Norwegian University of Science and Technology NTNU

Faculty of Social Science and Technology Management

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MASTER THESIS

for

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Field of study	**Accounting and Finance** Investering, finans og økonomistyring
Start date	January 15, 2007
Title	**Empirical Analysis of Hydropower Generation** Empirisk analyse av vannkraftproduksjon
Purpose	Electricity companies owning storage hydroelectric plants have a complex task of scheduling the release of water from reservoirs. This thesis will investigate the factors that drive the production schedules and how scheduling is performed.

Main contents:

1. Gather and present data from Norwegian hydropower producers, and other relevant data.

2. Develop hypotheses regarding hydropower scheduling and test these empirically.

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I hereby declare that I have written the above mentioned
thesis without any kind of illegal assistance

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Empirical Analysis of Hydropower Generation

Helga Kristine Lumb and Vivi Kristine Weiss

June 8, 2007

Preface

This thesis has been written for the degree of Master of Technology at the Norwegian University of Science and Technology (NTNU), Department of Industrial Economics and Technology Management. Our work falls within the Group of Accounting and Finance.

We would specially like to thank our teaching supervisor, Associate Professor Stein-Erik Fleten for helpful assistance and valuable discussions. In addition, we owe Jussi Keppo thanks for constructive feedback. Last but not least, we thank the thirteen anonymous hydropower producers who have contributed with data. Without their contribution this thesis would not have been possible.

Trondheim, June 8, 2007

Helga Kristine Lumb Vivi Kristine Weiss

Abstract

Empirical studies of hydropower production scheduling are rare. In this thesis we discuss hydropower scheduling from an economical point of view and emphasize why information from the forward market can be used in the scheduling. Based upon this we develop several hypotheses regarding qualitative aspects of the scheduling decision and test these empirically using linear regression. The main focus is to investigate the factors that drive the generation schedules.

Prior to the analysis, we gather and present data relevant to the production decision from thirteen Norwegian hydropower producers. In addition, relevant data from Nord Pool is presented. The time span of the data is from 2000 to 2006 and has a resolution of one week. The hypotheses are divided in a general hypothesis and specific hypotheses. The general hypothesis states that the production decision is dependent on inflow, spot and forward prices, seasonal variation and lag of production. Dynamic panel models are estimated using GMM. The best model is selected by the out-of-sample R^2 criteria and has an out-of-sample R^2 equal to 88,56%. The general hypothesis is accepted.

Further we present and test eight specific hypotheses related to situations regarding reservoir contents, characteristics of the producers and market conditions. These hypotheses are tested applying the best models from the general hypothesis testing. Results show that a positive deviation from expected reservoir content results in increased production. A critical high or low reservoir content makes the producer less dependent on prices. Moreover, a critical high reservoir level makes production more sensitive to inflow. We reject the hypothesis that an extremely high spot price results in an increased production. Further, we conclude with that an extreme increase in variance in spot prices reduces production. Likewise, it is tested whether an extreme increase in variance in inflow reduces production. The testing rejects this hypothesis. Further we reject the hypotheses that state that producers with a low relative regulation or a low relative time of production are differently affected by price and inflow in the scheduling. Neither is the hypothesis stating that there has been a maturation in the producers willingness to let the forward price affect the production decision accepted.

Most of the results from the hypotheses testing presented in this thesis are in accordance with theory. With this analysis one better understands the dynamics of the hydropower scheduling problem.

Contents

Chapter 1

Introduction

1.1 Background and Motivation

Hydropower producers with storage possibilities face a difficult task when scheduling production in a liberalized market. The problem is a dynamic one because water used in production today may alternatively be used tomorrow. In addition, the high number of units involved and the stochastic nature of key variables like inflow and price complicate the scheduling problem. Traditionally the scheduling of the power system has been an engineering task and this is reflected in literature within the field. Little focus has been on the scheduling problem from an economic point of view. (Edwards 2003) and (Førsund 2007) are among few exceptions. In this thesis we discuss the economic aspects of hydropower scheduling.

As mentioned, the emphasis within this field has been from an engineering point of view and much research is aimed at how producers should optimally schedule production. However, practice is not always in accordance with theory. Moreover, the Norwegian media tend to speculate around motives and strategies behind the hydropower production, in particular in times with high electricity prices. It is therefore of interest to reveal how the hydropower producers actually act by carrying out an empirical analysis.

