variables, so that all the sub period prices can be expressed as function of the state variable for demand, l_k, for a given combination of capacity states. l_k is here equal to the maximum base load, since $c_{L1,max}$ = 1. Figure 5.12 shows the expected spot price during base, medium, and peak demand hours as function of the demand state variable for the initial supply system (l_0), with 5 % price flexible demand.

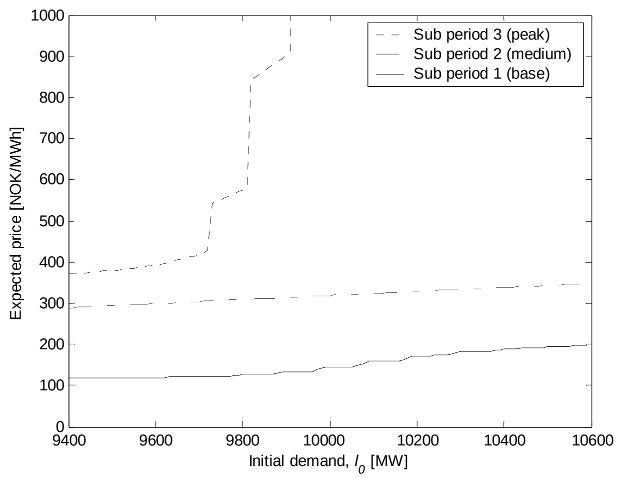

Figure 5.12 Expected spot prices in the three sub periods as function of demand in initial system (l_0). The expectation is taken over short-term uncertainties (ω_s). $c_{L,flex}$ = 0.05.

We see from Figure 5.12 that the expected spot price in sub period 1 increases very slowly as long as the initial capacity of base plants ($X_{1,old}$ = 10000MW) is sufficient to meet the base demand. The rise in base price after approximately 9800 MW is due to the increasing probability that base demand exceeds $X_{1,old}$, and the use of peaking capacity becomes necessary to meet base period demand. On the other hand, the demand in sub period 2 is always met by the initial peaking capacity, so that the medium price increases very smoothly for all values of l_0 in Figure 5.12. For sub period 3, we see that the peak price starts to increase very quickly in the region above

9700MW. This is when the peak demand approaches total installed capacity, and load shedding becomes necessary to clear the market. The stepwise increase in the peak price in this region is due to the discrete representation of short-term uncertainties in demand (ω_s), which in turn causes discrete jumps in the probability for load shedding during peak demand. The peak period price actually continues to increase until it reaches 10000 NOK/MWh (i.e. *VOLL*) at l_0 = 10750MW. At this demand level load shedding is required in the peak demand period for all realisations of ω_s, unless new capacity is added to the system.

In order to find an optimal static investment strategy that also takes into account the effect of existing technologies in the system we can compare the prices in the initial system to the unit cost of the new technologies. Since the old plants in the system have higher marginal costs than the new technologies, it will be optimal for a new base load plant to run throughout the entire year, while a new peaking plant should run during medium and peak load periods[47]. With the assumptions in Table 5.1 the total unit costs[48] for new base and peak load plants are 202 and 349 NOK/MWh, given that they operate 8760 and 3000 hours per year respectively. These total cost numbers can be interpreted as the long-run marginal costs (LRMC) of increasing the base and peak capacity in the system. According to marginal cost theory it is therefore optimal to invest in new base capacity as soon as the average price for the entire year approaches 202 NOK/MWh. Similarly, new peaking capacity should be added when the average price over sub period 2 and 3 reaches 349 NOK/MWh. This is when the short-run marginal cost (SRMC) in the system equals the LRMC of system expansion. SRMC is the same as the price in our system, since we assume that suppliers bid their marginal cost and end-user bid their marginal willingness to pay into the spot market[49]. Under these assumptions the investment levels found in the analysis of marginal costs should represent a centralised social optimum as well as a decentralised investor optimum, as long as P_{cap} equals *VOLL*.

A static assessment of the optimal threshold for investment in new base load capacity in the initial system can now be accomplished by plotting the average price over all sub periods and compare it to the total unit cost for

[47] Outages due to maintenance are taken into account by using investment cost figures per unit of average available capacity over the year for the new technologies. Therefore, we can assume up to 8760 hours of operation for the new technologies in the calculations.
[48] Total unit cost = annualised unit capital cost adjusted for the number of operating hours and construction lead time + unit operating and fuel costs.
[49] Here we define SRMC as the least expensive of either a marginal increase in generation or a marginal decrease in load in the current system. SRMC therefore represents the immediate marginal utility of system expansion, which is also how price is represented in the model through the supply and demand curves.

technology 1. Similarly, technology 2 can be assessed by looking at the average price over the medium and peak demand periods. This is illustrated in Figure 5.13, where the total unit costs for the two new technologies are compared to the relevant average prices for two different levels of the price cap in the spot market. We still assume that there is only 5 % price flexible demand in the system, so that the average prices are direct functions of the sub period prices depicted in Figure 5.12. Optimal investment levels based on this static assessment are indicated in Figure 5.13. We see that when P_{cap} equals *VOLL* (i.e. 10000 NOK/MWh), the break even points for both technologies are close to each others at an initial load level of about 9900 MW. However, when P_{cap} is lowered to 1000 NOK/MWh the average prices are also reduced, so that higher demand is required before the average prices exceed the unit costs for the new technologies. A profit maximising investor would therefore require higher demand before investing in new capacity, and a discrepancy arises between the centralised and decentralised investment criteria. The change in investment criterion is most significant for the peaking technology, whose break even point increases more than 300 MW due to the lower price cap. In total the analysis shows, not surprisingly, that the lower P_{cap} discourages private investments in new peaking capacity. The profitability of investments in new base capacity is also affected by P_{cap}, but to a much lower extent.

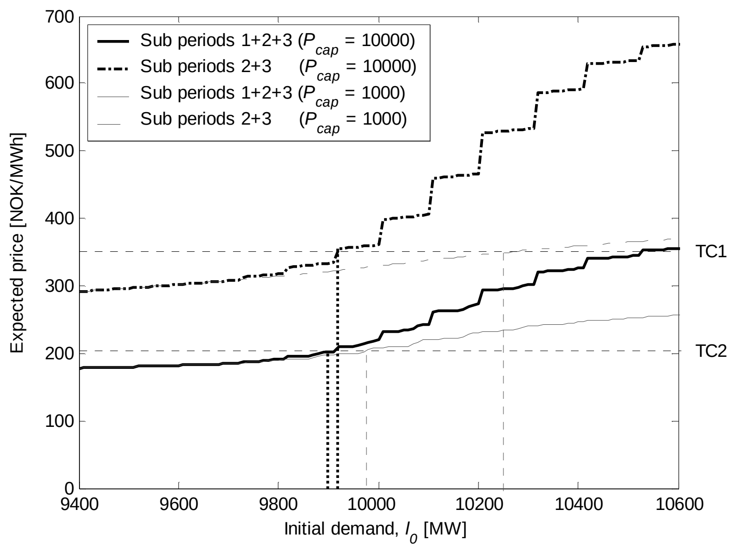

Figure 5.13 Average prices over all three sub periods (1+2+3) and over medium and peak sub periods (2+3) as function of demand in initial system (l_0). TC1 and TC2 are total unit costs for technology 1 and 2. The expectation is taken over short-term uncertainties (ω_s). $c_{L,flex}$ = 0.05.

The same static analysis of the initial system is also performed with a higher fraction of price flexible demand (15 %). Figure 5.14 shows that the increase in price flexible demand gives higher investment levels for both technologies. At the same time, the relative difference in investment criteria between the two technologies increase, making technology 1 more attractive to invest in. This is because the rise in price flexible demand reduces the need for load shedding in the system, and therefore also the likelihood for the spot price to reach the price cap during peak demand. This also explains why the reduced P_{cap} now does not give any change in investment levels in Figure 5.14. A reduction in P_{cap} causes a deviation in average prices only when load shedding is required in the system, and with 15 % price flexible demand load shedding does not occur until after the unit costs for both technologies are reached. The higher price elasticity of demand therefore removes P_{cap}'s impact on the investment decisions, and the corresponding difference in centralised and decentralised investment criteria. The optimal investment levels from the static analyses presented here are summarised in Table 5.2.

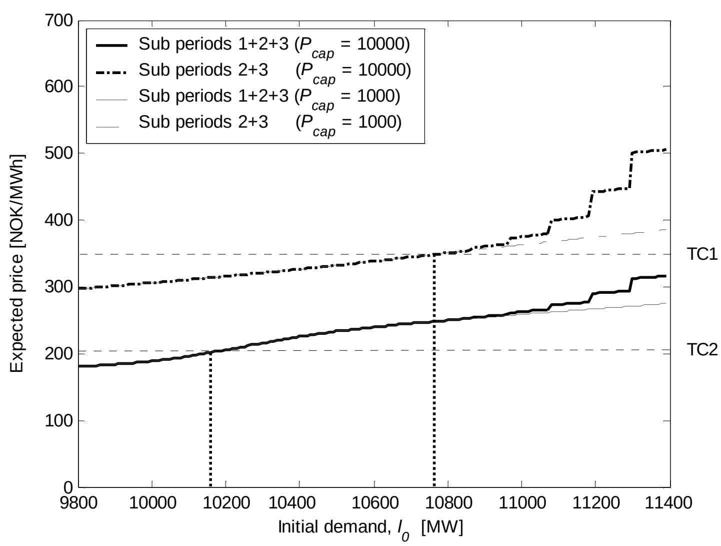

Figure 5.14 Average prices over all three sub periods (1+2+3) and over medium and peak sub periods (2+3) as function of demand in initial system (l_0). TC1 and TC2 are total unit costs for technology 1 and 2. The expectation is taken over short-term uncertainties (ω_s). $c_{L,flex}$ = 0.15.

Table 5.2 Summary of optimal demand levels (l_0) for investment in technology 1 and 2, based on static analysis of prices for the initial conditions in the test power system.

Technology	$c_{L,flex}$ = 0.05		$c_{L,flex}$ = 0.15	
	P_{cap} = 10000	P_{cap} = 1000	P_{cap} = 10000	P_{cap} = 1000
1 (base)	9900 MW	9970 MW	10160 MW	10160 MW
2 (peak)	9920 MW	10240 MW	10770 MW	10770 MW

It is important to bear in mind that the static analysis presented here only looks at the power system in a "snapshot" of time. Hence, the optimal investment thresholds found here do not take into account neither growth nor long-term uncertainties in underlying variables. It is also a marginal analysis, in the sense that incremental investments are optimal at the indicated demand levels. However, in the case of large-scale investments, new plants will influence the marginal costs and prices in the system, and therefore also the optimal investment levels. The stochastic dynamic investment model takes all these factors into account, and we now use the same input data in a dynamic analysis of optimal investments in the test power system.

5.3.3 Stochastic Dynamic Analysis of Optimal Investment Criteria

Five different scenarios are analysed in the stochastic dynamic analysis of investments (Table 5.3). All the scenarios are analysed with 5 % and 15 % price responsive demand in the system. In the SW scenario we find the optimal investment strategy according to the social welfare objective in (5-9). The PI1 scenario represents a competitive market where P_{cap} equals *VOLL*, and there are always investors acting as new entrants to the market (i.e. MS_{init} = 0). Scenarios SW and PI1 should give the same investment strategy, according to the static analysis in section 5.3.2. In scenario PI2 we analyse the effect of a reduction in the price cap in the spot market, still assuming profit maximisation. The results from section 5.3.2 showed that the effect of reducing P_{cap} is highly dependent on the fraction of price flexible demand in the system. In scenario PI3 we use the model to examine how a capacity payment can be used to compensate for lower profits because of the price cap in the spot market. The magnitude of the capacity payment is set so that the initial investment threshold is the same as in the SW scenario[50]. In the end, in scenario PI4, we look at how the optimal investment strategy changes for an investor with a market share in the initial generation capacity in the power system, combined with an exclusive right to invest in new capacity. As we will see, it turns out that the impact on the optimal investment threshold is very significant even for low market shares. Note that we in this chapter only consider optimal investment thresholds

[50] We use the same representation of capacity price as we did in section 4.3.4(Figure 4.10). The capacity factor, *CF*, is now equal to the fraction of total installed capacity to expected peak load, i.e. $CF_k(x_k, l_k, \omega_s) = \dfrac{\sum_{i=1}^{2}(x_{i,new,k} + X_{i,old,k})}{\underset{\omega_s}{E}(Q_{3,k}(x_k, l_k, \omega_s))}$. CF_{limit}, is set to 1.15. *CP*(*CF*=1), is set to 200000 NOK/MW with 5 % price flexible demand and 115000 NOK/MW with 15 % price flexible demand. The initial investment thresholds in scenario PI3 are thereby brought down to the same levels as under social welfare maximisation (scenario SW). Unless otherwise stated we assume that the capacity payment is only paid to new capacity.

under stochastic dynamic optimisation. Consequently, all the investment criteria presented below represent optimal investment decisions according to decision rule d, as defined in section 4.4 (Figure 4.11).

Table 5.3 Description of scenarios in the stochastic dynamic investment analysis. P_{cap} is the price cap in the spot market in NOK/MWh. MS_{init} is the market share of initial generation capacity. CP is capacity payment.

Scenario	Objective	P_{cap}	MS_{init}	*CP*
SW	Centralised social welfare maximisation	10000	-	no
PI1	Decentralised profit maximisation	10000	0	no
PI2	Decentralised profit maximisation	1000	0	no
PI3	Decentralised profit maximisation	1000	0	yes
PI4	Decentralised profit maximisation	10000	0.03	no

We start the stochastic dynamic analysis by finding optimal thresholds for investments in new capacity with 5 % price flexible demand. The initial conditions in the power system are the same as in the static analysis, and still described by Table 5.1. The growth and uncertainty (l_{growth} = 100 MW/year, l_{sdv} = 200 MW/year) in the state variable for demand (l_k) are now taken into account in the optimisation. Furthermore, new capacity additions are lumpy ($\Omega_{\boldsymbol{u}}$ = [400 200] MW]), and construction delays are explicitly represented as construction states in the mathematical description of the investment model, as illustrated in Figure 5.7.

First, we use the stochastic dynamic optimisation model to find the optimal investment strategy for scenario SW. Optimal investment thresholds under social welfare maximisation can be visualised by plotting the expected gain in social welfare from investing along with the expected gain from postponing the investment (Figure 5.15). The gain in social welfare is here defined as the difference in social welfare between the respective investment alternatives and the situation where no investments are made throughout the entire planning horizon. Thus, there is also an expected social welfare gain from postponing an investment decision, as long as the investment can be undertaken at a later stage in the planning period. The optimal investment threshold occurs when the expected social welfare gain from investing exceeds the expected gain from postponing the investment decision. The initial demand at which investment becomes optimal is indicated as $l_0{*}_{,SW}$ in Figure 5.15. The general theory for investments under uncertainty from Chapter 4 is also valid when social welfare is used in the objective function of the investment model. Hence, the growth and uncertainty in demand should have similar effects on the optimal investment threshold under social welfare and profit maximisation. The only difference is that the social welfare objective also takes into account the uncertain changes in consumer surplus in addition to the investor's profit, as discussed in section 5.2.5. From Figure 5.15 we see that it is not optimal to invest until the initial demand level approaches 9700MW, although the expected gain in social welfare from investing is positive also at much lower demand levels. This is due to the option value of the investment opportunity, which arises from the growth and uncertainty in future demand. We can also see that the optimal technology choice at $l_0{}^{*}{}_{,SW}$ is the base load plant (tech 1). When comparing to the results from the static analysis (Figure 5.13 and Table 5.2) we see that the optimal technology choice is the same, while the investment level appears to be lower in the stochastic dynamic analysis. However, the two investment thresholds are not directly comparable, as the construction delay is not included in the static analysis. The construction time for the base load plant is three years, so that with an expected growth in demand of 100MW/year, the demand level actually reaches a higher level than in the static analysis before new capacity is added to the system.

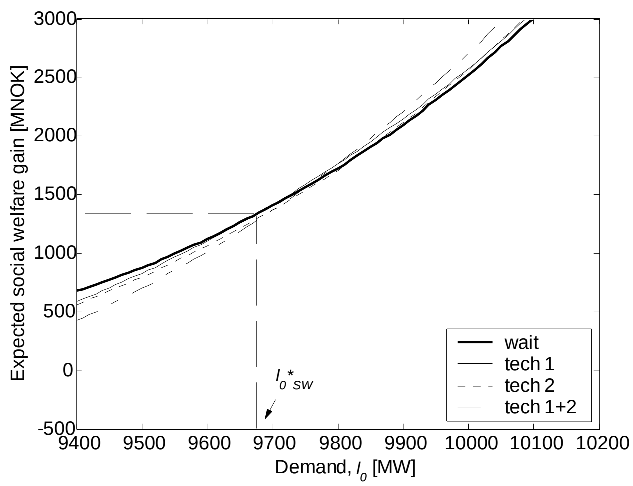

Figure 5.15 Expected gain in social welfare as function of initial demand level, l_0, for the four possible investment strategies (wait, tech 1, tech 2, tech 1+2), scenario SW. $c_{L,flex}$ = 0.05.

The investment model is now used to find optimal investment criteria under decentralised profit maximisation for scenario PI1-PI4. The results are shown in Figure 5.16 and also summarised in Table 5.4. We see that the investment threshold in scenario PI1, which represents a free market with no disturbances in the price formation, is actually higher than in the SW scenario. This difference in the optimal investment levels between the social welfare and profit maximisations can not be seen from the marginal analysis in section 5.3.2. It is due to the lumpiness in capacity additions, which causes a feedback from investment to price and thereby different changes in profit and social welfare, as discussed in section 5.2.5.

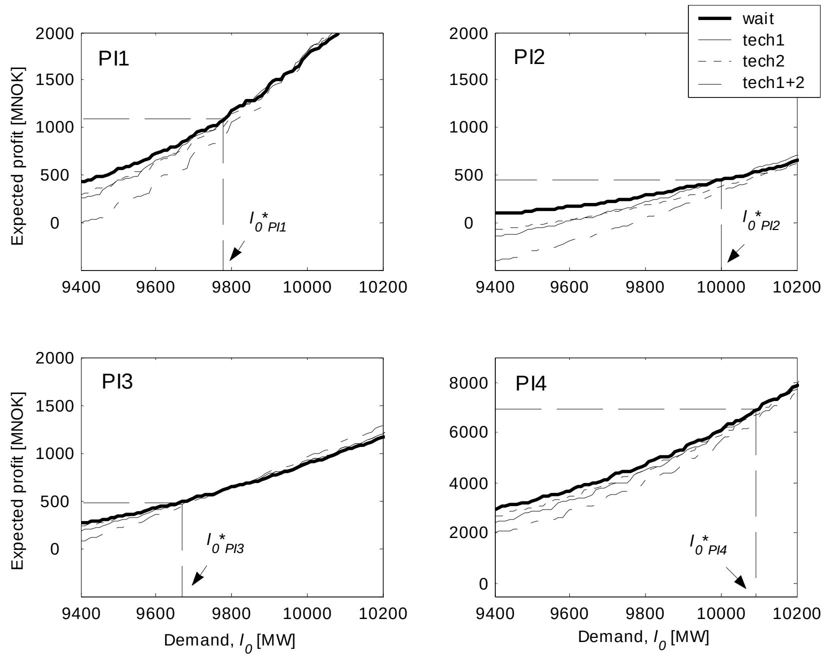

Figure 5.16 Expected profit as function of initial demand level, l_0, for the four possible investment strategies (wait, tech 1, tech 2, tech 1+2), scenarios PI1-4. $c_{L,flex}$ = 0.05.