In this thesis we present an empirical analysis where we investigate which factors drive hydropower production. More specific, we test how production is determined by inflow, spot and forward prices, seasonal variation and lag of production. In addition we examine how producers respond to specific situations regarding reservoir content, producer characteristics and market conditions. Data input for the analysis is gathered from thirteen adequate Norwegian hydropower producers and from Nord Pool. The purpose of the empirical analysis is not to present the best possible generation model that can be used as a decision-support tool, but rather to reveal and discuss qualitative aspects of the scheduling problem.

Deregulated electricity markets are young and empirical electricity market studies are rare. A study has been accomplished on demand, generation and price by (Johnsen 2001). However, this study does not apply cross-sectional data from different producers, but rather looks at the joint determination of electricity generation. To our knowledge no other empirical studies based on hydropower producer panel data have been published. This may be caused by the lack of data material since some producers tend to be unwilling to give away data for research.

1.2 Structure of the Thesis

The structure of the thesis is as follows; Chapter 2 is an introduction to the Nordic power market. Further, in chapter 3 the concept of hydropower scheduling from an economic point of view is presented. In chapter 4 we discuss how the information from the forward market can be applied in hydropower scheduling. Based on theory in previous chapters, we present our hypotheses in chapter 5. Data from hydropower producers and Nord Pool is presented in chapter 6. The different models based on the hypotheses are formulated in chapter 7. Further, in chapter 8 and chapter 9, the models are applied to testing of the general hypothesis and specific hypotheses, respectively. Finally in chapter 10 we present some general comments and results regarding the analysis. Chapter 11 states a conclusion and suggests some improvements left for future work.

Chapter 2

The Nordic Power Market

2.1 Nord Pool

Nord Pool ASA is the Nordic power exchange. It has developed from being solely a Norwegian power exchange to be a multinational exchange for electrical power which serves Denmark, Finland, Sweden and Norway. In addition to being an exchange, Nord Pool also publishes important market information such as total reservoir content in the Nordic countries and outages for maintenance and repair.

2.1.1 Elspot

The market for physical contracts, Elspot, is an auction-based day-ahead market where electrical power contracts are traded for each hour the following day. Elspot gives the participants the possibility to balance their portfolios of power contracts close to real-time load. Participation at Elspot is voluntary and about 40% of the Nordic consumption is traded at Elspot (NVE 2006*b*).

The participants at Elspot submit sales- and purchase bids for every hour of the following day and from these bids the spot price for every hour is calculated. The calculation is done without considerations to congestions in the grid. When such congestions exist separate area prices are established. The system price is the average of the 24 spot prices within a day (Nord Pool 2006*b*).

2.1.2 Eltermin

Eltermin is the financial market organized by Nord Pool where futures and forward contracts are traded. The participants take part at Eltermin to meet different needs. Producers, retailers and end-users use the products as risk management tools, while speculators profit from volatility in the market and contribute to transparency and efficiency. The system price established at Elspot constitutes the reference price.

In chapter 4, the forward market and how forward contracts can be used in hydropower scheduling will be discussed thoroughly.

2.2 Characteristics of the Nordic Power Market

Electricity is an essential good in a modern society and its special features makes it a unique commodity. In this section we will look at some characteristics of electricity and the Nordic power market.

2.2.1 Non-storability: Balance in Supply and Demand

Since electricity can not be stored, at least not in significant quantities, the electricity market must be in instant balance regarding generation and consumption. This fact affect how the power market has to be designed.

For most commodities there is a simultaneous balance between supply and demand. The balance is created by the prices which the producers and consumers observe and adapt to. In the power market the price mechanism can not work fast enough to balance generation and consumption in real time. One practical consequence is that electricity pricing always has to be either ahead of real time or after real time (Wangensteen 2007). For instance, generally a spot market is a market place where goods are traded and delivered immediately. But in contrast to other commodities or financial markets, the price at the Nordic electrical spot market is set the day before delivery. Hence, the electricity spot market is in reality a day-ahead market.