Table 5.4 Summary of characteristics for optimal investment thresholds. $P_{av,1+2+3}$ and $P_{av,2+3}$ are average prices over the entire year and for sub periods 2 and 3. J_0 is the value of the objective function at optimal investment threshold (i.e. expected social welfare gain for scenario SW and expected profit for scenario PI1-4). $c_{L,flex}$ = 0.05.*

Scenario	Optimal investment threshold				
	l_0* [MW]	Tech-nology	$P_{av,1+2+3}$ [NOK/MWh]	$P_{av,2+3}$ [NOK/MWh]	J_0* [MNOK]
SW	9680	1	184.1	306.4	1352
PI1	9770	1	188.5	315.6	1060
PI2	10000	1	208.4	329.3	451
PI3	9680	2	184.1	306.4	484
PI4	10090	1	242.7	404.9	6869

For scenario PI2 we see that a reduction in P_{cap} to 1000 NOK/MWh lowers the expected profit from investing in new capacity. The optimal investment threshold is therefore increased with more than 200 MW compared to scenario PI1. This also results in significantly higher prices at the optimal investment level in scenario PI2, as seen from Table 5.4. However, the expected profit at the optimal investment threshold is lower than in scenario PI1, because of the price cap which lowers the expected price and profit in the peak demand sub periods. Technology 1 is the preferred technology in both scenarios. When comparing to the results in Table 5.2 we see that the base load plant also has the lowest investment threshold in the static analysis. However, the increase in investment threshold due to the lower price cap is more significant in the dynamic analysis. This is because the dynamic model also takes into account how the lower price cap affects future prices and not only the price in the initial system.

In scenario PI3, the capacity payment increases the profitability of investing compared to scenario PI2. Still, the expected profit is kept down by the price cap, and is still much lower than in scenario PI1. The capacity payment brings down the demand and prices at the optimal investment criterion to the same level as in the SW scenario, but it also causes a change in the optimal choice of technology. This is because the capacity payment reduces the level of income which is required from sales in the electricity spot market, for investments in new power generation capacity to become profitable. However, a new peaking plant operates fewer hours than a new base load plant, and can therefore allow a larger reduction in the price earned in the electricity market. The corresponding reduction in the optimal investment threshold depends on the relationship between demand and spot price in the three demand sub periods. In our case the effect is more significant for the peaking plant. Hence, the introduction of the capacity payment in scenario PI3 causes the optimal choice of technology to change to the peaking plant (technology 2).

In scenario PI4 the investor optimises the sum of profits from new investments and from his 3% share of initial capacity in the system. The expected profit is therefore much higher than in the other profit maximising scenarios, PI1-3. Investments in new capacity reduce the spot price and the profitability of existing generation assets. Consequently, an investor with a market share in existing capacity and an exclusive right to invest, has an incentive to postpone new investments in order to avoid lower profits from current assets. It is not optimal to invest until the profits from new investments compensates for the loss in income from the existing capacity. This effect is very significant, and the optimal investment threshold increases more than 300 MW compared to scenario PI1, where the only difference is that the investor acts a new entrant, i.e. with no initial capacity. The large increase in optimal demand level in scenario PI4 occurs despite the investor's low market share, only 3% of total installed capacity. From Table 5.4 we see that effect on prices is even more significant, with average prices over the year rising more than 50 NOK/MWh and the average price over the medium and high demand periods rising almost 90 NOK/MWh compared to scenario PI1 at the optimal investment threshold.

To further explore the relation between market share and optimal investment thresholds, we plot the optimal demand level for investment, l_0*, as function of the investor's market share (Figure 5.17). It turns out that the increase in investment threshold due to the investor's ownership of initial capacity is almost the same in scenarios PI1-3[51] for small market shares (up to 3 %). However, in scenario PI1 the investment criterion makes a distinct jump up already at a market share of 4 %. This extreme rise in investment threshold occurs when the investor no longer finds it optimal to invest in order to meet the demand in the peak sub period. Instead, the investment is postponed until the medium demand approaches installed capacity. For scenarios PI2 and PI3 this transition in investment criterion takes place at higher levels of initial market share. This is because of the lower price cap in the spot market, which reduces the profitability also of existing power generation assets. In scenario PI3 the capacity payment also contributes to push back the extreme rise in l_0*, since the capacity payment is assumed to be paid only to new capacity in the system.

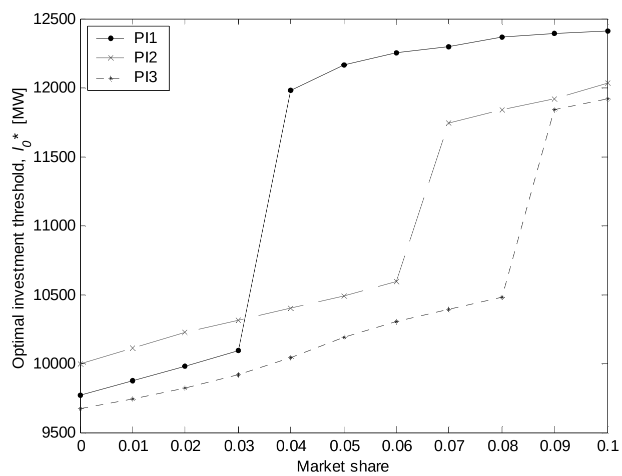

Figure 5.17 Optimal investment threshold as function of market share. $c_{L,flex} = 0.05$.

The effect of market power and monopolistic investment conditions in this example represent a situation where a profit maximising investor has an exclusive right to invest throughout the 10 years planning horizon. This is of course an extreme assumption as there in real world power markets usually would be several competing participants considering investments at the same time. A situation with exclusive investment rights can still arise, for instance if the number of construction permits in the market is kept very low. The results presented above illustrates the importance of having low barriers for new entry to the power market, to avoid that participants with

[51] Note that scenario PI4 is the same as scenario PI1, with an investor market share in initial generation capacity of 3%.

high market shares hold back on investments in order to increase prices. Furthermore, the long-term effect of strategic investment decisions caused by market power combined with high barriers for entry can be detrimental to the system, even if the participants do not exercise market power in the short-term bidding into the spot market.

We now repeat the analysis with a higher fraction of price flexible demand in the system. Optimal investment thresholds with 15 % price flexible demand are illustrated in Figure 5.18 and Figure 5.19, and also summarised in Table 5.5. If we compare to the results for 5 % price flexible demand, we see that the optimal initial demand levels for investment have increased in all scenarios. This is simply because the higher price elasticity of demand results in lower prices and loads for the same realisation of the demand state variable, l_k. The same effect is seen in the static analysis in section 5.3.2. If we now compare the investment thresholds in scenario SW and PI, we see that there is still a discrepancy between the investment criteria under the social welfare and profit objectives, and the difference in initial demand is actually larger than it was with 5 % price flexible demand. However, the effect of a lower P_{cap} in scenario PI2 is much less significant after the increase in price elasticity. From Table 5.5 we see that scenarios PI1 and PI2 now have exactly the same investment threshold and technology 1 is the optimal technology in both scenarios. The only difference is that the lower price cap results in a reduction in the expected profit at the optimal investment level. In turn, this means that the importance of regulatory intervention, in terms of defining a price cap in the spot market, has been considerably reduced due to the increased price elasticity of demand. However, a capacity payment is still required in scenario PI3 to bring the investment threshold down to the level in scenario SW, although the magnitude of the payment is reduced[52].

For scenario PI4 we see that the effect of an initial market share combined with an exclusive investment right still makes a huge impact on the optimal investment criterion. The initial demand at the optimal investment threshold, l_0*, increases with more than 400 MW due to the investor's market share in existing capacity. However, the corresponding price increase is less significant than it was with 5 % price flexible demand, particularly for the medium and peak demand sub periods. This is because of the higher price elasticity of demand, which effectively reduces the price effect of increased demand in the system. From Figure 5.20 we still see a distinct increase in the optimal investment threshold, l_0*, as function of increasing market share. However, the extreme shifts in l_0* now occur at higher levels of

[52] *CP*(*CF*=1) in scenario PI3 is now 115000 NOK/MW, as compared to 200000 NOK/MW in scenario PI3 for 5 % price flexible demand.

market share than in Figure 5.17 with 5 % price flexible demand. In addition, Figure 5.20 shows that the lower price cap in scenario PI2 and PI3 still reduces an investor's incentive to exploit his market share in existing capacity, also in the scenarios with higher price elasticity of demand.

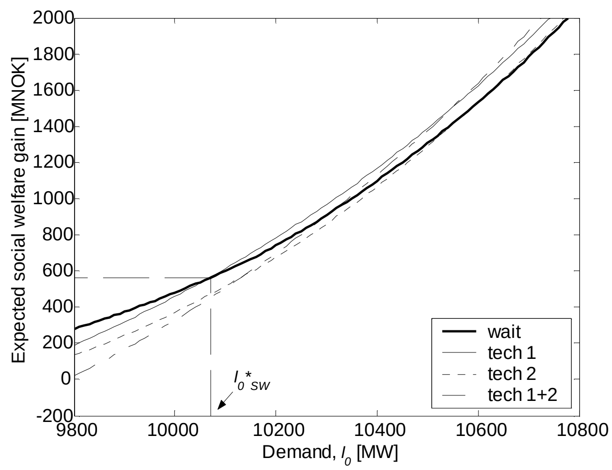

Figure 5.18 Expected gain in social welfare as function of initial demand level, l_0, for the four possible investment strategies (wait, tech 1, tech 2, tech 1+2), scenario SW. $c_{L,flex}$ = 0.15.

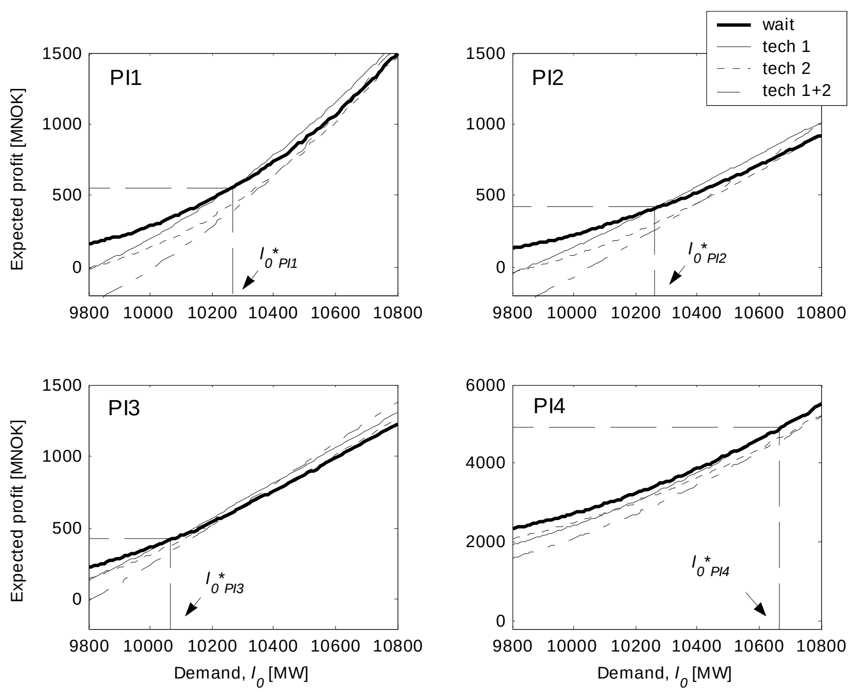

Figure 5.19 Expected profit as function of initial demand level, l_0, for the four possible investment strategies (wait, tech 1, tech 2, tech 1+2), scenarios PI1-4. $c_{L,flex}$ = 0.15.

Table 5.5 Summary of characteristics for optimal investment thresholds. $P_{av,1+2+3}$ and $P_{av,2+3}$ are average prices over the entire year and for sub periods 2 and 3. J_0 is the value of the objective function at optimal investment threshold (i.e. expected social welfare gain for scenario SW and expected profit for scenario PI1-4). $c_{L,flex}$ = 0.15.*

Scenario	Optimal investment threshold				
	l_0* [MW]	Tech-nology	$P_{av,1+2+3}$ [NOK/MWh]	$P_{av,2+3}$ [NOK/MWh]	J_0* [MNOK]
SW	10070	1	193.6	309.4	566
PI1	10260	1	211.9	318.9	551
PI2	10260	1	211.9	318.9	407
PI3	10070	1	193.6	309.4	423
PI4	10670	1	243.6	342.8	4902

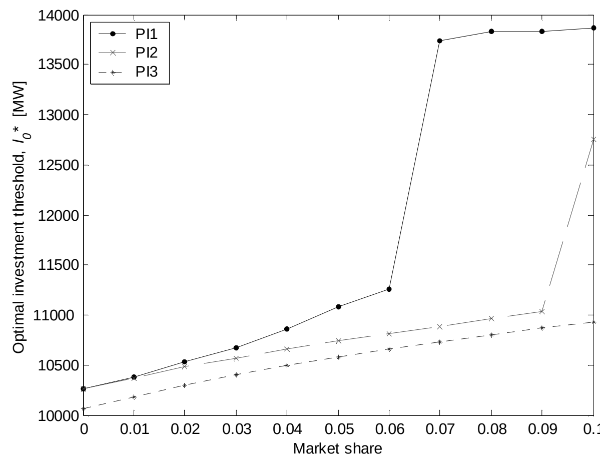

Figure 5.20 Optimal investment threshold as function of market share. $c_{L,flex}$ = 0.15.

In the end we use the stochastic dynamic investment model to find optimal investment thresholds for marginal investments in new capacity. The fraction of price flexible demand is now varied between 1% and 20%. Table 5.6 shows that marginal investments give lower initial demand levels for optimal investments, l_0*. This is not surprising, since the feedback from investment to price disappears when investments are marginal. Furthermore, we see from Table 5.6 that the optimal investment thresholds and technology choices are now identical in scenarios SW and PI1, independent of the amount of price flexible demand in the system. Hence, when investments are marginal the social welfare and profit maximising objectives yield the same result, also in the dynamic analysis. In the marginal case, there should therefore be no need for regulatory intervention. Indeed, we see that the price cap in scenario PI2 still gives too high investment thresholds when price elasticity of demand is low. Moreover, the capacity payments in scenario PI3 results in too low investment thresholds when the fraction of price flexible demand is high. Note that the investment thresholds now deviate from the social welfare optimum, since we are using the same levels of capacity payments as we did with lumpy investments. For scenario PI4, Table 5.6 shows that the effect of monopolistic investment conditions is still a rise in investment threshold, also when investments are marginal.

Table 5.6 Investment thresholds, l_0, for marginal investments, $\boldsymbol{\Omega_u}$=[1 1] MW. [1]CP(CF=1) = 200000 NOK/MW. [2]CP(CF=1) = 115000 NOK/MW.*

Scen	1%		5%		10%		15%		20%	
	$l_{o,thres}$	tech	$l_{o,thres}$	tech	$l_{o,thres}$	tech	$l_{o,thres}$	tech	$l_{o,thres}$	tech
SW	9310	1+2	9470	1	9670	1	9860	1	9980	1
PI1	9310	1+2	9470	1	9670	1	9860	1	9980	1
PI2	9520	1	9610	1	9750	1	9870	1	9980	1
PI3	9310[1]	1+2	9420[1]	1+2	9560[1]	1+2	9680[2]	1	9800[2]	1
PI4	9400	1	9520	1	9790	1	10080	1	10290	1

The analysis of marginal investments confirms that the discrepancy between the investment thresholds in scenarios SW and PI1 in Table 5.4 and Table 5.5 are caused by the lumpiness in investment. In those analyses we assumed that new plants of technology 1 and 2 have an available capacity of 400 MW and 200 MW respectively. This amounts to 2.5 % and 1.25 % of the total installed capacity of old technologies in the power system. The relative magnitude of these capacity additions might be higher than what would be the case for new power generation projects in most power systems today. On the other hand, we have not taken into account how transmission constraints can influence the spot price at the site of the new plant. Bottlenecks in the transmission system would increase the feedback from new investments to the local spot price of electricity, since a new capacity addition would change the local capacity balance. Therefore, we argue that discrepancies between the optimal investment criteria under social welfare and profit objectives for large-scale investments in new power generation capacity can also occur in real world power systems. In such situations, the model results show that a capacity payment can contribute to bring a decentralised and profit maximising investor's investment criterion closer to the optimal level from a social welfare point of view. However, it would probably be very difficult for regulators to decide on appropriate investment incentives. We have already seen that the level of capacity payments, which brings the decentralised investment threshold down to the same level as under the social welfare objective, depends on the fraction of price flexible demand in the system. In addition, Table 5.6 shows that the correct level also depends on the size of the new investment alternatives. Uncertainties are attached to both of these factors in the real world. An optimal scheme for capacity payments would therefore be hard to design.

5.3.4 Analysis of Investment Dynamics, 5 % Price Flexible Demand

In order to analyse the long-term dynamics of investments, prices and reliability in the test power system, we simulate the system's behaviour under the 5 different scenarios in Table 5.3. Investment decisions are simulated based on the stochastic dynamic optimisation model, as explained in the description of the market simulator in section 5.2.7. We limit the analysis to simulate only one realisation of growth in demand, by assuming that l_k grows at the expected rate of 100 MW/year throughout the simulation period. However, the long-term uncertainty in demand is still taken into account when the stochastic dynamic investment model calculates the optimal investment criteria (i.e l_{sdv} = 200 MW/year). Investments in new capacity are simulated over a period of 30 years, with both 5 % and 15 % price flexible demand in the system. The new capacity additions for technology 1 and 2 are still assumed to consist of plants with 400 MW and 200 MW of available capacity. Hence, the initial investment thresholds are given by Table 5.4 and Table 5.5. We assume that there is surplus capacity in the system at the beginning of the simulation period, as the initial demand, l_0, is set to 9300MW.

In this section we present the results from the analysis of long-term investment dynamics with 5 % price flexible demand in the system. Figure 5.21 shows the timing of capacity additions in the five different scenarios. Note that the simulator takes into account that there is a construction delay from an investment decision is made until new capacity is added in the system. Therefore, investment decisions for technology 1 are taken 3 years prior to capacity additions, while the construction delay for technology 2 is 1 year. From Figure 5.21 we see that investments in technology 1 are triggered later for all the profit maximising scenarios (i.e. scenario PI1-4) than under the social welfare objective (i.e. scenario SW). Scenario PI4 has the slowest rate of capacity additions for base load plants. This is due to the investor's incorporation of his market share in existing assets into the investment optimisations. For the peaking technology we see that the capacity payment in scenario PI3 results in earlier investments than in scenario SW, despite the low price cap in the spot market. The rate of investment in technology 2 remains higher in scenario PI3 compared to the other scenarios. This is because the capacity payment improves the relative profitability of investing in the new peaking technology compared to new base load plants. The investments in technology 2 in scenario PI1 follows the SW scenario closely, while the capacity additions of technology 2 in scenario PI2 and PI4 are lower than in the SW scenario. In scenario PI2, where P_{cap} is reduced without any additional capacity payment, we see that the investments in technology 2 disappear almost completely.

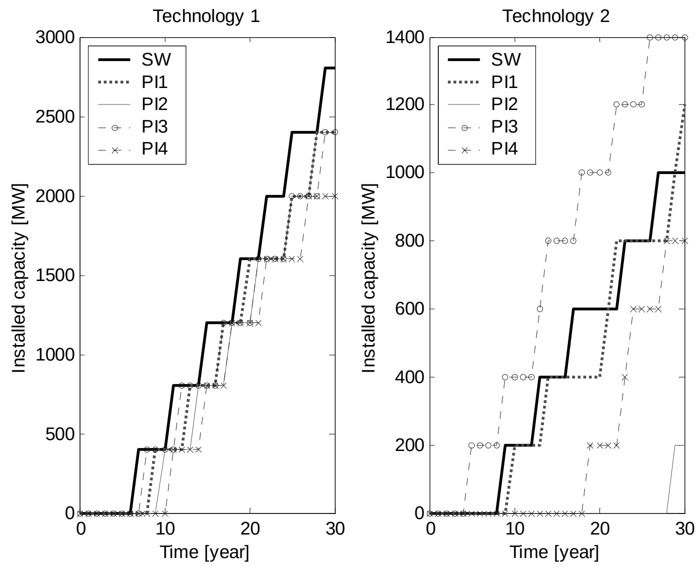

Figure 5.21 Simulated capacity additions for technology 1 and 2 in the five scenarios. $c_{L,flex} = 0.05$.

The different timing of investments is directly reflected in the simulated spot prices in the system. Figure 5.22 shows the simulated expected spot prices for the three different demand sub periods in the model. All scenarios follow the same price projection for the first few years in the simulation period, due to the excess capacity in the initial system and therefore no need for investments in new capacity. However, after the first five years we see that the prices in the profit maximising scenarios deviate from the SW scenario, particularly in the peak demand period. In scenario PI1 the prices in all sub periods are fluctuating at higher levels than in scenario SW, after the first period of excess capacity. This is due to the higher investment thresholds in scenario PI1, which are again caused by the lumpiness in investments. Still, we see that when new investments are made in scenario PI1, the sub prices tend to fall back down to the same level as in scenario SW. In scenario PI2 new investments are held back due to the low price cap in the spot market, and we see that the expected spot prices in base and medium demand are much higher than in scenarios SW and PI1. However, in the peak demand period the price is held down by the price cap of 1000 NOK/MWh. For scenario PI3, where a capacity payment is added to compensate for the lower price cap, the base demand price is still considerably higher than in scenario SW. However, the prices in sub period 2 and 3 are below the SW scenario most of the time. This is explained by the capacity payment, which favours investments in the peaking technology. The prices during high demand are therefore kept down, while the base demand price increases due to less base load capacity in the system. In scenario PI4 the capacity of both technologies are held back, due to the investor's strategic investment tactic. As a result, the prices in all sub periods increase substantially. The highest rise in prices naturally occurs in the peak demand period, where the prices reach an equilibrium level in scenario PI4 which is actually close to *VOLL* (10000 NOK/MWh). The simulated prices in Figure 5.22 clearly illustarte that the exercise of market power in investment decisions can have a drastic effect on the long-term development of prices in the system.

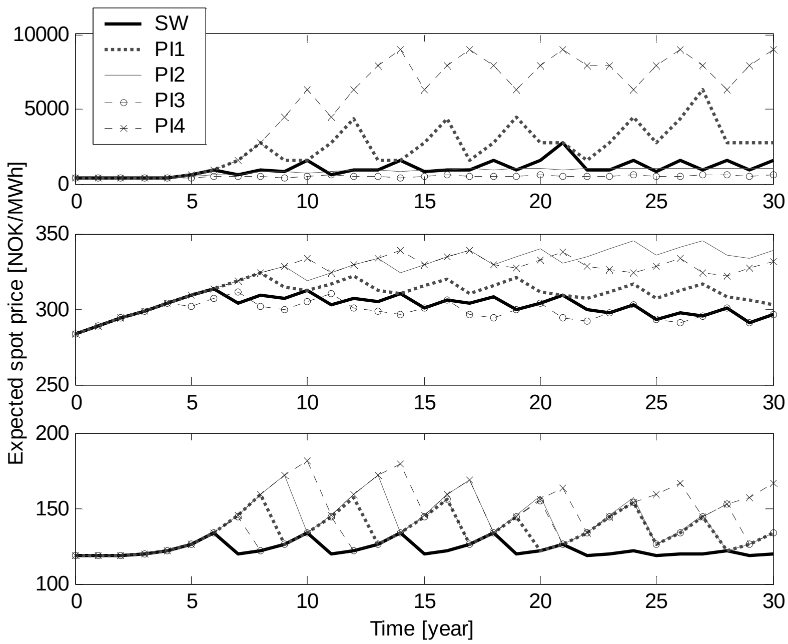

Figure 5.22 Expected spot prices during base (lower), medium (middle) and peak demand (upper) in the different scenarios. The expectation is taken over ω_s. $c_{L,flex}$ = 0.05.

It is also interesting to analyse the average prices for the entire year and over sub period 2 and 3. These average prices are of course given by the sub period prices, but can be compared more directly to the total unit costs of the new power generation technologies. The total unit costs for the new technologies can be considered as the LRMC of system expansion, as discussed in the static analysis in section 5.3.2. Figure 5.23 shows that in scenario SW the average price over all sub periods fluctuates around the total unit cost for the base load technology (202 NOK/MWh), while the average price for sub period 2 and 3 is kept on or below the total unit cost for the peak load plant (349 NOK/MWh)[53]. For scenarios PI1 and PI4 we

[53] The comparison of average price in sub period 2 and 3 to the total unit cost of technology 2 is not completely fair, as the total unit cost is calculated based on the assumption that a new plant only operates during medium and peak demand (i.e. 3000 hours/year). However,

see that the average prices fluctuate high above the LRMC of system expansion. In scenario PI2 the price cap keeps the average prices over sub period 2 and 3 down to a level around the total unit cost of technology 2, whereas the average price over the year is considerably above LRMC and close to scenario PI1. In scenario PI3, the capacity payment and subsequent investments in the peaking technology keeps the average price in sub period 2 and 3 below LRMC. The average price over the entire year is at the same level as in the SW scenario, i.e. close to total unit cost for technology 1.

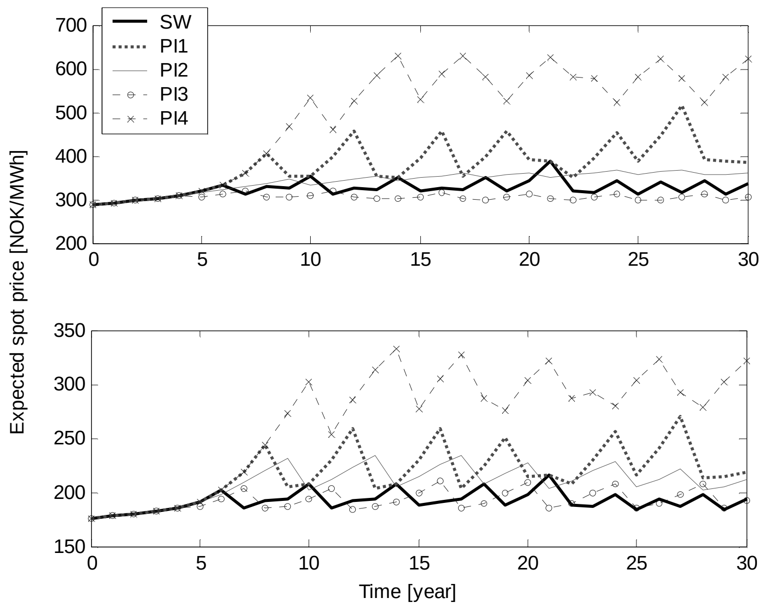

Figure 5.23 Expected spot prices for all sub periods (lower) and for sub period 2 and 3 (upper). The expectation is taken over ω_s. $c_{L,flex}$ = 0.05.

The analysis of average prices shows that social welfare optimisation apparently keeps the prices in the system close to the LRMC of system expansion. The average prices in the profit maximising scenarios deviate more or less from the total unit costs for the new technologies, depending on the assumptions about regulations and market structure. As pointed out in section 5.3.2, the traditional static analyses of system expansion conclude that LRMC is the optimal long-term equilibrium price in the system. This result seems to be valid also for stochastic dynamic investment optimisation in this example. This is somewhat surprising, since we in Chapter 4 argued that the inclusion of growth and uncertainty in the optimisation would result in optimal investment thresholds which deviate from the static NPV

in high demand situations, e.g. due to short-term uncertainties, a new peaking plant can also expect to operate in base load hours and profit from that. This explains why investments in technology 2 occur, even if the average expected price in sub period 2 and 3 is below the total unit cost of technology 2.

criterion. However, the direct comparison of the simulated average prices and the LRMC of system expansion presented here does not give the full picture, as we only simulate the expected realisation in demand growth. At the same time, it is assumed in the simulated investment optimisations that the load growth is stochastic and can deviate from the expected growth. The uncertainty in demand growth is symmetric in the model, but positive deviations will in general cause larger upward changes in price than the downward price changes caused by negative deviations. Consequently, a simulation of expected growth is likely to give lower prices than the true expected price when the long-term uncertainty is properly taken into account. The analysis of prices and LRMC could be extended by running Monte Carlo simulations, using the same procedure as in section 4.4.4. However, we do not pursue a more detailed analysis of these topics here, and focus instead on the differences between optimal investments under centralised and decentralised decision making. These differences can not be comprehensively analysed, without using a dynamic model.

The investments in new power generation also determine the reliability in the power system. The level of reliability can now be examined by plotting the simulated expected load shedding in the different scenarios (Figure 5.24). We assume that load shedding is implemented by the system operator as soon as the fixed part of the demand can not be met by the total available capacity of old and new technologies. This means that the required level of operating reserves is never compromised. Moreover, we assume that the system operator during load shedding is able to disconnect exactly the amount of load which is required, so that the remaining part of the price inelastic demand can be met by the total generation capacity in the system. Figure 5.24 shows that load shedding is expected to occur in all the scenarios. Hence, we can conclude that with 5 % price flexible demand in the system it is too expensive to invest in new capacity so that demand is always met, also from a social welfare point of view. During the first five years of the simulation period we see that there is no load shedding in the system, due to the initial surplus of installed capacity. The initial reliability of the system therefore appears to have been too high, based on an economic assessment. For scenarios SW, PI1 and PI3 the expected load shedding is kept at relatively low levels throughout the simulation period. However, the shedding of load reaches much higher levels in scenarios PI2 and PI4, due to the lower price cap in PI2 and the strategic investment behaviour in PI4. Table 5.7 shows that total expected load shedding in the 30 years simulation period increases as much as 25-35 times in these two scenarios compared to the social welfare scenario. This is another result that underlines the importance of organising markets that provide correct long-term incentives for investments.

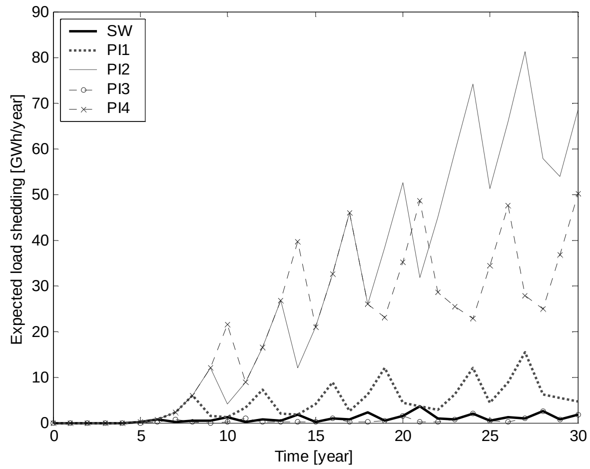

Figure 5.24 Simulated expected load shedding in the five scenarios. Total annual load in initial system (for k=0) is 91979 GWh. The expectation is taken over ω_s. $c_{L,flex}$ = 0.05.

Total investments in new capacity and total expected load shedding are summarised in Table 5.7. The table also shows the total simulated profit for investors in new capacity and the total gain in social welfare caused by the new investments. It turns out that in the SW scenario investors do not recover their investment costs completely, through sales of electricity in the spot market. In contrast, the net present values of profits from new investments are positive in all the profit maximising scenarios. When comparing scenarios PI2 and PI3 we see that the capacity payment in scenario PI3 increases the investor's total profit, despite the lower prices caused by the much higher rate of investments in technology 2. Table 5.7 also shows that the decentralised decision making in scenario PI1 results in lower social welfare than in the SW scenario. However, the reduction in social welfare is small compared to scenarios PI2 and PI4, where the delayed investment schedules cause large losses in social welfare compared to scenario SW. In scenario PI3 we have seen that the capacity payment leads to earlier investments and thereby lower prices than in the other profit maximising scenarios. However, from Table 5.7 we see that the change in investment schedule in scenario PI3 does not result in increased social welfare in the system, as the simulated social welfare in scenario PI3 is at a slightly lower level than in scenario PI1. Hence, although the average prices and level of load shedding in the system in scenario PI3 is brought closer to the social welfare scenario, it does not necessarily mean that the capacity payment gives a better solution from a social welfare point of view. This is probably because the capacity payment in scenario PI3 gives a too high rate of investments in new peaking capacity compared to the actual need in the system.

When interpreting the results we must remember that we have only simulated one realisation of demand growth, while the investment decisions are optimised based on an assumption of a stochastic future. A better assessment of the different scenarios would therefore require a stochastic simulation of investment decisions, similar to the Monte Carlo simulations in section 4.4.4. However, a further investigation of the power system's performance under centralised and decentralised decision making under stochastic simulations of demand growth is left for future work.

*Table 5.7 Summary of aggregate results for simulations of capacity additions in the test power system. Total profits and social welfare gain are net present values. *Includes operating profits from 3% market share in existing generation assets.* $c_{L,flex} = 0.05$.

Scen.	Tot. capacity technology 1 [MW]	Tot. capacity technology 2 [MW]	Total profit for investors [MNOK]	Total social welfare gain [MNOK]	Total load shedding [GWh]
SW	2800	1000	-1033	18202	25.6
PI1	2400	1200	2229	18087	133
PI2	2400	200	800	16216	894
PI3	2400	1400	1285	18077	14.1
PI4	2000	800	13086*	16489	664

The socio economic consequences of the different planning scenarios are further examined in Table 5.8. The table shows relative changes in socio economic results for the four scenarios with decentralised decision making, using the centralised SW scenario as a reference. Here we also consider the distribution of social welfare between consumers and producers in the system. Table 5.8 clearly shows that the distributive effect can be very large, although the change in total social welfare is limited. This is because the distribution of welfare from existing capacity in the system is also highly dependent on the prices in the electricity market, which in the long run are decided by the new investments in power generation capacity.

Table 5.8 Relative changes in social welfare, consumer surplus, producer surplus, total load and average price for scenarios PI1-4, using scenario SW as reference. Changes in social welfare, consumer and producer surplus are net present values. PI3a – capacity payment to new capacity only. PI3b - capacity payment to all capacity. $c_{L,flex} = 0.05$.

Scenario	Social welfare [MNOK]	Consumer surplus [MNOK]	Producer surplus [MNOK]	Total load [GWh]	Average price [NOK/MWh]
PI1	-115	-37534	37419	-2162	25.4
PI2	-1986	-22259	20275	-5086	16.8
PI3a	-125	2113	-2238	-763	0.0
PI3b	-125	-38155	38030	-763	0.0
PI4	-1713	-111060	109347	-5560	75.6

For scenario PI1 we see that the NPV of the total reduction in social welfare is 115 MNOK, compared to the SW scenario. This change in social welfare by going from maximisation of social welfare to investor profits might appear as rather small in a 30 years horizon. However, we see that the changes in consumer and producer surpluses are very high in comparison. The consumers loose in total more than 37000 MNOK during the simulated period, mainly because of the higher average price in the PI1 scenario. In addition, the aggregate reduction in total system load because of fewer investments and higher prices also contributes to the loss in consumer surplus. In scenario PI2 there is a much higher loss in total social welfare. At the same time, we see that the negative effect for consumers is reduced, due to the price cap which keeps the prices in peaking periods down. This is reflected in the average price, which increases less in scenario PI2 than in scenario PI1. However, the total reduction in load is now more than 5 TWh. The loss in social welfare and reduced system reliability in scenario PI2 is probably not acceptable for any of the participants in the power system.

In scenario PI3 we have seen that the increased investment incentives along with the price cap in the spot market keep the average price over the simulation period at the same level as in scenario SW. Still, the relative change in social welfare is at the same level as in scenario PI1. The distributional effect of the capacity payment is highly dependent on how it is implemented, as the payment in reality is a transfer of welfare from consumers to producers in the system. In scenario 3a in Table 5.8 we have assumed that the capacity payment is only paid to new power generation capacity in the system. In this case we see that the relative changes are small in consumer and producer surplus. The other extreme is represented in scenario 3b, where the capacity payment goes to all the capacity in the system. It is likely that such a huge transfer of wealth to producers in the system would trigger large protests from consumers. In this situation the producer surplus rises above the level in scenario PI1. In the end, for scenario PI4 we see that the exercise of strategic investment behaviour causes extreme losses for the consumers in the system. From this we can conclude that the end-users would be exposed to detrimental effects of market power, if monopolistic investment conditions are present in the system over a longer period of time. Hence, it is very important that the power market is designed to discourage participants from exploiting their market share in existing generation capacity.

5.3.5 Analysis of Investment Dynamics, 15 % Price Flexible Demand

The analysis of price and investment dynamics in the test power system is now repeated, with the only difference that the fraction of price flexible demand is increased to 15 %. Many of the results have the same characteristics as in the scenarios with 5 % price flexible demand. However, there are also some significant differences, and these are pointed out as the results are presented below.