2.2.2 Hydropower Dominance

The Nordic power market, particularly the Norwegian part, is hydropower dominated. In Norway almost 99% of electricity generation comes from hydropower, and in the whole of the Nordic region hydropower constitutes over 50% of the power production (Nordel 2006). Due to Norway's almost total reliance on hydropower the yearly variations in generation can be high.

As mentioned previously, electricity cannot be stored. But in a hydropower system one has the possibility to store the water. In this case the electricity is stored as water in the reservoirs. Norway has a reservoir capacity of about 84 TWh which roughly constitute 70% of yearly generation in Norway (NVE 2006*a*). This gives the producers some degree of flexibility and the possibility to schedule generation to the periods with the highest prices. Hence, the producers can control parts of their generation on a short notice. Notice that the retailers who buy in the market and deliver electricity to the consumers do not have this opportunity. Hence, it could be argued that the buyer side of the marked has a higher need for risk management tools such as forward contracts. This kind of market asymmetry may influence the forward price and this is discussed in section 4.3.

2.2.3 Seasonal Variations

The consumption of electricity in the Nordic countries is distinguished by seasonal variation, mainly due to a high degree of electrical heating. Low temperature and short day-length lead to higher consumption in the winter than in the summer (Johnsen 2001).

Limitations in reservoir capacities and variation in precipitation also contribute to price variations between seasons. Since most of the inflow comes during late spring and summer when the snow in the mountains melts, the reservoir capacity is sometimes not sufficient. The limited storage capacity makes it impossible to transfer enough water into the winter season which normally faces high demand and low inflow. Hence, the plants must produce at high level during summertime in order to avoid costly spill from overflow in the reservoirs (Fleten & Lemming 2003).

2.3 Competitive Markets

In a perfectly competitive market the participants' optimal action will lead to maximum economic efficiency (Schotter 2001). In this case maximum economic efficiency means social optimal management of the water over time. According to (Schotter 2001) there are some conditions that have to be fulfilled in order to obtain a perfectly competitive market:

- There are many market participants, each of which has an insubstantial share of the market.
- There is free entry into the market.
- There is a homogeneous product.
- There is perfect factor mobility.
- There is perfect information in the sense that all participants in the market are fully informed about its price and about its profit opportunities.

Clearly, the notion perfectly competitive market is a theoretical one and all the above requirements would never be fully fulfilled.

Effective competition in the spot market is important from several perspectives, directly for cost efficiency, transaction costs and the potentially large distributional effects of market power, indirectly for its impact on related financial markets (Hjalmarsson 2000). A well developed wholesale market with sufficient liquidity is required to produce reliable price signals to the financial markets. Since the spot price constitutes the reference price for the financial products, it is important that the spot price is "fair".

2.3.1 Is the Nordic Power Market Competitive?

The intention behind the liberalization of the Nordic power market was the belief that increased competition would raise industry efficiency to the benefit of the consumers (Amundsen & Bergman 2006). Hence, the power market was designed to imitate a perfectly competitive market. For instance, to give all market participants equal information as simultaneously as possible, important market information is made available at Nord Pool's homepage. At an early stage in the liberalization process, information about reservoir levels was kept confidential by each producer. This created an asymmetric information situation in the sense that large producers with several reservoirs had more information than small ones. In addition, producers in general had more information than the consumer side. This asymmetry of information was harmful for the market, and information about the total reservoir content is now made public at a regular basis (Wangensteen 2007).

From time to time, especially at times with high prices, the Norwegian media argue that the Nordic power market does not contribute to economic efficiency. Particularly, the issue about market power by major producers has been discussed. The largest Norwegian producer, Statkraft, accounts for some 30% of the total Norwegian power generation, but most of the producers are small with market shares of 5% to 6% or lower (von der Fehr, Amundsen & Bergman 2005). In a hydropower dominated market like the Norwegian, market power is exercised by releasing the water from reservoirs in a way that is not socially optimal. Since the decision whether to produce or to store the water largely depends on expectations about the future development, an outside observer cannot easily judge whether a given reduction of production reflects exercise of market power or just conservative expectations (Førsund & Hoel 2004).

Despite these difficulties, several studies on market power in the Nordic power market show that there is little misuse of market power and that the Nordic power market is in general competitive. See for instance (Amundsen & Bergman 2006), (Johnsen, Verma & Wolfram 1999), (Halseth 1998) or (Hjalmarsson 2000). Hence, the spot price reflects the short-term marginal costs of production and all producers act as price takers.

Chapter 3

The Hydropower Scheduling Problem

3.1 Hydropower Plants

In general, there are three types of hydropower arrangments; impoundment facilities, diversion facilities and pumped storage facilities. Since the producer has the possibility to store the water for later release, impoundment facilities represent perhaps the most flexible arrangement (Edwards 2003). The focus in this paper will be on impoundment systems. Hydropower plants may have quite complex topologies with several cascaded reservoirs or power stations in the same river system. In this thesis we will focus on stations which have only one reservoir and no hydraulically coupling to other stations. Hence, when the term hydropower station is used, it is assumed to be a hydropower station with only one reservoir connected to it.

3.2 Hydropower Generation

The process of generating hydroelectric power is quite simple and involves converting the kinetic energy in the moving water into mechanical energy created by the turbines. Then in turn the turbines spin a generator rotor which produces electrical energy. Since water is the initial source of this electricity, we refer to the electricity generated by this process as hydropower.

The power generated at the hydropower station is a nonlinear function of the release of water r and the station's net head, that is the difference between the headwater elevation and the tail water elevation. The release of water is in turn a function of the volume of the reservoir R so that the net head can be represented by some function $h(r, R)$. An efficiency function $\eta(h, r)$ represents the loss of power in the transfer of water release to electricity. In summary, the power generated by a turbine with release r and reservoir volume R is

$$p = g(r, R) = r \times h(r, R) \times \eta(h, r) \tag{3.1}$$

Depending on the size of the reservoir and the time horizon, it is sometimes reasonable to make the assumption that $h(r, R)$ does not vary much with R. Then the generation function (3.1) is only dependent on the flow rate r and becomes $g(r)$. The function $g(r)$ is typically a concave function or it can be approximated by a concave function (Philpott, Craddock & Waterer 2000). To simplify further, one may use the energy coefficient, i.e. how many kWh of electricity one m^3 of water produces for some fixed values of r and R. These fixed values are usually the average volume of the reservoir and the release of water which gives the highest production efficiency. Hence, the energy coefficient will reflect the topology and the embodied technology at the station. The relationship between the power generated in period t, p_t, and the flow of water r_t reduces to

$$p_t = \alpha \times r_t \tag{3.2}$$

where α is the energy coefficient with denomination kWh/m^3. In many cases this approximation will be sufficient and in the basic model presented next this will be used.

3.3 A Basic Hydropower Model

The key economic question in hydropower production is the time pattern of the use of water in the reservoir, given the production capacity for each time period. With enough storage capacity the water can be used today or alternatively be used tomorrow. The analysis of hydropower is therefore essentially a dynamic one. The objective of the hydropower scheduling problem is to find an optimal management of the the hydro system over time (Førsund 2007).

For a profit maximizing producer participating in a spot market with deterministic prices π_t, the following basic model can be stated

$$\max \sum_{t=1}^{T} \pi_t p_t \tag{3.3}$$

subject to

$$R_t \leq R_{t-1} + w_t - p_t, \qquad t \in T \tag{3.4}$$

$$R_t \leq R_{max}, \qquad t \in T \tag{3.5}$$

$$p_t \leq p_{max}, \qquad t \in T \tag{3.6}$$

$$R_t, p_t \geq 0, \qquad t \in T \tag{3.7}$$

where the electricity production, p_t, and the reservoir filling, R_t, are the decision variables. The deterministic inflow is denoted w_t and the first constraint describes the reservoir dynamic. For notational ease it is assumed that all units are expressed in kWh. Hence, the water variables originally measured in m^3 of water are converted into energy units using the energy coefficient α. The second and third constraint tells us that the reservoir filling and the production have to be equal or below its maximum values.

In our basic model we have not regarded uncertainty, although it is clear that the future inflow and future price have to be treated as stochastic parameters. Since the scope of this section is only to give an introduction to how the producers think when they schedule production, uncertainty is omitted. In a more comprehensive and realistic model stochasticity should be included.