The simulated trajectories for installed capacity of the new technologies are shown in Figure 5.25. The most striking change from the scenarios with 5 % price flexible demand in Figure 5.21 is that the rate of investment in the peaking technology is now much lower. Actually, capacity additions of technology 2 only occur in scenario PI3, where a capacity payment contributes to enhance the attractiveness of new peaking plants. For investments in technology 1 we see that scenarios SW and PI3 have the highest frequency of investment. In the profit maximising scenarios PI1 and PI2 the capacity additions seem to follow with a time delay of 2 years. Another interesting observation is that scenario PI1 and PI2 give almost exactly the same investment pattern. This indicates that the lower price cap in scenario PI2 now has a much lower impact on investment decisions. In turn, this is due to the increased price elasticity of demand, which makes it less likely that load shedding will be needed in the system. For scenario PI4 we see that strategic investment behaviour due to monopolistic investment conditions would still cause extensive delays in capacity additions. A general observation which is valid for all scenarios is that investments are now triggered later than in Figure 5.21. The higher fraction of price flexible demand reduces the effect on price from the gradually increasing demand in the system. Consequently, it is optimal for both centralised and decentralised investors to further postpone investment decisions, to wait for optimal investment conditions to occur in the system.

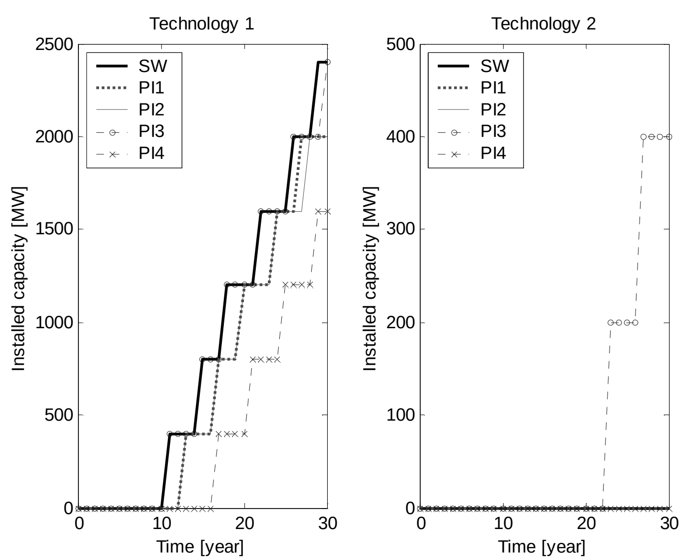

Figure 5.25 Simulated capacity additions, tech 1 and 2 in the five scenarios. $c_{L,flex} = 0.15$.

The observed changes in simulated investment patterns are also reflected in the spot prices. From Figure 5.26 we see that the prices in scenarios SW and PI3 follow each others closely. The match between scenarios PI1 and PI2 is even closer, due to the similar investment strategies. The prices in scenario PI4 are still much higher than in the other scenarios. However, the deviation in prices is still lower than in Figure 5.22, because the rise in price flexible demand subdues the price effect of lower investments. This is also reflected in Figure 5.27, where we see that the prices in all scenarios are closer to each others than in Figure 5.23. The average price over the year in scenario SW fluctuates around the total unit cost for technology 1, while the average price over sub period 2 and 3 levels out slightly below the total unit cost for technology 2. This is the same picture as we see in Figure 5.23, although the difference between the average price over the year and the average price over medium and peak demand is now reduced due to the higher price response on the demand side.

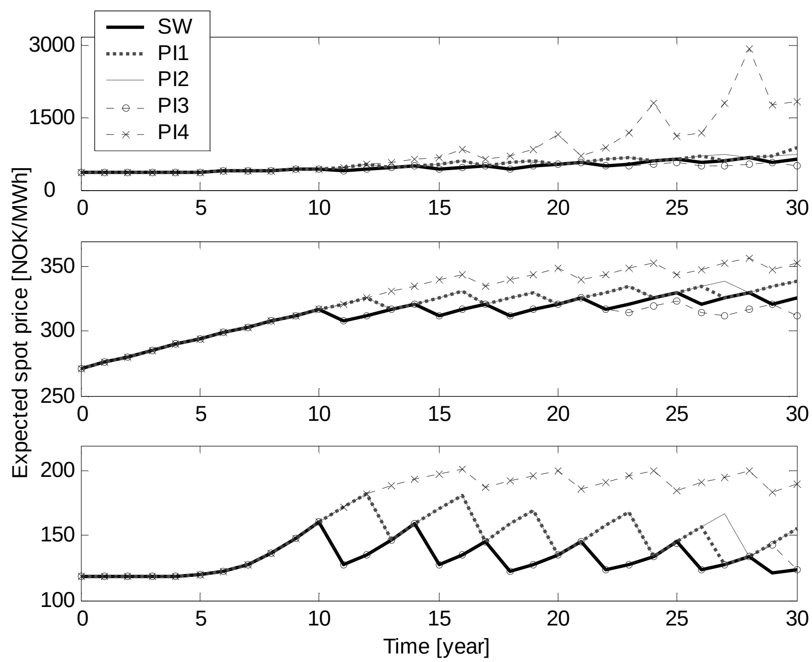

Figure 5.26 Expected spot prices during base (lower), medium (middle) and peak demand (upper) in the different scenarios. The expectation is taken over ω_s. $c_{L,flex} = 0.15$.

The need for load shedding has been vastly reduced, following the higher price flexibility on the demand side. Figure 5.28 shows that scenario PI4 is now the only scenario that has a significant amount of load shedding, which only occurs towards the end of the simulation period. This result illustrates that an increase in the amount of price flexible demand from 5 % to 15 % drastically improves the market's ability to settle correct prices on its own.

Consequently, the need for the regulator to interfere in the market with load shedding and a corresponding price cap has been significantly reduced. Active demand side participation in the market is therefore crucial to obtain a robust and viable market for electrical power.

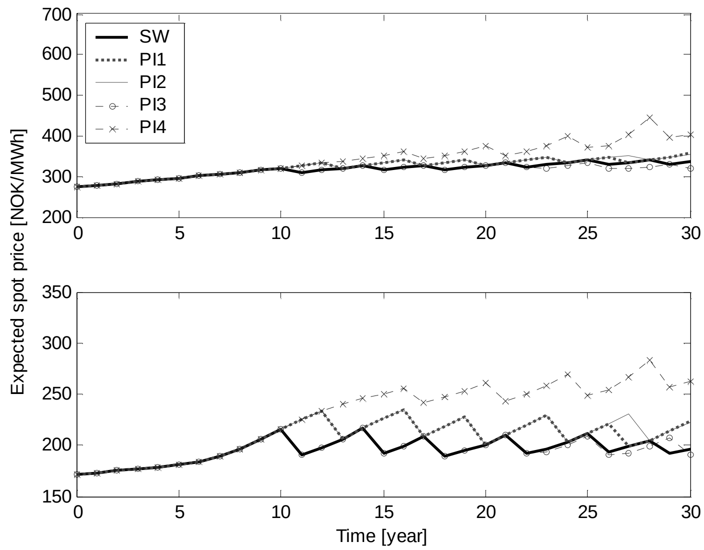

Figure 5.27 Expected spot prices for all sub periods (lower) and for sub period 2 and 3 (upper). The expectation is taken over ω_s. $c_{L,flex}$ = 0.15.

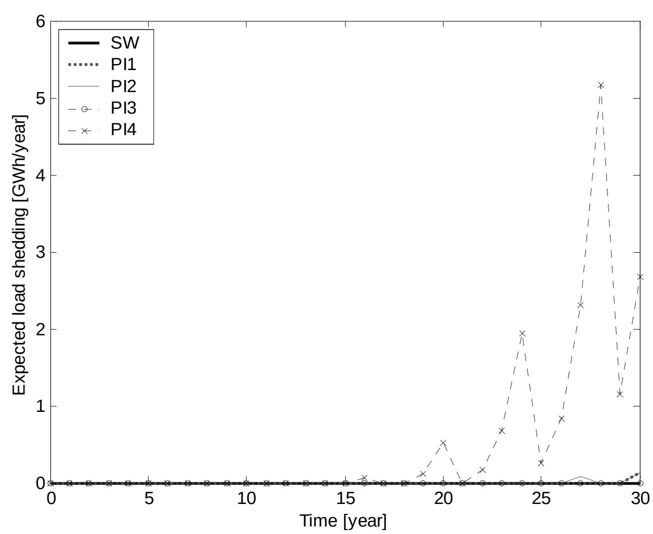

Figure 5.28 Simulated expected load shedding in the five scenarios. Total annual load in initial system (for k=0) is 90293 GWh. The expectation is taken over ω_s. $c_{L,flex}$ = 0.15.

The main results for the analysis are summarised in Table 5.9. We see that investors' aggregate profit is still negative in the social welfare scenario, while the investor profits in scenarios PI1-PI3 are positive. There are now only small differences between the simulated profits in these three profit maximising scenarios. In contrast, the total profit in scenario PI4 is of course still much higher than in the other scenarios. However, the simulated profit in scenario PI4 is reduced with more than 50 % compared to the same result in Table 5.7. This is mainly because of the increased amount of price flexible demand, which effectively lowers the possibility for pressing up prices by holding back on investments. The effect is particularly significant during peak demand periods, where the price is now much less likely to reach up to *VOLL*. From the simulated gain in social welfare we see that the differences between the scenarios are smaller than in Table 5.7. This is another indication that the higher amount of price flexible demand enhances the power market's robustness, by reducing the spot prices' sensitivity to installed capacity in the system.

*Table 5.9 Summary of aggregate results for simulations of capacity additions in the test power system. Total profits and social welfare gain are net present values. *Includes operating profits from 3% market share in existing generation assets.* $c_{L,flex} = 0.15$.

Scen.	Tot. capacity technology 1 [MW]	Tot. capacity technology 2 [MW]	Total profit for investors [MNOK]	Total social welfare gain [MNOK]	Total load shedding [GWh]
SW	2400	0	-218.3	3834	0
PI1	2000	0	556.1	3752	0.14
PI2	2000	0	648.1	3744	0.23
PI3	2400	400	518.6	3808	0
PI4	1600	0	5816*	3015	16

In the end we also here examine the socio-economic consequences further, by calculating the relative distributional effects in the profit maximising scenarios, using scenario SW as a reference. Table 5.10 shows that relative changes in consumer and producer surplus are reduced compared to the results in Table 5.8 with only 5 % price flexible demand. This is due to the lower impact on price from the differences in investment schedules. The increased changes in total load, which follow naturally from higher price elasticity of demand, are of less importance for the distributional effects. Table 5.10 also confirms that the difference between scenario PI1 and PI2 disappears almost completely. However, there is still an extensive loss in consumer surplus in going from the social welfare maximisation in scenario SW to the profit maximisation in scenarios PI1 and PI2. The capacity payment in scenario PI3 can contribute to remove this loss in consumer surplus, but only if the payment is limited to the new investments in power generation capacity. A capacity payment to all installed capacity in the system (scenario PI3b) makes the consumers worse off than in scenarios PI1 and PI2. However, the worst case scenario for end-users is still scenario PI4, where a producer exploits a monopolistic investment opportunity by holding back on investments in order to increase prices and profits.

Table 5.10 Relative changes in social welfare, consumer surplus, producer surplus, total load and average price for scenarios PI1-4, using scenario SW as reference. Changes in social welfare, consumer and producer surplus are net present values. PI3a – capacity payment to new capacity only. PI3b - capacity payment to all capacity. $c_{L,flex} = 0.15$.

Scenario	Social welfare [MNOK]	Consumer surplus [MNOK]	Producer surplus [MNOK]	Total load [GWh]	Average price [NOK/MWh]
PI1	-82	-11985	11903	-5509	11
PI2	-90	-12686	12596	-6059	12
PI3a	-26	-182	156	465.6	-0.54
PI3b	-26	-21215	21189	465.6	-0.54
PI4	-819	-33486	32667	-15790	34

The most important finding in this section, which has been commented several places throughout the analysis, is that an increase in price flexible demand from 5 % to 15 % makes the power market in this case study much more robust. The higher fraction of price flexible demand does not remove the differences in investment strategies between the social welfare and profit maximising scenarios. However, the system consequences of these differences are significantly reduced, due to the demand side's increased ability of adjusting load according to the prices in the system. Consequently, the necessity of regulatory intervention into the market is also significantly reduced. Nevertheless, it is worth noting that a capacity payment now apparently brings the investments and prices in the system closer to optimum from a social welfare point of view. It does so by reducing the gap in investment criterion between social welfare and profit maximisation, which arises from the lumpiness of the investment projects.

5.3.6 Computational Issues

The optimisation model presented in this chapter is an extension of the model in Chapter 4, and is therefore also implemented in MATLAB. The size of the state space increases quickly as a function of the length of the planning period and the number of capacity states for the two power generation technologies. However, with the limited state space representation used in the examples presented here, the computing time for an investment optimisation for a given level of initial demand is in the range of 3-4 seconds on a computer with a 1.2 GHz processor and 256 MB RAM.

5.4 Chapter Summary and Concluding Remarks

In this chapter we have extended the stochastic dynamic framework for investment optimisation to include two power generation technologies. At the same time we now describe the electricity market explicitly in terms of supply and demand curves. With this market description we can find optimal investment strategies with regards to maximisation of either profits from new investments or total social welfare in the system. The temporal variation in demand is now represented in the model by using three demand sub periods. At the same time we assume that parts of the demand are responsive to price. A similar representation of demand is used in the static optimisation models for peak load pricing. With our stochastic dynamic framework we are able to include the effect of growth and uncertainty in demand on the optimal investment strategies. These factors are rarely represented in the traditional literature on dynamic pricing of electricity.

With this version of the investment optimisation model we can analyse the long-term effects of different planning regimes in the power system. Results from the case study show that the optimal investment strategies under social welfare and profit maximisation react similarly to growth and uncertainty in demand. However, the profit maximising investment criterion tends to deviate from the social welfare result when the new investment is lumpy and thereby causing a significant reduction in the electricity price. A price cap in the spot market below *VOLL* can contribute to increase this difference, and thereby lead to under investment in new power generation capacity. The introduction of an appropriate capacity payment will bring the investment criterion to the same level as under the social welfare measure. However, the capacity payment tends to give too much investment in peaking capacity in the case study, and the effect on the total social welfare in the system is not necessarily positive. The distributional effect of the capacity payment is also highly dependent on how it is implemented. The design of an optimal scheme of investment incentives is also very difficult given all the uncertainties in the system.

The model can also be used to analyse how a decentralised investor with ownership in existing generation assets can exploit an exclusive right to invest in the system. In the case study it turns out that the profit maximising investment strategy changes drastically when this effect is included in the optimisation model, even if the investor’s initial market share is very low. A price cap contributes to reduce the incentive to strategically postpone investment decisions, but only to a limited extent. These results underline the importance of having low barriers for entry into the market, so that monopolistic investment conditions do not occur.

In general, the results from the model show that the necessity and importance of regulatory intervention in the power market is significantly reduced as the amount of price elastic demand in the system rises. It is therefore highly desirable to increase the price responsiveness of the demand side, in order to obtain a market for electric power which is robust and viable in the long run. Increased price elasticity also contributes to reduce the negative effects of delayed capacity additions which can follow from strategic investment planning.

The examples in this chapter illustrate a range of possible applications of the stochastic dynamic investment model. Some of the issues that are addressed in the analyses, such as the effect of a price cap and monopolistic investment conditions, are hard to include properly into a static analysis. At the same time, we see that some of the results in the case study deviate from what we would expect from a static and marginal analysis. For instance, differences can arise between the centralised social welfare and the decentralised profit criteria for new investments, even without exercise of market power. In addition, the long-run equilibrium price in the system is not necessarily equal to the LRMC of system expansion. In reality, the equilibrium levels of investments and prices in the power system are dependent on trends and uncertainties in underlying variables. In order to assess and improve the long-run performance of liberalised electricity markets it is therefore important to use planning models that take these effects into account.

Chapter 6 CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

This thesis describes the development of three decision support models for long-term investment planning in restructured power systems. The model concepts address the changing conditions for the electric power industry, with introduction of more competitive markets, higher uncertainty and less centralised planning. Under these circumstances there is an emerging need for new planning models, also for analyses of the power system in a long-term perspective. This thesis focuses particularly on how dynamic and stochastic modelling can contribute to the improvement of decision making in a restructured power industry. We argue that the use of such modelling approaches has become more important after the introduction of competitive power markets, due to the participants' increased exposure to price fluctuations and economic risk. Our models can be applied by individual participants in the power system to evaluate investment projects for new power generation capacity. The models can also serve as a decision support tool on a regulatory level, providing analyses of the long-term performance of the power system under different regulations and market designs.

The system dynamics model in Chapter 3 is a descriptive model, which simulates investments in a number of different power generation technologies. The investment decisions in the model are static and based on a deterministic projection of prices, which in turn indicates expected future profitability of investing in the different technologies. Technology choice and timing of new capacity expansions also depend on a number of underlying factors, such as regulatory incentives (permit approval policy, taxes, and subsidies), construction delays and technology learning. The simulated investments are not necessarily optimal, but rather meant to describe real world decision making, which in most cases is based on limited foresight and bounded rationality. Results from the model show that construction cycles are likely to occur in a power system where the most competitive power generation technologies are large-scale with long lead times. However, the introduction of investment incentives for renewable power generation technologies can substantially change the pattern of investments and prices. In general, the model can contribute to better understanding of the long-term dynamics of investments and prices in the power market.

The investment model in Chapter 4 is a prescriptive optimisation model. It builds upon real options theory and calculates the optimal timing of investments in new power generation for a decentralised and profit-maximising investor. The stochastic dynamic algorithm takes uncertainty in load growth, and its effect on future electricity prices, explicitly into account in the optimisation. Prices and profits are calculated in a separate model, whose parameters can be estimated based on historical data for load, prices and installed capacity in the power system. Investment decisions by other participants can also be represented in the model, although the case study shows that this has a limited effect on the investor's optimal strategy for new investments. In the case study we use the model to analyse how the representation of dynamic decision making and stochastic load growth changes the optimal investment strategy. The results show a substantial increase in the investment threshold when going from a static to a dynamic project evaluation. A stochastic representation of load growth contributes to further postpone the investment decisions, although this effect is less significant. Monte Carlo simulations show that an investor increases his profits by using stochastic dynamic optimisation, as opposed to static and deterministic approaches, to decide the timing of new investments. In addition to calculate optimal investment strategies, the model can also be used for analysis of long-term system consequences. Results from the case study show that the investment strategy which follow from the stochastic dynamic model result in a long-term price level which is above the long-run marginal cost of system expansion. Hence, an average electricity price above the static long-run equilibrium price is likely to occur before new investments are triggered. This is not necessarily an indication of market failure. However, if the energy prices in the power market do not provide adequate investment signals, regulatory incentives can trigger earlier investments and thereby reduce the long-term prices. Our analysis indicates that direct investment subsidies would give lower additional costs to the end user than dynamic capacity payments, which depend on the future capacity balance in the power system. This is because constant investment subsidies do not give rise to an option value of postponing investments in new power generation capacity.