3.3.1 Qualitative Characteristics of the Optimal Solution

The optimization problem presented above is a discrete time dynamic programming problem. Due to the complexity of the hydropower scheduling problem special solution procedures have been developed and it is common practice to decompose the problem into a long-, medium- and short-term problem, each being solved by suitable models and solution techniques (Fosso, Haugstad & Mo 2002). In this section the objective will be to use the Kuhn-Tucker conditions to discuss some qualitative characteristics of the optimal solution. We therefore have to derive the necessary first order conditions based on the Lagrangian for the problem (3.3) to (3.7) which are

$$\frac{\partial L}{\partial p_t} = \pi_t - \lambda_t - \rho_t \leq 0 \quad (= 0 \text{ for } p_t > 0) \tag{3.8}$$

$$\frac{\partial L}{\partial R_t} = -\lambda_t + \lambda_{t+1} - \gamma_t \leq 0 \quad (= 0 \text{ for } R_t > 0) \tag{3.9}$$

$$\lambda_t \geq 0 \quad (= 0 \text{ for } R_t < R_{t-1} + w_t - p_t) \tag{3.10}$$

$$\gamma_t \geq 0 \quad (= 0 \text{ for } R_t < R_{max}) \tag{3.11}$$

$$\rho_t \geq 0 \quad (= 0 \text{ for } p_t < p_{max}) \tag{3.12}$$

From the conditions one sees that there are some events that are crucial for the hydropower scheduling problem; the reservoir running empty, the reservoir running full and the production being bound by the production capacity limit. These three situations will be discussed in turn, but first an important concept in hydropower scheduling, the water value, is introduced.

The shadow price of the stored water, λ_t, is referred to as the water value. When evaluated at an optimal solution, the water value illustrates the change in value of the objective function when there is a marginal change in the constraint. The water value for period t, λ_t, expresses the alternative value of using water in the next period $t+1$. How a hydropower producer can derive the water values is discussed later in section 3.5.

Given that the production is not bound by the upper capacity i.e. $\rho = 0$, under which circumstances will the producer choose to produce electricity? The answer to this question can be found from condition (3.8) which under the assumption can be restated as the two following equations.

$$\pi_t < \lambda_t \Leftrightarrow p_t = 0 \tag{3.13}$$

$$\pi_t = \lambda_t \Leftrightarrow p_t > 0 \tag{3.14}$$

From equation (3.13) one sees that the producer will not supply any energy if his water value is higher than the market price. In the periods he produces a positive amount, i.e. equation (3.14) is prevailing, the market price will equal the water value.

On the other hand, if the production constraint is binding i.e. $\rho > 0$, condition (3.8) tells us that

$$\pi_t - \rho_t = \lambda_t \tag{3.15}$$

This means that the water value is lower than the market price. The producer is forced to use less water than he wants, resulting in a forced accumulation of water or a smaller drawdown than wanted. The opportunity cost of water is therefore lower than the market price.

If one assumes that there are no threat of neither scarcity of water or overflow i.e. $\gamma_t = 0$, the second condition (3.9) states

$$\lambda_t = \lambda_{t+1} \tag{3.16}$$

Thus, the water values are equal in the consecutive time periods. When overflow threatens, i.e. $\gamma_t > 0$, the water value will be adjusted downwards for that period compared with the next period. To see this, consider condition (3.9) again which under the assumptions is

$$\lambda_t = \lambda_{t+1} - \gamma_t \tag{3.17}$$

The producer is willing to sell at a lower price now to prevent overflow, contra selling at a higher price in a later period. But to the right price he may sell in an even earlier period and prevent an overflow situation happening.

The conclusion is that the producer will strive to sell all his energy in the period with the highest price, but may be prevented from doing so by the production capacity constraint and by the threat of overflow due to the reservoir constraint. The problematic period of scarcity in Norway is during late April weeks. From August to November it is normal to let the reservoirs be filled up again to meet the winter demand, so in this period the problem is to manage without overflow. But probably the most acute problems from a management point of view, arise at the end of the drawdown of the winter period and the filling up again during snow melting. In a few weeks the situation may change quickly from short-term scarcity to threat of future overflow (Førsund 2007).

3.3.2 Choice of Time Horizon

As mentioned in section 3.3.1, it is common to decompose the hydropower scheduling problem into a long-, medium- and short-term model. These models are closely linked and the output from one model serves as input to a model with shorter timer horizon. The choice of time horizon, T, in the long-term model is an important one since it decides how many future time periods the producer includes in his strategy.

One factor that can be used to determine the time horizon is the so called relative regulation, Υ, of the reservoir.

$$\Upsilon = \frac{R_{max} - R_{min}}{\overline{w}} \tag{3.18}$$

where R_{max} and R_{min} are the upper and lower bound on the reservoir level and $\overline{w}$ is the expected annual inflow. Roughly speaking, the relative regulation states how many years it takes to fill the reservoir given average annual inflow and no generation (Fosso & Gjengedal 2006*a*).

A well regulated reservoir will have a high relative regulation which means that decisions regarding water release may affect the state of the reservoir far into the future. Due to this, when scheduling hydropower from a well regulated reservoir one needs to consider a planning horizon of several years. On the other hand, if the relative regulation is low, one can manage with a shorter time horizon. This is because with a low relative regulation there is a high probability that regardless of the state of the reservoir, water will be spilled at a certain point of time, T. Since spilled water will have a water value equal to zero and add no value to the producer, it is not necessary to consider a planning horizon beyond T.

3.4 Inflow and the Hydrologic Balance

Due to the Nordic power market's dependence on hydropower the reservoir content and the inflow to the reservoirs are factors one expect to influence the market and the electricity production. Inflow, snowfall and temperature are stochastic variables, and the producers update their information regarding these variables regularly (Johnsen 2001).

Since water can be lost through overflow, it is important to estimate the future inflow which has to be considered as a stochastic variable. In Norway one has long series of historical observed inflow from a large amount of metering locations, and hence one has a good opportunity to estimate the future inflow. The risk of overflow is particularly considerable after the snow melt in the spring. This risk can be reduced if the producer has knowledge of the snow reservoir. Then the future inflow will consist of a known part, the melted snow, and an unknown part, the future precipitation minus possible evaporation (Fosso & Gjengedal 2006*a*). Due to this many producers not only keep track on the water reservoir content and the inflow, but the snow reservoirs are also measured.

The Norwegian Water Resources and Energy Directorate (NVE) collects data from almost 600 metering locations in rivers all over the country which measure the water level continuously. This information is recorded in the national database Hydra II and is used as the foundation in their calculation of power and flood forecasts (NVE 2005). NVE in cooperation with Nord Pool also publishes water reservoir statistics. The statistics contains information about the percentage filling in the whole of Norway. The statistics are published on a weekly basis and gives the producers important information of the hydrologic balance in Norway.

3.5 The Concept of Water Values

In section 3.3 we saw that the water values play a crucial role in the hydropower scheduling problem. In this section the water values are further discussed and a more formal derivation is presented.

To be able to schedule production optimally it is necessary to set a value on the water stored in the reservoirs. Even though water is for free, it has a value given that it is a scarce resource and one is free to decide whether to produce today or to store it for later production. This opportunity cost is often referred to as the water value. The water value is traditionally derived with a minimize operational cost expression. But in a liberalized market it is more reasonable to maximize the value of the production, that is to maximize the discounted present value of the profits. Since a hydropower station generally is assumed to have no production cost this can be seen as to maximize the discounted present value of the revenues. What follows is based upon (Winnem 2006).

Let $\widetilde{\pi}_t$ be the uncertain price and $p(R,r)$ the generated amount of electricity as a function of the reservoir level R and the release of water r. The present value of the expected production can then be stated as

$$PV_0 = \max_{R_t,r_t} E\left[\sum_{t=0}^{\infty} \frac{\widetilde{\pi}_t p(R_t,r_t)}{(1+\rho)^t}\right] \tag{3.19}$$

where ρ is the appropriate discounting rate.

Given that the current period is t, equation (3.19) could obviously be formulated as

$$PV_t = \max_{R_t,r_t} \left\{ E\left[\widetilde{\pi}_t w(R_t,r_t)\right] + \frac{E\left[V_{t+1}\right]}{(1+\rho)} \right\} \tag{3.20}$$

where we have split the expression into a term for the expected revenues in the current period and one term for the expected value of the production in the next period.