In Chapter 5 we extend the stochastic dynamic framework to include investments in two different technologies. In addition, the power market is now represented with explicit supply and demand curves. With the alternative market description the model can calculate optimal investment strategies under both a centralised social welfare and a decentralised profit objective. Results from the case study show that the dynamic and stochastic aspects have the same effect on the optimal investment thresholds under both objectives. However, a difference arises between the centralised and decentralised strategy when investments are large-scale and thereby causing a significant reduction in the electricity price. A price cap below the value of lost load will increase this discrepancy, particularly for investments in peak load technologies. The introduction of a capacity payment can eliminate the difference between the centralised and decentralised investment thresholds. However, the design of an appropriate investment incentive will be very difficult, given all the uncertainties in the system, and does not necessarily lead to an increase in total social welfare. The case study also illustrates the crucial role of a price responsive demand side in the power system. The necessity and impact of regulatory intervention in the market will be significantly reduced if the fraction of price flexible demand rises. Increased price elasticity of demand also reduces the negative consequences of delayed capacity additions, which could follow from inappropriate regulations, and possibly also from strategic investment planning. In the case study it is shown that new investments are delayed dramatically if an investor owns existing generation capacity and at the same time exploits an exclusive right to invest in the system. Hence, it is very important that the regulators maintain competition in the power system, by reducing the barriers to entry into the market for new investors.

The main scientific contributions in the thesis lie in the combined use of economic theory for restructured power systems and theory for optimal investments under uncertainty. With an explicit representation of the power market, the dynamic investment models can identify profit maximising investment strategies under different regulations and market designs. The use of physical state variables in the models also facilitates analyses of the long-term consequences for the power system, which result from the optimal decentralised investment decisions. Decision support models for expansion planning in the regulated power industry do not address the aspect of competition and decentralised decision making. At the same time, long-term uncertainties and their impact on optimal investment decisions are rarely represented in planning models for the competitive industry. The stochastic dynamic models in this thesis therefore provide a new framework for long-term analysis of investments and prices in restructured power systems.

Throughout this thesis we have focused on developing models that can describe the long-term dynamics of investments and prices in restructured power systems. Less attention has been given to the representation of the short-term operation of the power system. A natural direction for future work is therefore to take more of the short-term factors into account in the dynamic investment models. A number of extensions could be implemented within the flexible modelling approaches proposed in this thesis. For instance, an explicit representation of the transmission network would make it possible to also address the locational dimension of the expansion planning problem within the framework of our dynamic investment models. Another very relevant extension is to add more details to the modelling of demand, for instance by increasing the time resolution in the models and by better representing the long-term relationship between electricity price and demand. Improved modelling of demand would facilitate a more balanced analysis of the long-term consequences of power system restructuring for both the supply- and demand-side of the market.

A second direction for future research lies in the representation of uncertainty and risk preferences in the investment models. In the stochastic models in Chapter 4 and Chapter 5 we have only included growth in demand as a long-term uncertainty. An interesting extension would therefore be to include other long-term uncertainties, such as fuel prices and market regulations, as stochastic variables in the models, and see how this affects the optimal investment decisions. Alternatives to the use of binomial trees with constant probabilities for representation of long-term uncertainties could also be explored. When it comes to risk preferences we have applied the expected value paradigm for decision making, and only taken risk into account in terms of a risk-adjusted discount rate. Decision makers' risk preferences could be directly represented in the models by using expected utility instead of expected profit in the investor's objective functions. Future research efforts could also look further into how the investment problem can be formulated, so that the principles in contingent claims analysis and risk-neutral valuation from the real options theory are more directly applicable to the problem.

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APPENDIX A PAPER 1

"Futures and spot prices – an analysis of the Scandinavian electricity market"

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Futures and spot prices – an analysis of the Scandinavian electricity market

Audun Botterud, *NTNU*, Arnob K. Bhattacharyya, *MIT*, and Marija Ilic, *MIT*

***Abstract*--In this paper we first give a presentation of the history and organisation of the electricity market in Scandinavia, which has been gradually restructured over the last decade. A futures market has been in operation there since September 1995. We analyse the historical prices in the spot and futures markets, using general theory for pricing of commodities futures contracts. We find that the futures prices on average exceeded the actual spot price at delivery. Hence, we conclude that there is a negative risk premium in the electricity futures market. This result contradicts the findings in most other commodities markets, where the risk premium from holding a futures contract tend to be zero or positive. Physical factors like unexpected precipitation can contribute to explain parts of the observations. However, we also identify the difference in flexibility between the supply and demand sides of the electricity market, leaving the demand side with higher incentive to hedge their positions in the futures market, as a possible explanation for the negative risk premium. The limited data available might not be sufficient to draw fully conclusive results. However, the analysis described in the paper can be repeated with higher significance in a few years from now.**

***Index Terms*--Futures prices, price dynamics, restructured electricity markets, risk premium, spot prices.**

I. Introduction

One of the consequences of the ongoing deregulation of the power sector around the world, is that futures and forward markets for electricity have gained increased interest for suppliers and consumers of electricity. Long-term contracts provide participants in the power market with an important tool for reducing their risk exposure, and economic risk management has become more important in the new market setting. The futures and forward markets can also serve as a profitability indicator for investments in the power system, and thereby contribute to a balanced development of demand and supply. In order to use these markets in an optimal way, it is important for the power industry to gain knowledge about the information hidden in the long-term prices, and in particular the relationship between the long- and short-term prices of electricity. Scandinavia[1] is one of the regions of the world that has the longest experience with a restructured power market, and futures contracts have been traded on the Nordic Power Exchange, Nord Pool, since 1995. In this paper we take a closer look at the experiences from the Scandinavian market. In order to do this we first describe the conditions in, and organization of, the Nord Pool market. Then we look into finance theory for pricing of commodities futures contracts. The historical data from Scandinavia is analysed in order to assess the applicability of the traditional theory to the conditions in the electricity market. We are particularly interested in the relation between the long- and short-term prices in the market.

II. The Scandinavian Electricity Market

A. *The history of deregulation in Scandinavia*

Norway was the first country in Scandinavia to introduce competition in the power sector when a new energy act went into effect January 1st, 1991. The act mandated separation of transmission from generation activities, at least in accounting. Point-of-connection tariffs, which help to increase the competition in the market considerably, were established in 1992. At the same time all networks were opened for third party access. A similar tariff structure was established in Sweden in January 1995, and a legislation providing for competition became effective January 1st, 1996. Finland's new energy market legislation instituted market competition beginning June 1st, 1995, and a point-of-connection tariff was introduced in November of the same year. Denmark instituted a stepwise opening of the market, beginning in 1996, but with a shorter transition period than required by the EU directives. By January 2003 the market will be fully open to competition, as in the other three countries [1].

The power exchange, Nord Pool, has evolved in parallel with the deregulation process in the Scandinavian countries.

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Audun Botterud is with Dept. of Electrical Power Engineering, Norwegian University of Science and Technology (NTNU), N-7491 Trondheim, Norway, but is visiting Laboratory for Energy and the Environment, MIT, to Dec.-02. (e-mail: audun.botterud@energy.sintef.no).

Arnob K. Bhattacharyya is with Dept. of Electrical Engineering and Computer Science, Massachusetts Institute of Technology (MIT), Cambridge MA 02139 (e-mail: bobz@mit.edu).

Marija Ilic is with Laboratory for Information and Decision Services and Laboratory for Energy and the Environment, Massachusetts Institute of Technology (MIT), Cambridge MA 02139 (e-mail: ilic@mit.edu).

[1] By Scandinavia we here mean the four countries Norway, Sweden, Denmark and Finland, although strictly speaking it does not include Finland.

When established in 1993, it only served the Norwegian market. The Swedish and Norwegian markets merged into a common market, served by Nord Pool, in January '96. Finland joined in September '98, followed by western Denmark in January '99, and eastern Denmark in October 2000. Nordpool is owned by the Norwegian and Swedish transmission system operators (Statnett and Svenska Kraftnett), but all Scandinavian TSOs cooperate closely on operational and market aspects in the common power market. The core responsibilities of the power exchange can be summarized as [1]:

1. Provide a price reference to the power market
2. Operate a physical spot market and a financial market for derivative products (e.g. futures contracts)
3. Act as a neutral and reliable power-contract counterpart to market participants
4. Use the spot market's price mechanism to alleviate grid congestion. Report all traded power delivery and take-off schedules to the respective TSOs

B. Supply and demand of electricity

The power generation in the three countries are based on various energy sources, as shown in Fig. 1. In Norway, nearly all electricity is generated from hydropower. Sweden uses a combination of hydropower, nuclear power, and conventional thermal power. Hydropower stations are located mainly in northern areas, whereas thermal power prevails in the south. Denmark relies mainly on conventional thermal power, but wind power's share of the generation is rapidly increasing. The high share of controllable hydropower in the system makes it easy to regulate the generation on short notice. Hence, the spot price of electricity varies less over the day than what we see in pure thermal systems. However, the seasonal price fluctuations tend to be higher, due to the variations in inflow to the reservoirs. The price volatility is therefore high in the Scandinavian power market.

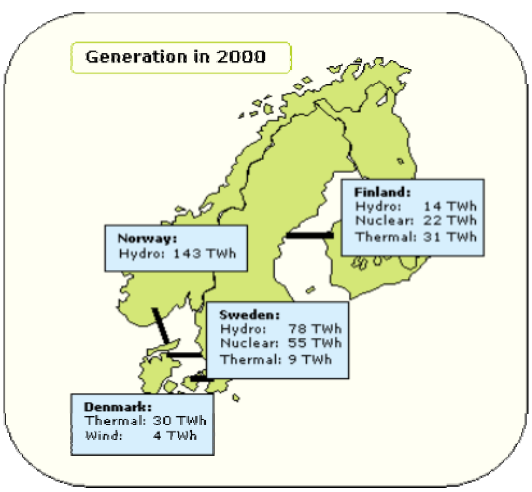

Fig. 1. Power generation by source in Scandinavia, 2000. Note that the hydro generation was record high in 2000. The generation in years with average inflow are 118, 64 and 13 TWh in Norway, Sweden and Finland respectively. The black lines in the figure represent undersea transmission lines. Source: [1].

In addition to the inflow to hydro reservoirs, the demand for electric power also plays an important role in the electricity price formation. When looking at the demand of electricity we see that the seasonal variations in electricity consumption in Norway and Sweden follow the same pattern (Fig. 2). This is because both countries use a substantial amount of electricity for heating purposes. In Denmark, where most of the heating demand is met by gas and district heating networks, the variation in electricity consumption over the year is much lower. Finland lies somewhere in between when it comes to seasonal variations. The seasonality in consumption also contributes to seasonal prices in the electricity market. Another fact that is worth noting is that there still seems to be a considerable load growth in the system. The gross consumption increased on average with 1.55 % pa. in the 90's. Finland and Norway have experienced the highest growth rates, while the increase in Sweden and Denmark has been more modest [4].

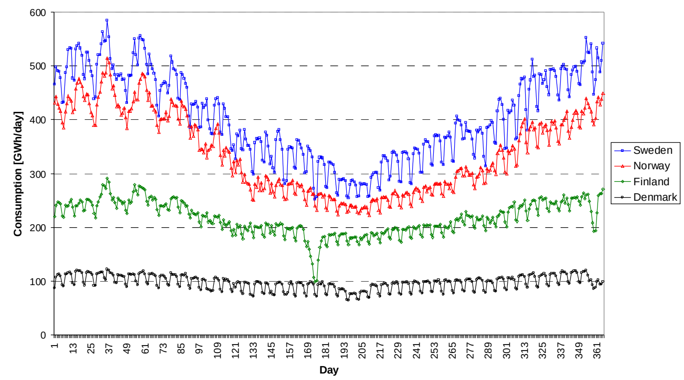

Fig. 2. Daily electricity consumption in Scandinavia, 2001. The annual figures are 147.3, 123.3, 79.1 and 35.5 TWh/year for Sweden, Norway, Finland and Denmark respectively. Source: [5].

C. The spot market

The spot market serves several purposes in the Nord Pool market area. First of all it distributes relevant neutral market information in terms of a transparent reference price for both the wholesale and retail markets. It also provides easy access to a physical market, and it creates the possibility of balancing portfolios close to time of operation. At the same time, the spot market in Scandinavia serves as a grid congestion management tool. Market splitting is used to relieve bottlenecks within Norway, and at the interconnections between the four countries. So called bidding areas may become separate price areas if the contractual flow of power between these bid areas exceeds the capacity allocated for spot contracts by the TSOs[2].

The spot market is in reality a day-ahead market, and it is based on bids for purchase and sale of hourly contracts and block contracts[3] that cover the 24 hours of the next day. The

[2] Within Sweden, Finland and Denmark, grid congestion is managed by counter-trade purchases based on bids from generators.

[3] A block contract bid has the same fixed price and volume for a number of hours of the day.

participants use specific bidding forms to submit their bids, and the spot prices are determined through auction trade with uniform price for each delivery hour. Table 1 shows when the different activities in the spot market take place. The *system price* is calculated by aggregating the supply and demand functions from all participants in the market for each individual hour, without taking transmission congestion into account (Fig. 3). Therefore, this price is also referred to as the unconstrained market price. It serves as reference for the contracts traded in the financial derivatives market. The system price prevails throughout the whole market area when there is no grid congestion between the bidding areas. However, several different area prices might occur in periods with bottlenecks in the system. 97 TWh was traded on Nord Pool's spot market in 2000, and that amounts to about 26% of total annual generation in the market area. Fig. 4 shows the system price in the spot market since 1993.

TABLE 1
TIME LINE OF ACTIVITIES IN NORD POOL'S SPOT MARKET

Time	*Activity*
11:00	Deadline for TSOs to submit their capacity allocations for the spot market
12:00	Deadline for submitting bids to the spot market for the following day
14:00	Calculation of system price and area prices finished and published
24:00	The contract period starts

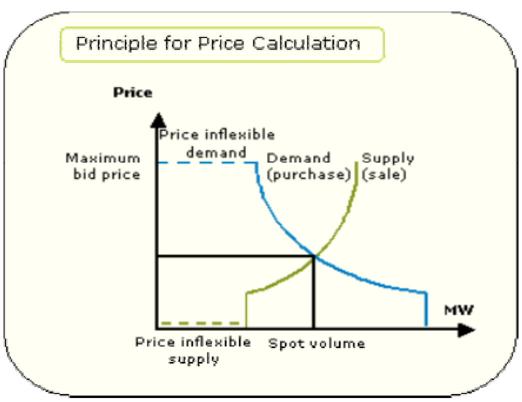

Fig. 3. The principle for calculation of the system price. Source: [2].

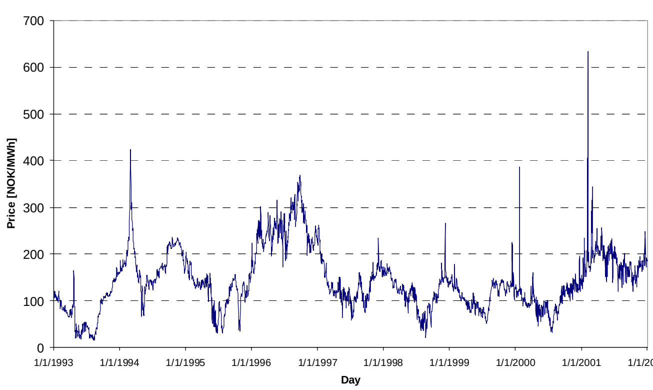

Fig. 4. System price in Nord Pool's spot market, 1993-2001. \$1 ≈ NOK 9. Source: [5].

Due to the long time span (up to 36 hours) between spot market price fixing and delivery, participants may need access to markets closer to real-time. In addition to the spot market Nord Pool therefore also operates a balancing market, called Elbas. In this market participants can trade one-hour contracts until two hours before delivery. The Elbas market is currently only available for the Swedish and Finish market areas, but there are plans to extend it to also include Norway and Denmark. Deviations from the scheduled power generation and consumption in the spot and Elbas market are traded in real-time markets operated by the TSOs. These markets are used to balance power generation to load in real-time, and is open to participants who can regulate their generation or load on short notice. The TSOs in the four countries apply slightly different rules for how the real-time prices are calculated and how power imbalances are cleared.

D. The financial derivatives market

Four types of contracts are traded in Nord Pool's financial derivatives market: base load futures, base load forwards, options and contracts for difference. All four contract types are pure financial contracts, i.e. there is no physical delivery. The contracts are settled using the system price in the spot market as a reference. Hence, the physical trade takes place in the spot market. The derivatives market has been designed to serve as risk management tools for generators and retailers that want to hedge their future profit. At the same time, the market also tries to attract speculators who seek to profit from the highly volatile electricity prices in order to increase the liquidity in the market. The current organization of the futures and forward markets are further described below[4].

The *futures market* contains day, week and block (consisting of 4 weeks) contracts. The selection of available contracts is updated dynamically for every week. Trading of the daily contracts starts every Friday for contracts with delivery the following week. The block contracts are split into week contracts four weeks before the delivery period starts, while new block contracts are issued one year before delivery. Consequently, the futures market has a time horizon of 8-12 months. The settlement of the futures contracts involves a daily mark-to-market settlement during the trading period, and a final settlement in the delivery period. The mark-to-market settlement covers gains and losses from the daily changes in the market price of the futures contracts. The final price-securing settlement covers the difference between the last closing price of the futures contract and the system price during the delivery period [3]. Fig. 5 gives an illustrative example of how the settlement procedure in the futures market works. By taking a position in the futures market, and making a corresponding trade in the spot market during the delivery week, a participant is completely hedged for the

[4] Minor modifications to the organization of the market have taken place several times since the start in Sept.-1995.

contractual volume. The settlement procedure therefore removes the basis risk from the electricity futures market[5]. Still, the participants cannot use the futures market to hedge against uncertainties concerning future load (volume risk).

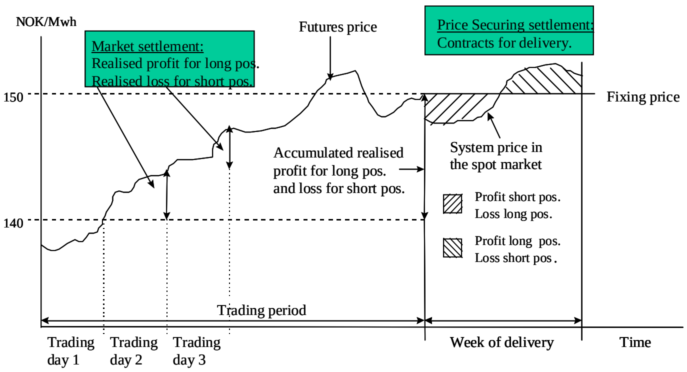

Fig. 5. Illustration of the settlement procedure for a futures contract traded at Nord Pool. The purchaser of the contract receives 10 NOK/MWh in the mark-to-market settlement. Deviations from the futures price on the last day of trading (the fixing price) is taken care of in the price-securing settlement, so that contract holder ends up with a final price equal to the initial price of the futures contract, when buying the contractual amount in the spot market. Source: [6].