Given that one knows the price in the current period t, (3.20) reduces to

$$PV_t = \max_{R_t,r_t} \left\{ E\left[\pi_t w(R_t,r_t)\right] + \mu_{V_{t+1}} \right\} \tag{3.21}$$

where $\mu_{V_{t+1}}$ is the discounted present value of production in the next period which is a function of all the future uncertain parameters, i.e. price, $\widetilde{\pi}$ and inflow $\widetilde{w}$. Formally expressed

$$\mu_{V_{t+1}} = \frac{E\left[V_{t+1}(\widetilde{\pi}_t, \widetilde{w_t})\right]}{1+\rho} \tag{3.22}$$

Since the producer wants to maximize the present value of production, optimal production strategy is found when one differentiate (3.21) with respect to the water release.

$$\frac{d\left(\pi_t p(R_t, r_t) + \mu_{V_{t+1}}\right)}{dr_t} = \frac{\partial\left(\pi p(R_t, r_t)\right)}{\partial r_t} + \frac{\partial \mu_{V_{t+1}}}{\partial R_{t+1}} \frac{\partial R_{t+1}}{\partial r_t} \tag{3.23}$$

The marginal change in the reservoir level caused by a marginal change in the energy discharge in the anterior period is equal to -1, hence to fulfill the first order optimality the condition above rearranges to

$$\pi_t \frac{\partial\left(p(R_t, r_t)\right)}{\partial r_t} = \frac{\partial \mu_{V_{t+1}}}{\partial R_{t+1}} \tag{3.24}$$

Equation (3.24) states that in order to maximize the value of the production, the producer should produce such that the marginal change of the discounted expected future value equals the marginal revenues from producing immediately. The right side of equation (3.24), the marginal change of the discounted expected future value, constitutes the water value.

The derivation shown does not account for physical restrictions which we know from section 3.3 are important. If the reservoir is overflown, the water will have no value. To account for such a situation one can define the water value as the Lagrange multiplier associated with the water balance, i.e. the restrictions on the reservoir. From this discussion we can define the water value as

$$\lambda_t = \begin{cases} \frac{\partial \mu_{V_{t+1}}}{\partial R_{t+1}}, & \text{When spilling can be avoided} \\ 0, & \text{When spilling can not be avoided} \end{cases} \tag{3.25}$$

This is equivalent with our definition of the water value in section 3.3 and the conclusion is the same. The producer should increase the release of water as long as the marginal revenue which in short-term equals the price, is larger than the water value.

3.5.1 Water Values Calculation

In section 3.3.2 it was discussed that if the end of the planning horizon T is chosen properly the water values at T could easily be derived. If the water values are known at the T, the water values can be derived by calculating backwards in time using the following strategy: Given none binding restrictions and optimal production strategy the water value in t equals the water value in period $t+1$. This is identical to what equation (3.16) expresses. The problem is complicated by the fact that optimal strategy assumes that prices and inflow are known and it is therefore important to have accurate price and inflow forecasts which the producers base their calculation of the water values on. Since the water value at a given time is directly linked to a certain reservoir level, the calculation of the water values also imply that an optimal reservoir strategy is derived. Hence, based on the water values and the expectations of prices and inflow which is embedded in the water values, the producers have an optimal reservoir path from t to T.

3.6 Future Spot Prices

A forecast of future market prices is needed in order to estimate the water values, and hence the optimal production strategy. Forecasting the future development of prices and other uncertain factors such as inflow from now up to several months or years into the future is important for trading and risk management. Short-term forecasting of prices, loads and inflows is important for short-term production scheduling (Wallace & Fleten 2003).

These forecasts must include not only an estimate of the expected price, but also a description of the distribution. According to (Wangensteen 2007) there are three different approaches to the forecasting problem:

- One can use prices from the future/forward market.
- One can use observed prices in the past and make forecasts based on trends and patterns in these historical observations.
- One can use a bottom-up model, which is a fundamental model that describes the price formation.