The *forward market* facilitates hedging of positions further ahead into the future, and consists of season and year contracts. The year contracts are split into three season contracts[6] following specific rules, while the season contracts are not subject to further splitting. As opposed to the futures market, there is no mark-to-market settlement in the forward market. Therefore, the accumulated profit and loss during the trading period is not realized until the delivery period starts. This contributes to increase the liquidity for the long-term forward contracts, since no cash payment is required during the trading period. The additional settlement throughout the delivery period is, however, organized in the same way as for the futures contracts. The total volume traded in Nord Pool's derivatives market, including options and contracts for difference (CfDs), was 359 TWh in 2000. Estimates for the total volume of financial power contracts traded in Scandinavia in 2000 are between 1500 and 2000 TWh. This amounts to almost 5 times the annual physical power delivery, a figure that is similar to what is found in other commodities' markets ([1] and [3]).

III. Futures Pricing Theory

A. The relationship between spot and futures prices

There are two main views of the relationship between commodity spot and futures prices [8]. The first theory is closely linked to the cost and convenience of holding inventories, while the second theory applies a risk premium to derive a model for the relationship between short-term and long-term prices. Both theories are briefly presented below, followed by a discussion about their relevance in the electricity market.

Inventories play a crucial role in the price formation in markets for storable commodities [7] (also sometimes referred to as "cash and carry markets"). The theory of storage explains the difference between current spot prices and futures prices in terms of interest foregone in storing a commodity, warehousing costs and a convenience yield on inventory. The convenience yield can be regarded as a liquidity premium and represents the privilege of holding a unit of inventory, for instance to be able to meet unexpected demand. By assuming no possibilities for arbitrage between the spot and futures market one can easily derive the following formula [7] for the futures price ($F_{t,T}$) at time t for delivery at time $t+T$:

$$F_{t,T} = S_t e^{r_T} - \psi_T + k_T \qquad (1)$$

where S_t is the spot price of the commodity at time t, r_T is the risk-free interest rate for the period T, ψ_T is the convenience yield and k_T is the cost of physical storage over the holding period.

The second pricing theory explains the price of a futures contract in terms of the expected future spot price ($E_t(S_{t+T})$) and a corresponding risk premium, $p_T = -(r_T - i_T)$, for the commodity. i_T represent investor's appropriate discount rate for investing in the futures contract, while r_T still is the risk-free interest rate. The futures price can now be expressed as[7]:

$$F_{t,T} = E_t(S_{t+T})e^{(r_T - i_T)} = E_t(S_{t+T})e^{-p_T} \qquad (2)$$

One way of explaining the risk premium in (2) would be to look at the conditions within the specific commodity market. An overweight of risk-averse producers wanting to hedge their products in the futures market would probably result in futures prices lower than the expected future spot price ($p_T > 0$). The opposite relation ($p_T < 0$) would occur when the demand side is the most risk averse. The risk premium could also be traced back to the concepts of storage cost and convenience yield for the commodity. A second way of explaining the risk premium is to consider the futures contract as a financial asset and compare it to other assets in the stock market. Hence, if the return on the futures contract is positively correlated to the level of the stock market, holding the contract involves positive systematic risk and an expected return above the risk-free rate is required ($i_T > r_T$ or $p_T > 0$)[8]. It is worth noting that this price theory also can be

[5] Basis risk is usually present in other commodities markets and occurs when the futures contract does not match completely the exposure in the spot market. See [6] for a discussion about basis risk and the electricity market.

[6] Winter 1, Summer and Winter 2 cover week 1-16, 17-40 and 41-52.

[7] This formula is derived by looking at the net present value of purchasing a futures contract at time t, holding it until expiry, and selling the commodity in the spot market at time T. The net present value at time t of this investment equals $-F_{t,T}e^{-rT} + E_t(S_{t+T})e^{-iT}$, assuming that all transactions take place at time T, and that the investor earns the risk-free interest rate on the payment of the futures contract. See [12] for more details.

[8] See [6] and [9] for a further explanation of systematic risk and the futures market, and how the Capital Asset Pricing Model (CAPM) can be used for pricing futures contracts.

applied in markets where the commodity is perishable (also sometimes referred to as "price discovery markets"). The no arbitrage argument underlying (1) cannot be applied when it the commodity is non-storable, as there is no possibility of obtaining a risk-free position by buying the commodity in the spot market and selling in the futures market.

The futures market is said to exhibit *backwardation* when the expected spot price exceeds the futures price ($p_T > 0$). The term *contango* is used to describe the opposite condition when the futures price exceeds the expected future spot price ($p_T < 0$), as shown in Fig. 6.

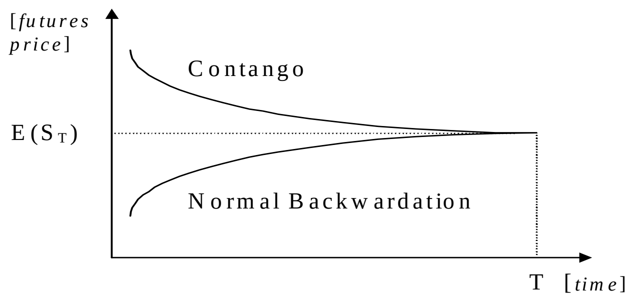

Fig. 6. Illustration of contango and normal backwardation in the futures market [9].

Before we analyse the electricity market in further detail it is worth taking a look at studies of futures markets for other commodities. *Pindyck (2001)* [7] studies the futures markets for petroleum products (crude oil, heating oil and gasoline) and finds support for the backwardation theory in these markets, particularly when the variance in the spot price is high. *Fama and French (1987)* [8] find marginal evidence of normal backwardation when 21 commodities (agriculture, wood, animal and metal products) are combined into portfolios but conclude that the evidence is not strong enough to resolve the existence of a nonzero risk premium. *Bodie and Rosansky (1980)* [10] studied risk and return in commodities futures for all major commodities traded in the United States between 1950 and 1976. They found that the mean rate of return on a portfolio consisting of their selected commodity futures contracts in the 27 years period was well in excess of the average risk free rate. Their findings lend support to the normal backwardation hypothesis. *Chang (1985)* [11] also finds evidence of normal backwardation for wheat, corn, and soybeans over the time interval from 1951 to 1980. In sum, the empirical research carried out on commodities futures prices finds evidence to support normal backwardation for some products. The risk premium may be time varying, but is not related to the general level of the stock market.

B. The electricity market

The lack of direct storage possibilities for electricity, and the physical requirement of constant match of supply and demand, makes the electricity market somewhat different from most other commodities markets. It can be argued that power generators can "store" the commodity, for instance as water reservoirs for hydropower plants or as coal for thermal power plants. However, it is not possible to buy the electricity today and store it for future sales, at least not in substantial amounts[9]. The argument about no arbitrage that (1) is based on is therefore not applicable to the conditions in the electricity market, which must be characterised as a price discovery market.

It is more interesting to look at the possible existence and motivation for a risk premium in the electricity futures market, and to what degree (2) can be used to characterise the market. A risk premium could arise if either the number of participants on the supply side differs substantially from the number on the demand side, or if the degree of risk averseness varies considerably between the two sides. Most of the companies participating in the market are both generators and load serving entities. Hence, there is no reason to believe that the futures market is biased towards any of the two sides in terms of the number of participants. However, if we look at the flexibility of adjusting the quantity on the supply and demand side there is a significant difference. The generators can control parts of their generation on a very short notice[10]. This allows them to take advantage of the price fluctuations that occur in the market, by adjusting their generation. Therefore, it does not necessarily make sense to fix the price in the futures market for all of the planned future generation. The flexibility in generation creates a possibility of profiting from the price peaks in the day-ahead spot market, and possibly also in the markets even closer to real time. The situation is different on the demand side, where the load serving entities have very limited ability to adjust the demand according to the price. Hence, it makes sense to lock in as much as possible of expected future demand in the futures market, given that the participants on the demand side are risk averse. In this sense the electricity market deviates from most other markets, where the demand side can stock up the commodity for some period ahead in time, and in that sense use the stock to adjust to fluctuating prices instead of the futures market. If the difference in flexibility on the demand and supply leads to an excess demand for futures contracts, this would translate into a negative risk premium in (2), i.e. $p_T < 0$. The futures price would, in turn, exceed the expected future spot price, and on average one would experience negative returns from holding futures contracts.

A study of Nord Pool's futures market was carried out in 1997 [6]. Hypothesis testing was used to analyse the returns

[9] One could of course argue that consumers have the possibility to store electricity in batteries, but this option is not available in large scale. Energy systems in the future could possibly include large-scale storage capacity, e.g. in hydrogen reservoirs. On the supply side there is a limited amount of pumped hydro storage in the system today. However, all these storage options involve substantial losses and costs, and we do not see them as possible tools for making arbitrage from the difference between spot and futures prices.

[10] The fast controllable part of the power generation in the Scandinavian system is particularly big, due to the large share of hydropower in the system.

on futures contracts over various holding periods, and also on portfolios of futures contracts. The null hypothesis was that the futures price equals the expected future spot price (p_T = 0). The analysis did not find sufficient evidence to reject the hypothesis, although the results showed that the returns on the futures contracts on average were below the risk free rate (i.e. contango; $p_T < 0$). The study also looked at the relations between the returns in the futures market and in the stock market, and found no significant evidence for using the systematic risk in the futures market as an explanatory factor for the observed futures prices. The reliability of the analysis in 1997 was low, due to the short time period the market had been in operation (2 years). It is therefore of interest to revisit the problem and carry out a new analysis of the market with data that now covers more than 6 years.

IV. Empirical Analysis

In the analysis of the historical data we first present some general graphs and figures to look for obvious trends and relations in the observed spot and futures prices. We then turn to analyse the relationship between the long- and short-term prices in more detail using the framework presented above.

A. The data

The analysis is based on historical spot and futures prices from Nord Pool covering the period from the opening of the futures market in September 1995 until the end of 2001. The futures data contained the closing price for each day of trading for all futures contracts traded. Although we had futures data for each day of trading, only the closing price on the last day of trading for each week was used in our analysis. The spot data used in the analysis contained spot prices for each hour of each day of the year. To consolidate the data, the spot price for a particular day was calculated by averaging the spot price for each hour of the day. To further consolidate the data, the daily spot prices are averaged over the week to get an average weekly spot price. Although we do not use the hourly spot price data explicitly, the average daily and weekly values are functions of the hourly spot price.

B. Spot prices

Fig. 7 shows the daily spot prices for all six years from 1996 to 2001. There is a lot of similarity in the spot prices for the years from 1997 to 2000. Although the prices vary, the shape of the graphs is similar in many respects. We clearly see the seasonal pattern with low prices during the summer when the demand is low, and high prices in the winter when demand is high (compare to demand in Fig. 2). The level of the spot prices in 1996 is much higher. The prices remain high throughout the summer, and increase even further in the fall. This is due to very low precipitation and inflow to the water reservoirs that year. The prices come back down again in the winter of 1997. Also in 2001 the prices are higher than what we see from 1997 to 2000. This can again be explained from lower inflow to the reservoirs. These observations illustrate how dependent the prices are upon the hydropower generation in the region. Another observations is that the price peaks in the beginning of 2001 occurs at the same time as the peak values for demand in the system. Hence, the current system runs into capacity problems on cold winter days with high demand. Actually, hourly prices above 1500 NOK/MWh occurred four times in the two first weeks of February 2001.

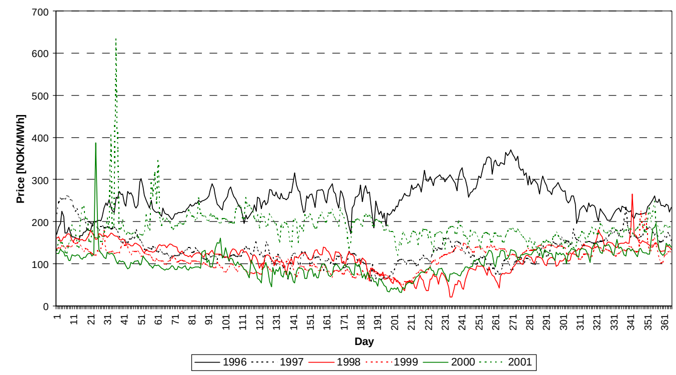

Fig. 7. Average daily prices in Nord Pool's spot market for years 1996-2001. Source: [5].

C. Futures prices

Fig. 8 shows prices for weekly futures contracts at the last day of trading, for delivery the following week. As can be seen from the graph, the futures prices follow the same trend as the spot prices, as we would expect for futures contracts with short time to delivery. It is reasonable to believe that the market expects the prices for the next week, as reflected in the futures prices, to resemble the spot price for the current week. The daily price fluctuations do not appear for the futures contracts though, since the prices shown are for weekly contracts.

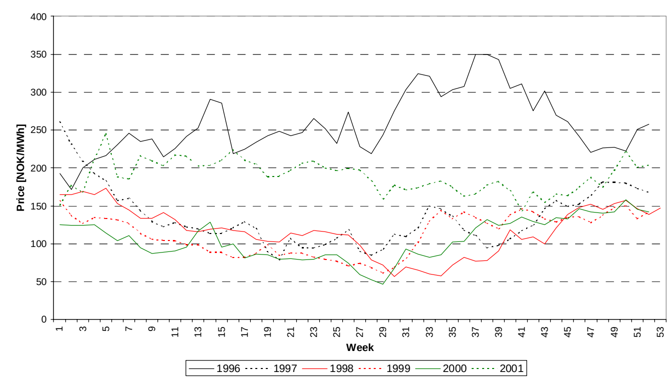

Fig. 8. Prices of a futures contract at the end of week t, for delivery week t+1, 1996 to 2001. Source: [5].

To further analyze the data, we compared the futures prices one week and one year ahead to the actual spot price in the delivery period (Fig. 9). For instance, for 1996 we recorded the futures prices with delivery one year ahead, in 1997, and plotted it together with the weekly spot prices for 1997. The futures price one week ahead is presented in the same way. We repeated this process for 1997 through 2000. As can be seen in the figure, the futures price one year ahead do not correspond very well with the actual spot prices in the delivery period. Looking closely at the graph, we see that both the futures and spot prices show a seasonal pattern. The long-term contracts with delivery one year ahead are season contracts[11], and the distinct jumps in this futures price curve occurs at changes between contracts (e.g. from Winter 1 to Summer). On average the futures price seems to overestimate the actual spot price in this period. However, in 2001, the futures price underestimates the actual spot price. There are several points of intersection between the two graphs. At these points, the futures price actually equaled the actual spot price for that week. In general however, the one-year ahead futures prices' ability to predict the spot prices is rather low, and there are large differences between the futures and spot prices in most of the period. For the contracts with delivery one week ahead, the fit is naturally much better, due to the much shorter time to delivery.

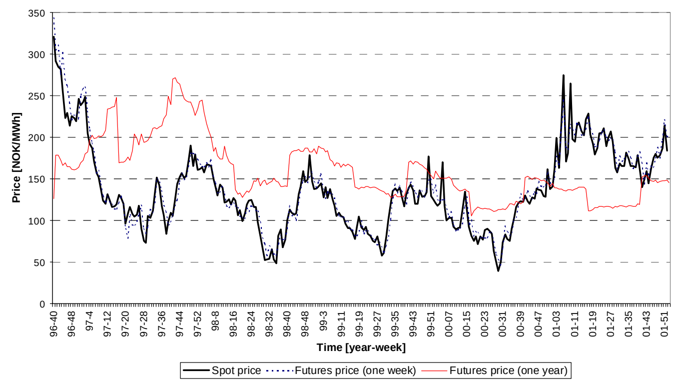

Fig. 9. Futures prices for last trading day before delivery and 52 weeks before delivery, compared to spot price in delivery week. Weekly values. Source: [5].

D. The risk premium in the futures market

We now try to estimate the observed risk premium in the Scandinavian electricity market based on the data presented above. From (2) we derive the following estimate for the risk premium, p_t, of a futures contract with holding period T:

$$p_T = \ln \frac{E_t(S_{t+T})}{F_{t,T}} \quad \rightarrow \quad \hat{p}_T = \ln \frac{F_{t+T-1,1}}{F_{t,T}} \qquad (3)$$

where $F_{t+T-1,1}$ is the price at the last day of trading for the futures contract with delivery in week $t+T$, which in turn is a good approximation for the spot price in the delivery week. In other words, we assume that the market participants in the long run have an unbiased prediction of the future spot price[12]. We calculated the estimate for the risk premium for futures contracts with 1 week, 4 weeks, ½ year and 1 year holding periods, assuming that the contracts are held until expiry. In our calculations we used all historical data that was accessible from the futures market. The results are show in Table 2. We see that the average risk premium is negative for all holding periods. The magnitude and standard deviation of the premium increases naturally with the length of the holding period. The p-values for the z-test show that we can reject the hypothesis that the futures price equals the expected future spot price with high significance for all holding periods. This is confirmed by the negative values for both the upper and lower limits of the 99 % confidence intervals for the risk premium. Our findings therefore lend support to the contango hypothesis for the electricity futures market in Scandinavia, i.e. there is a negative risk premium for holding a futures contract.

TABLE 2

STATISTICAL ANALYSIS OF THE RISK PREMIUM ESTIMATE, $\hat{p}_T$, FOR 1, 4, 26 AND 52 WEEKS' HOLDING PERIOD OF THE FUTURES CONTRACT

	1 week	4 weeks	26 weeks	52 weeks
Sample size	326	323	300	275
Mean	-0.015	-0.035	-0.085	-0.183
St. deviation	0.101	0.187	0.432	0.399
p-value, z-test[1]	0.9968	0.9996	0.9997	1.0000
CFI[2], up-limit	-0.001	-0.008	-0.020	-0.122
CFI[2], lo-limit	-0.030	-0.062	-0.149	-0.245

[1]The z-test tests for $p_T < 0$, given $p_T = 0$ as null hypothesis.

[2]CFI is the 99% confidence interval.

E. Discussion

The negative risk premium that we find in the futures price data is in line with our observation of the difference in flexibility on the supply and demand side of the electricity market, leaving the demand side with a higher incentive for hedging in futures contracts. However, there are most likely also other factors that can contribute to explain our findings. To further examine possible explanations we therefore look at the main source of power in the Scandinavian system – namely hydropower. As stated in section II the precipitation, and thereby the water level of the reservoirs, has a high degree of influence on the short-term prices of electricity in Scandinavia. However, the expectations about the spot prices far ahead into the future are probably based on assumptions of average reservoir levels. To investigate this further we plotted the average reservoir level in Norway along with the actual reservoir level in Fig. 10[13]. We also add the spot price and the one year ahead futures price. Looking closely at the graph, we see that the actual reservoir level is higher than the average for most of the period from 1998 through early 2001. High reservoir levels results in low spot prices, and during this period the spot price was below the futures price. In 2001, when the actual reservoir level falls below the average, we notice a sharp increase in the spot price. During most of 2001, the actual reservoir level is below the average and the

[11] Nord Pool stopped the trading of seasonal futures contracts (with one year or more to delivery) after 1999, and replaced them with seasonal forward contracts. The one-year ahead futures prices with delivery in 2001 (traded in 2000) are therefore actually forward contract prices.

[12] Note that the estimate of p_T equals the return (in excess of the risk-free rate) on a futures contract purchased at time t and sold at the last day of trading (in week $t+T-1$). It also equals the return on a contract that is held throughout delivery, if the contractual amount is purchased in the spot market during the week of delivery. This is due to the price securing settlement in the futures market, as described in section II.

[13] More than 60% of the hydropower capacity in the current Nord Pool area is installed in Norway.

spot price is higher then the futures. Thus, the analysis of the inflow is helpful in explaining the deviation between the spot and futures prices. However, the deviations in reservoir levels can only be used as an explanatory factor for the behavior of futures contracts with long maturity. The change in reservoir level is very limited in the near future. Therefore, it cannot contribute to explain the negative risk premiums for the contracts with only 1 and 4 weeks to delivery.

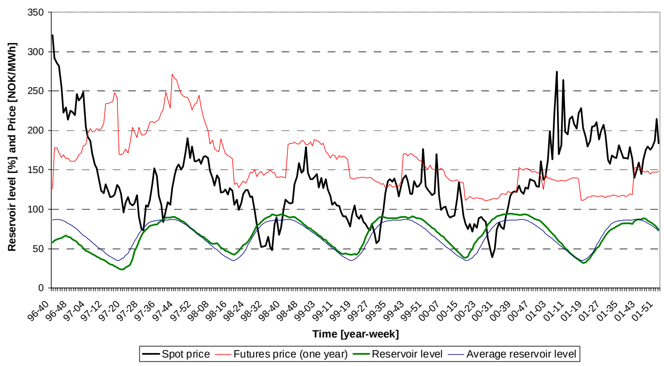

Fig. 10. Spot price, futures price one year ahead, average reservoir level (1990-2000) and actual reservoir level for Norway. Source: [5] and [13].

It is important to treat the results in this analysis with caution, as the data period is still limited to 6 years. A longer time period is usually used in similar analyses of futures prices for other commodities. The results for the z-test and confidence intervals in Table 2 also rely on a strong assumption of normality in the observed risk premiums. However, the existence of a negative risk premium can be stated with considerably higher significance than what was the case after the study in 1997.

V. Conclusion and Future Work

Spot and futures markets for electricity have existed in the restructured Scandinavian electricity system for more than 6 years. The considerable history of prices makes it interesting to study the relationship between long- and short-term electricity prices in this market. Our analysis shows that the futures prices on average have been above the spot prices in the actual week of delivery, and we find significant evidence for a negative risk premium in the electricity futures market. Our results contradict to the findings in most other commodities futures markets, where the risk premium tends to be zero or positive. Physical factors like unexpected precipitation can contribute to explain parts of the observations. However, we also identify the difference in flexibility between the supply and demand sides as a possible explanation for the negative risk premium. In the future we will try to develop models that are better at capturing the dynamics between short and long-term prices in the electricity market. Our aim in the long run is to model how these prices influence the investments in new technology on the supply and demand side in the system, using methods for model aggregation from large-scale dynamic systems theory.

VI. Acknowledgements

The authors would like to acknowledge Jason Black at the MIT Laboratory for Energy and the Environment for useful discussions in the preparation of the paper. The authors also acknowledge Nord Pool for providing the necessary historical data for the analysis.

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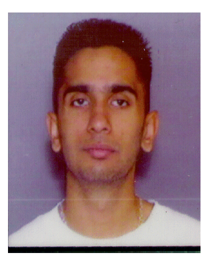
VIII. Biographies

Audun Botterud graduated from the Norwegian University of Science and Technolgy (NTNU), Trondheim, Norway, in 1997. He then worked for 2 years at SINTEF Energy Research with models for hydropower scheduling and risk management, before starting on a PhD programme at NTNU in 2000. He is now visiting MIT Laboratory for Energy and the Environment. His current research interest is in long-term modelling and planning of power systems.



Arnob K. Bhattacharyya will be graduating with his Masters in Electrical Engineering/Computer Science from the Massachusetts Institute of Technology (MIT), Cambridge MA, in 2003. He plans to concentrate in the area of financial modeling in power markets. He will be working at UBS Warburg this summer in the Equity Sales & Trading Department.

Dr. Marija Ilic has been a Senior Research Scientist in the Department of Electrical Engineering and Computer Science at MIT since 1987. Her interest is in control and design of large-scale systems. She conducts research and teaches graduate courses in the area of electric power systems. Prior to her years at MIT, Dr. Ilic was a tenured faculty member at the University of Illinois, Urbana-Champaign. Dr. Ilic received her M.Sc. and D.Sc. degrees in Systems Science and Mathematics from Washington University in St. Louis.

APPENDIX B PAPER 2

“Alternatives for sustainable energy supply in Scandinavia”

Paper presented at the 2002 Annual Meeting for the Alliance for Global Sustainability World Student Community (AGS WSC), San Jose – Costa Rica, March 2002.

ALTERNATIVES FOR SUSTAINABLE ENERGY SUPPLY IN SCANDINAVIA

Audun Botterud[1]
Norwegian University of Science and Technology (NTNU)
N-7491 Trondheim, Norway
audun.botterud@energy.sintef.no
[1] Visiting MIT Laboratory for Energy and the Environment, Sept.01-Dec.02

Abstract – This paper presents an ongoing research project where the objective is to inform decision-makers about the trade-offs between costs and environmental performance when deciding how to meet the future demand for energy in Scandinavia. The paper starts with an overview of the current stationary energy supply within Norway, Sweden and Denmark. A short overview of future technological energy supply options for the respective countries is also presented. The main part of the paper is devoted to describing the framework we use in our analysis. The trend of liberalisation in energy markets, and thereby less centralised planning, gives rise to new planning challenges that require a new set of analytical tools. The conditions in the Scandinavian energy system, with a variety of energy resources, close links between the countries' electric power networks and a high degree of deregulation in the energy markets, makes the region particularly interesting for testing and applying such tools.

Keywords: ***Energy planning, decision support, multi-attribute trade-off analysis, power and energy system analysis, simulations, scenarios, Scandinavia***

1 INTRODUCTION

The increasing use of energy in the world is one of the major threats against a sustainable development for the earth's environment. As more attention is paid to the negative environmental consequences of our increased energy use, the objectives in energy system planning changes. The aim is no longer simply to meet the projected future energy demand for the lowest possible cost. The environmental consequences of different supply alternatives have to be given more careful attention. Predicting the environmental impacts from new energy-related investments is in its own a very demanding task, considering the wide range of pollutants occurring from different forms of energy conversion. The long lifetime of many energy system constructions contribute to increase the uncertainty of such environmental assessments. At the same time, there is a global trend of deregulation and liberalisation of energy markets. As a result, planning decisions are taken at more distributed levels in the system, and the authorities are left with less direct influence on what energy supply solutions are chosen for the future. Considering all the technological, social, economic, environmental and political factors that influence the development of the energy system, we realise that long-term energy system planning becomes an extremely complex task. Consequently, results from advanced simulation models are frequently used as decision support in the planning of local and regional energy systems.

The Scandinavian region faces some of the same challenges as many other countries when it comes to energy and environmental planning. New investments are required to meet the energy demand, and there are a number of technological alternatives to choose from. At the same time the countries are aiming at reducing emissions of greenhouse gases in order to meet their limits in the Kyoto treaty. Hydropower has traditionally played an important role in the energy supply in Norway and Sweden, but there are only limited resources remaining for new hydro projects. Other options must therefore be considered. Sweden also has a large fraction of nuclear power generation, but is planning to shut down these plants. Denmark has traditionally based its power generation on coal, but is now switching towards gas, biomass and wind. The power market in Scandinavia was one of the first to be deregulated, and there are close links between the power networks in each of the countries. The various energy resources within Scandinavia, the well functioning deregulated power market, and also the limited size of the region makes it well suited for testing of analytical tools for decision support in energy and environmental planning. Analytical tools applicable to this region should also be applicable to most other regions of the world.

The current and future energy supply in Norway, Sweden and Denmark is subject for a new research project where NTNU (Norway), MIT (USA) and Chalmers (Sweden) are the involved university participants. In this project we are going to apply scenario analysis to assess and illustrate the trade-offs between cost and environmental performance for a number of technological alternatives. Our aim is to take both supply and demand side options equally into account, to avoid the bias towards supply side solutions that usually occurs in similar studies. Since the project was recently started we do not yet have any firm conclusions to present. The aim of this paper is therefore to give a presentation of the historical energy supply within the three countries and also describe a set of future supply alternatives. Furthermore, the methodological framework within which we are planning to carry out our analysis is outlined. The preparation of the scenario results for discussion with stakeholders from authorities, energy companies, NGO's and others is also discussed.

2 CURRENT ENERGY SUPPLY

Some of the main characteristics of the current and historical energy supply and demand within Norway, Sweden and Denmark are presented in this section. The purpose is to highlight the differences in the energy systems between the three countries.

2.1 Norway

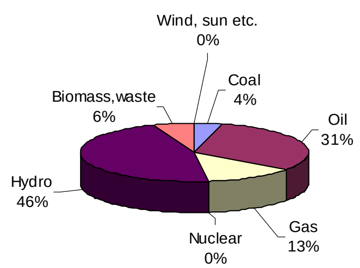


Figure 1: Total primary energy supply by source in Norway (2000), in total 26.27 mtoe or 230 GJ/capita. Source: IEA [1].

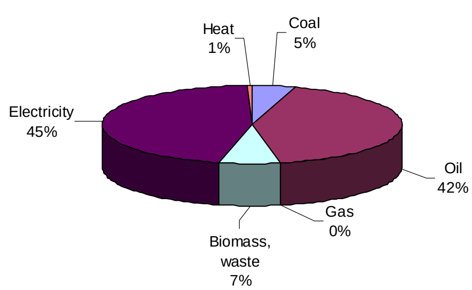


Figure 2: Total final energy consumption by energy carrier in Norway (1999), in total 20.33 mtoe or 191 GJ/capita. Source: IEA [1].

Figure 1 shows that hydropower is the primary source of energy in Norway, followed by oil and gas. It is worth noting that even if Norway is a major exporter of oil and natural gas to continental Europe, the infrastructure and end-use of gas on mainland Norway is very limited so far. The use of gas is mainly for own purposes within the oil and gas sector. Renewable energy resources like wind and waves do not contribute considerably so far, while biomass and waste delivers a substantial amount of energy. When looking at the distribution between the energy carriers (Figure 2) we see that electricity plays a major role in the Norwegian energy system, delivering 45 % of the final end-use of energy. This is related to the long history of abundant hydro power supply in Norway, which has been accompanied by huge investments in electricity based technology, as e.g. ovens for direct electric heating in most Norwegian households. When looking at the distribution of energy supply between the different sectors (Figure 3), we can see that the amount that goes to industrial purposes has been relatively stable the last 20 years, while the consumption in service, residential and transport sectors increased considerably.

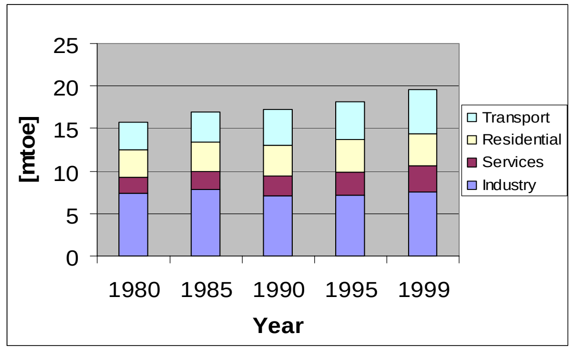


Figure 3: Total final energy consumption by sector in Norway (1980-1999). Source: IEA [1].

2.2 Sweden

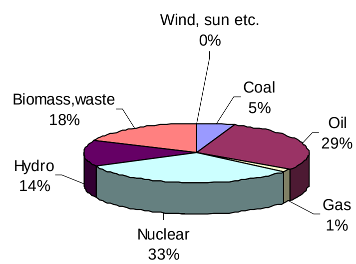


Figure 4: Total primary energy supply by source in Sweden (2000), in total 46.79 mtoe or 223 GJ/capita. Source: IEA [1].

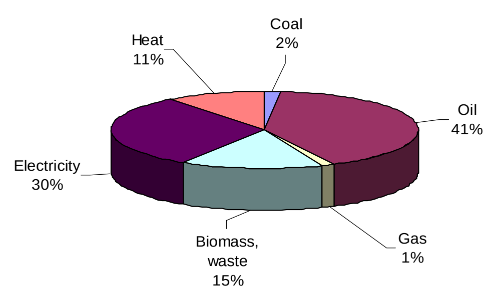


Figure 5: Total final energy consumption by energy carrier in Sweden (1999), in total 35.42 mtoe or 167 GJ/capita. Source: IEA [1].

Figure 4 shows that nuclear and oil are the most important sources of energy in Sweden, while hydropower, biomass and waste also makes a substantial contribution. Sweden has no resources of natural gas, and is not connected to any gas pipeline, so the use of gas is therefore low. The use of new renewable sources like wind and sun is also very limited so far in Sweden. When looking at the distribution between energy carriers (Figure 5) we see that energy as heat has a much higher share of the end-use delivery than in Norway. This is mainly due to the more widespread use of district heating in Sweden. Figure 6 shows that the total final energy consumption decreased during the 80's and then increased again to the 1980 level in the 90's. The energy use in the industry sector has also been stable in Sweden, while the use in service and transport sectors increased. The consumption in the residential sector is actually lower in 1999 than in 1980.

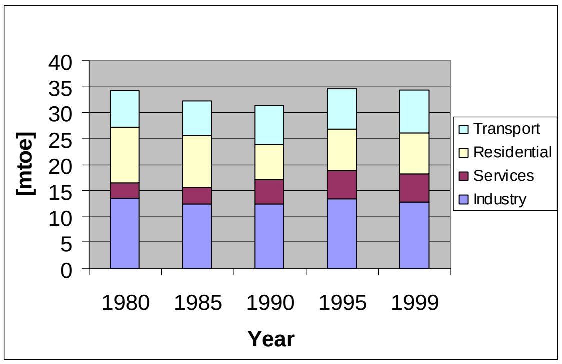


Figure 6: Total final energy consumption by sector in Sweden (1980-1999). Source: IEA [1].

2.3 Denmark

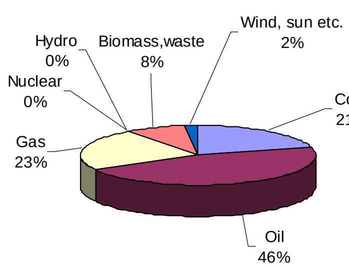


Figure 7: Total primary energy supply by source in Denmark (2000), in total 19.25 mtoe or 152 GJ/capita. Source: IEA [1].

The energy supply in Denmark is to a higher degree based on fossil fuels (oil, gas and coal), since Denmark has no hydropower resources and has chosen not to invest in nuclear power (Figure 7). However, there is an increasing focus on new renewable sources in Denmark, and it is worth noting that particularly wind power is starting to contribute to the total energy supply. Electricity as an energy carrier plays a much less important role than in Norway and Sweden. This is mainly because of the extensive district heating and gas networks that are present in Denmark (Figure 8). Figure 9 shows that the total final energy consumption fell in the mid 80's, but is now back to the same level as in 1980. The transport sector is the only one that has increased its energy use consistently for each 5-years period since 1980.

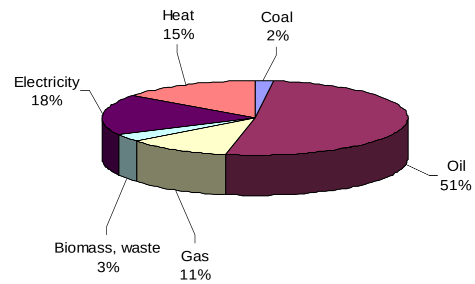


Figure 8: Total final energy consumption by energy carrier in Denmark (1999), in total 15.63 mtoe or 123 GJ/capita. Source: IEA [1].

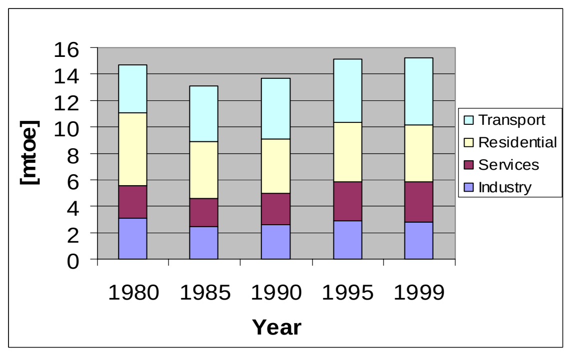


Figure 9: Total final energy consumption by sector in Denmark (1980-1999). Source: IEA [1].

2.4 The common electric power market

There are close connections between the electric power systems in Norway, Sweden and Denmark, both in terms of physical tie lines and a common organisation of the power markets. Several power lines are crossing the border between Norway and Sweden. There are also sea cables connecting the Norwegian and Swedish power systems to Denmark. All the three countries participate in the Nordic power exchange, Nordpool. The power exchange organises the physical day-ahead market for electricity, and also offers a number of longer term financial contracts for hedging and speculation in the power market. The process of deregulation started in Norway in 1991, and was then followed by Sweden in 1996 and later Denmark in 1999. Scandinavia is therefore one of the regions in the world with the longest experience with deregulated power markets. In fact, Nordpool became the first international commodity exchange for trading of electric power when Sweden became a member in 1996[1].

The power generation in the three countries have different characteristics (Table 1). In Norway, nearly all electricity is generated from hydropower. Sweden uses a combination of hydropower, nuclear power, and conventional thermal power. Hydropower stations are located mainly in northern areas, whereas thermal power prevails in the south. Denmark relies mainly on conventional thermal power, but wind power is providing an increasing part of the demand for electricity. From the table we can also see that the demand has increased considerably in Norway during the 90's, while the increase is much more modest in Sweden and Denmark.

Table 1: Electricity generation by source and gross consumption for Norway, Sweden and Denmark (1990 and 2000) in TWh. Source: IEA [1] and Nordel [2].

Source	*Norway*		*Sweden*		*Denmark*	
	'90	*'00*	*'90*	*'00*	*'90*	*'00*
Coal	0.2	0.2	1.8	3.3	23.3	16.9
Oil	0.0	0.0	1.2	2.0	1.1	4.4
Gas	0	0.3	0.4	0.3	0.6	8.8
Biom./Waste	0.2	0.3	1.9	3.7	0.2	1.8
Nuclear	0	0	68.2	57.0	0	0
Wind, sun	0	0.0	0.0	0.4	0.6	4.2
Hydro	121.2	141.6	72.5	78.6	0.0	0.0
Total	**121.6**	**142.4**	**146.0**	**145.3**	**25.7**	**36.2**
Consumption	105.7	123.8	144.2	146.6	32.8	34.9

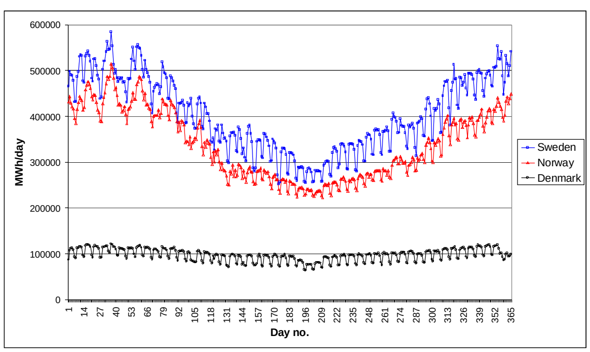


Figure 10: Daily electricity consumption in Norway, Sweden and Denmark 2001. Source: Nordpool [3].

The seasonal variation in electricity demand shows that the consumption in Norway and Sweden follows a similar pattern (Figure 10). This is because both countries use a substantial amount of electricity for heating purposes. In Denmark, where most of the heating demand is met by gas and district heating networks, the variation in electricity consumption over the year is much lower. The demand also varies over the day, according to the activity level in the countries. When looking at the variation over the day, it follows more or less the same pattern in the three countries.

The electricity supply system must be able to take care of the seasonal and daily variation in demand. The output from hydropower station is easy and fast to regulate, while thermal plants are slower with higher costs involved in changing the power output. There are therefore mutual benefits from exchanging power between the countries, and a substantial trade also takes place. In general power is exported from the hydro areas in Norway and Sweden to Denmark and continental Europe during daytime peak hours. In the nights, when the load is lower, the power flow goes the other way. As a result, the thermal power plants can operate with less fluctuation in their output. Another advantage of the exchange opportunity given by the transmission lines is that the hydropower dependent regions are less exposed to power shortages during longer periods of low inflow.

3 FUTURE ALTERNATIVES

A systematic and detailed study of the future energy resources is not yet carried out, as this project is still in its initial phase. Resource and technology assessments have been accomplished in a number of previous studies, so there are several sources of information available. However, the focus has usually been on the large-scale supply side solutions, so that we will need to put more work into estimating the possible contributions from distributed generation and demand-side technologies. The alternatives that we currently see as most likely to contribute considerably to change the future energy supply within the three countries are briefly listed below.

Large-scale supply options:

- Increased use of *gas*, as fuel for new power plants, but also for direct end-use purposes. In Norway and Sweden this would require large investments in pipelines and gas distribution networks. Environmental benefits arise if the new gas consumption replaces more polluting sources like coal and oil. Gas power plants with CO_2-sequestration are also on the energy agenda, particularly in Norway.
- *Biomass* from wood, waste or energy crops can also be used as fuel in power and heat plants.
- Large-scale *wind* parks are being planned in all the three countries. There are still huge wind resources available onshore in Norway and Sweden, while Denmark is focusing more on offshore windmills due to the high penetration of windmills on the land. However, the

[1] Finland also deregulated its power market and became a member of Nordpool in 1998. However, Finland is left out of this analysis.

economic attractiveness is limited for parts of the wind resources, due to the long distance to transmission lines and areas of demand.

- *Hydrogen* technology could possibly also start to contribute towards the end of the 30 years period we consider. However, considerable technological development has to take place before hydrogen technology can become a commercial alternative. A future "hydrogen society" also requires fundamental changes in the energy infrastructure system.

Small-scale options:

- *Distributed generation* of electricity is likely to play a more important role in the future energy system. Several sources of energy could be applied, from small windmills to hydrogen. If fuel cells are applied one could possibly generate both heat and electricity.
- *Geothermal energy* is an interesting option for heat supply in buildings of all sizes. Heat pump technology is improving quickly, making this into a more attractive alternative for end-users.
- *Energy conservation* is maybe the most important option to take into consideration. Conservation technologies ranges from increased insulation to better building design.
- The s*olar collector* is another technology that could contribute considerably to the heat supply in new buildings.

4 FRAMEWORK OF ANALYSIS

4.1 System boundary

The electric power system is considered as the core of the analysis in our scenario study. However, we also want to take other types of stationary energy use into account, like for instance district heating and direct end-use of gas. In order to compare the results from different simulation scenarios in a consistent way, we need to clearly specify our system boundary. One approach would be to look at the energy supply that is currently served by electricity, and constrain the scenarios to only include future projections of this part of the stationary energy supply. Alternative energy carriers could still come into account in the scenarios by replacing parts of the electricity demand. A more fundamental approach would be to look at the total stationary demand for energy, divided into end-use groups like light, mechanical work, heat etc. This would require the use of either a comprehensive energy system model like the MARKAL[2] model, or a number of models in addition to the electric power market model, in order to take all costs and emissions into account. All available energy carriers would have to be assessed with this approach. It is also possible to choose something in between, e.g. looking at the part of stationary energy use that is currently served by certain energy carriers, like e.g. electricity, gas and heat, as illustrated in Figure 11. We choose this approach in our scenario analysis, with the possibility of extending the system boundary in later stages of the project.

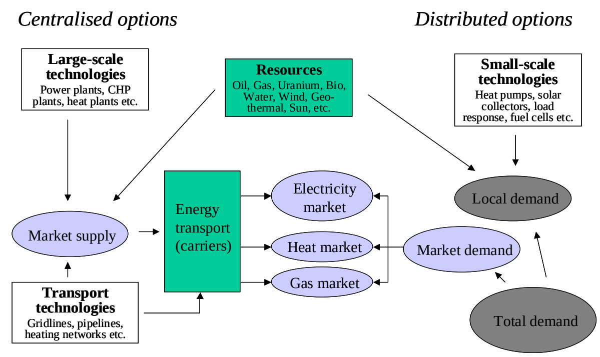


Figure 11: General framework of analysis, with centralised and distributed energy supply options. The part of the total initial energy demand met by the electricity, heat and gas carriers (market demand) defines the system boundary.

Figure 11 illustrates that the energy resources could go either through the supply side or directly to the demand side of the market, depending on whether or not the technologies are connected to energy transport systems before reaching the end-user. The proportion of energy demand met by the centralised large-scale technologies, through local or regional energy markets, depend on the current and future technology mix, the end-user's preferences, and the resulting energy prices. The mix of technologies changes as new investments are carried out at different places in the system. One possible scenario is for instance that parts of the demand that is met by the centralised large-scale technologies today will be met by distributed local technologies in the future. The participants on the supply and demand sides might have different motivation for investing in new technologies. Large-scale investments in new generation and transportation infrastructure are likely to be based on pure economic arguments in the liberalised market. The expected profit of the investments is usually less important for decisions on the demand side, particularly for small-scale consumers. Authorities will therefore need to use a set of different incentives to trigger the desired investments in the energy system. Investments on both sides contribute to alter the characteristics and prices in the electricity, heat and gas markets. In the first phase of the project we focus our analytical analysis on the economic and technological constraints in the electricity market. The

[2] MARket ALlocation model – a demand driven energy system model for optimization of stationary energy supply within a country or region. This model is used for planning purposes within several countries.

conditions in the heat and gas markets are also included in the analysis, but with less detail.

4.2 Multi-attribute trade-off analysis and stakeholder intervention

Multi-attribute trade-off analysis will be applied to assess different technological energy system solutions. Figure 12 describes the major steps in the approach. First we need to define the set of attributes that we want to use in the comparison of the alternatives. The attributes include both cost and environmental figures. In the initial phase of the project we only consider direct emissions from the energy conversion. However, in the long run we want to take into account the whole life-cycle impact of various alternatives. Multiple stakeholders in the society are affected by the choice of energy system. It is therefore crucial for the credibility of the project to establish a dialogue with representatives from authorities, energy companies, NGO's and others. Consequently, a stakeholder group is chosen in order to continuously give feedback on the work within the project. We are planning to have regular meetings with the stakeholder group, and input from the group is of importance already in the first step of identifying issues and attributes.

In the second step we define a set of alternatives that includes the technological options that we with today's knowledge mean could occur within a time horizon of 30 years into the future. We are aiming at putting equal emphasis on the demand and supply side technologies in our approach, to avoid the typical supply side bias that is usually present in similar studies. We also need to make assumptions about a number of uncertain non-technological factors that influence the operation of the energy system. These factors could include assumptions about general demand growth, fuel prices and the cost and performance of new technologies. By organising the uncertainties into a set of futures, we can carry out sensitivity analysis for the technological alternatives, in order to assess the risk and sensitivities involved in the various investment strategies. Each combination of a technological strategy and a future form one scenario. Computational models are then applied to analyse all the scenarios from a cost and environmental point of view, using the selected attributes from step 1. The results from the simulations can be expressed in so-called trade-off graphs, as shown in Figure 12. This visualisation of the results is useful in the process of communicating the results to the stakeholder group and also to public at large.

The results from the scenarios are then analysed, in order to find better technological strategies compared to the ones initially selected. This is step 3 in the figure. The choice of attributes could also be revised at the same time, following discussions with the stakeholder group. We expect a number of iterations with scenario runs and stakeholder meetings before reaching final consensus on what to include in the analysis. Changes in the selection of strategies, uncertainties and attributes are accompanied with further development of modelling tools and refinement of the input data base. In the end, by analysing the trade-offs between all the final attributes, our ultimate goal is to reach consensus on a set of preferable strategies within the stakeholder group (step 4).

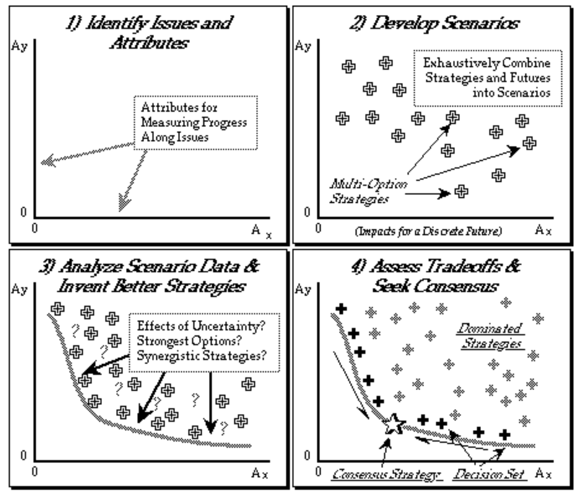


Figure 12: The four basic steps of performing multi-attribute trade-off analysis in a multi-stakeholder policy debate. Source: Connors, S.R. [4].

One of the important characteristics of the multi-attribute trade-off analysis approach is that we do not end up with only one optimal solution. That is usually the case when applying traditional optimisation procedures and models for energy and power system planning. The result from our analysis will instead be a number of solutions that meet the requirements for the given system attributes. At the same time we also analyse adverse strategies that are far from the optimal trade-off frontier. Awareness of such strategies is also useful information for decision makers, to avoid investments with negative implications.

The multi-attribute trade-off analysis has previously been applied in New England [4], Switzerland [5] and the Shangdong region in China. A more comprehensive description of the general trade-off approach can be found in [4] and [5]. The conditions in the current region of analysis, with three different countries and three very different energy systems involved, give rise to new research challenges from a modelling point of view. We also need to adjust the general framework of analysis, in order to take into account the new market conditions in the power sector. This is further discussed in chapter 5.

4.3 Computational models and input data

A set of models is required to simulate the different scenarios for the development of the energy system. We prefer to use so-called bottom-up models, with emphasis on the technical description of the system, for this purpose. Technology investment strategies and assumptions about future uncertainties are therefore decided exogenously and used as input to the models. The choice of computational models is dependent on the system boundary, and on the characteristics of the respective energy systems. Figure 13 shows a representation of models and input data. We want to use this framework to simulate the scenarios for a time period of 30 years into the future.

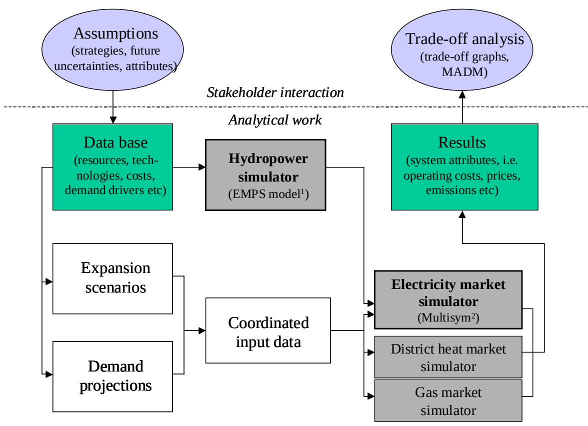


Figure 13: Schematic representation of models and input data. The differentiation between stakeholder interaction and analytical work is indicated. [1]*EMPS* – EFI's Multiarea Power Market Simulator is a hydropower optimization model developed by SINTEF Energy Research, Trondheim Norway. [2]*Multisym* is a power market simulator developed by Henwood Technologies, Sacramento CA USA.

As already stated the electric services are the core point of the analysis. A detailed representation of the power system is therefore a main priority. In the initial phase of the project we have therefore spent considerable time surveying different commercial models that are capable to meet our needs. In order to represent the hydropower generation in the system we need to apply a hydro scheduling model specifically developed for the conditions in Scandinavia (the EMPS model). This model has a weekly time resolution and is usually used to optimise the generation and storage of hydropower resources within a time horizon of 3-5 years. The representation of thermal power generation is not very detailed in the EMPS model. To model the operation of thermal plants, their costs and emissions, we therefore want to apply a more detailed power system model. We have chosen a chronological model (Multisym) with hourly time resolution. The model is able to represent start-up and shutdown costs, minimum up/down times and quadratic fuel consumption functions in thermal plants. On the other hand, the model has a simplified long-term description of hydropower. Consequently, it makes sense to first model the hydropower in the EMPS model, and then use the hydro results as input to the Multisym model. A somewhat realistic representation of the power transmission requires a multi-area description of the system. This is possible in both models. So far, we have not identified any particular models for the heat and gas markets. These two energy carriers will be treated with less analytical rigour in the first phase of the project. This approach is justified by the less complex technical constraints in these systems, combined with gas and heat's lower share of the total energy supply compared to electricity within the region.

A range of different data is necessary to develop consistent scenarios and to run reliable simulations with the computer models. Regional *resource data* is needed to assess the availability and cost of different energy resources. Renewable sources like hydro- and wind power must be converted, usually to electricity, at the location of the resource. Data about the stochastic nature of these sources, i.e. parameters describing their variability over day, season and year, are important to take them properly into account in the analysis. Combustible resources like oil, gas and biomass are also energy carriers, and can therefore be transported before conversion. These sources can also be stored before usage, and the access to them is more dependent on human activities than natural phenomenon. The important data are therefore resource constraints and price. *Technology data* are techno-economic parameters describing current and expected future fuel efficiencies, emissions and costs (operation and investment) for the various energy conversion and transportation technologies. The physical properties of a given technology are independent of location, but costs may vary due to different availability of resources. *Structural data* contains information about the current installed capacities of the different technologies and demand for the various energy carriers within the three countries. Existing plans for decommissioning of old equipment and construction of new are also important information when creating the set of strategies and scenarios. The organisation of the energy markets is also a part of the energy system structure. In order to establish demand forecasts we also need *macroeconomic data*, since the energy demand traditionally is closely related to the economic development. In the end we make assumptions about the future costs of the various fuel types. Such price forecasts go into the group of *global data*. Various sources of information will be used to obtain the required data. In the process of gathering data we can partly build upon previous work. There are for instance substantial amounts of relevant data available from the recent *Balmorel* model project [6]. In this project an investment optimisation model for analyses of the electricity and CHP markets in the whole Baltic Sea region was developed. The grouping of data presented above is based on the classification used in the Balmorel model.

5 MULTI-ATTRIBUTE TRADE-OFF ANALYSIS AND DEREGULATED MARKETS

Energy utilities have traditionally been frequent users of multi-attribute decision making for integrated resource planning within their own area of supply. The two major purposes of using the technique are to describe the trade-offs among different attributes, and to help participants apply the results rationally and consistently [7]. Usually, the alternative plans are ranked in the end, in order to make the decision making easier for the utility. A number of multi-objective optimisation methodologies have been developed for this purpose (see [7] and [8]). This approach makes sense when there is one decision maker, e.g. an energy utility, making one investment decision. In our project we are studying a region of 3 countries with a large number of decision makers, particularly when including investments in technologies on the demand side. The liberalisation of the power market has also resulted in more decentralised decision making. The importance of ranking the alternatives and identifying the optimal one is therefore less important, as there is no single decision maker that can make the optimal alternative become a reality. However, by identifying a set of several acceptable alternatives we still meet the two purposes of the trade-off technique, and also in a way that we mean are better suited for the conditions in the Scandinavian region.

The framework presented in this paper identifies a set of desired energy supply solutions, based upon the views within the stakeholder group. However, the results from the simulations do not address how to make sure that the right investments are made, so that the system develops in the desired direction. Even though the authorities have given up parts of their direct influence on the large-scale investment decisions, they still have an interest in controlling that the infrastructure changes in the system are to the better. They can do this through their direct ownership in the energy sector, although the trend is a movement towards more private ownership. Political decisions concerning project approvals, taxes, subsidies and research spending also affect the investment decisions. Other types of computational models, including investments as internal (endogenous) variables, are required to analyse the effect of such political measures upon the technology mix. Modelling of investment dynamics in the energy and power markets has gained increased attention in the deregulated market setting [9]. It is worth noting that we could possibly also address investment dynamics within our trade-off analysis project, by adding an extra step to the 4 basic steps presented in Figure 12.

The trade-offs between pollution attributes like SO_2, NO_x and CO_2-emissions on the one hand, and total system costs on the other hand, are usually the trade-offs that are given most attention in traditional integrated resource planning. In our setting, where the costs are spread between a large number of participants, the aggregate system costs might, however, be of less interest. The utilities' investments in new generation facilities are profit driven today, as opposed to the conditions in the regulated industry where investments were more based on expectations about future demand. Large-scale supply side investments have become more risky, as end-users now can switch between utilities. This makes it more difficult for the utilities to recover poorly judged investments simply by increasing the price to their customers. The risk profiles for different participants in the energy markets should therefore be taken into account when assessing aggregate cost figures, e.g. by adjusting the discount factor. The utilities' objective for operating the system has also changed, from cost minimisation in the old regime to profit maximisation today. As a result, the presence of market power and strategic bidding are topics that are frequently discussed, particularly in power markets. We include this into our analysis by using a power market model that can use bid-based instead of cost-based dispatch of the power system.

6 CONCLUSION AND FUTURE WORK

The current status for the energy supply within Norway, Sweden and Denmark are presented in the first part of the paper. The conditions in this region, with very different characteristics of the energy system in the three countries and a common deregulated power market, makes it very well suited for testing and applying new energy planning methodologies. The multi-attribute trade-off analysis framework, where frequent interaction with multiple stakeholders is one of the main features, could possibly become a very useful tool for energy and environmental assessments. However, the framework must be further developed, in order to adjust completely to a deregulated market setting. The methodological development will continue within the current project. At the same time we will carry out the specific analysis of the Scandinavian region under close cooperation with the stakeholder group.

ACKNOWLEDGEMENTS

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Appendix C Paper 3

"A dynamic simulation model for long-term analysis of the power market"

The paper appears in the Proceedings of the 14th Power System Computation Conference (PSCC'02), Sevilla – Spain, June 2002.

APPENDIX D PAPER 4

“Optimization of generation investments under uncertainty in restructured power markets”

The paper appears in the Proceedings of the Intelligent System Application to Power Systems (ISAP 2003), Lemnos – Greece, September 2003.