Among Norwegian producers it is customary to use a bottom-up model, but it is also common to adjust the forecasts from the model with information from the forward market (Gjelsvik 2006). In the next chapter we will discuss how the financial market can be used in the scheduling of production and it will be argued that this procedure is suitable.

Chapter 4

Electricity Forward Markets

4.1 Pricing of Electricity Forwards

In this chapter we will discuss what the electricity forward price represents. Because of limited storage of electricity, the forward contracts cannot be priced using the standard arbitrage arguments involving cost-of-carry relationships (Fleten & Lemming 2003). According to (McDonald 2003) and (Fleten 2007), the electricity forward prices are best explained by regarding it in conjunction with the expected future spot price and the market risk.

$$PV_t = \frac{E_t(S_T)}{(1+\rho)^{(T-t)}} = \frac{F_{t,T}}{(1+r)^{(T-t)}} \tag{4.1}$$

Equation (4.1) shows the link between the expected spot price, $E_t(S_T)$, at a future point in time T, and a forward price, $F_{t,T}$, with maturity at time T. The present value PV_t gives the value of receiving a unit of electricity at a future point in time T. The present value of both the expected spot price and the forward price equals each other given that the respective discount rates are correct. The expected spot price must be discounted by the risk adjusted interest rate, ρ, and the forward price must be discounted by the risk-free interest rate, r.

4.1.1 Price Discovery

The forward price of a financial asset can be expressed as; $F_{t,T} = S_0(1+r)^{T-t}$. Forward prices on stocks is largely redundant in the sense that it reflects information about the current stock price and interest rate because of the standard arbitrage argument used in the pricing of financial forwards. With electricity forwards, we know from equation (4.1) that we can express the forward price by the expected future spot price $E_t(S_T)$, the risk adjusted interest rate ρ, and the risk-free rate r. Both the expected future spot price and the risk adjusted interest rate are difficult to estimate. Hence, unlike financial forward prices which can be expressed with known quantities, electricity forward prices cannot easily be calculated. This illustrates that the electricity forward prices can only be revealed through the forward market. The electricity forward market provide price discovery because it reveals the forward price which cannot be calculated (McDonald 2003).

4.2 The Nordic Electricity Forward Market

The price volatility is high in the Scandinavian electricity market compared to other pure thermal systems (Botterud, Bhattacharyya & Ilic 2002). Investigation of risk related to prices in the Norwegian spot market for electricity indicates that about 65% of the variation in observed prices can be explained by the influence of seasonal factors.

The Nord Pools derivatives market has been designed to serve as a risk management tool for participants in the market who wants to hedge their future profit. At the same time, the market tries to attract speculators who want to profit from the volatile electricity prices in order to increase the liquidity in the market as explained in section 2.1.2. Hedgers may be producers and consumers of the commodity who enter into future positions to reduce risk associated with future price movements of the electricity. For example, a producer might enter into a short position to reduce risk associated with a future fall in electricity price, and a consumer might take an opposite long position to guard against a possible increase in price.

Whereas hedgers want to avoid an exposure to adverse movements in the price of an asset, speculators want to take a position in the market. Either they are betting that the price will go up or they are betting that it will go down (Hull 2003). International hedge funds, banks and other financial speculators are among this speculation group, but also producers and industry have trading desks that essentially manage speculative portfolio's.

4.2.1 Features of the Nordic Electricity Forward Curve

(Fleten, Tomasgard & Wallace 2001) are of the opinion that the main component in the pricing of forward contracts in the Nordic market are the market participants expectations of the future system prices. The forward curve captures the risk adjusted expected value of the future spot price. This is in accordance with equation (4.1) which expresses the relationship between the forward price and the expected spot price and the market risk. A common risk factor is weather conditions and inflow. The power producers regard risk as a negative factor, which make them risk averse decision makers who are willing to pay to reduce risk.

(Lucia & Schwartz 2002) conclude that seasonal systematic pattern throughout the year is of crucial importance in explaining the shape of the forward curve. Further they state that the seasonal component of the system price is incorporated by market participants in their valuation process of the forward price, and hence, is an important explanation for the shape of the forward curve. The shape of the forward curve displays one peak and one valley per year, in total accordance with the behavior of the system price. Hence, the market makes good expectations to the future spot price.

4.3 Scheduling using Information from the Forward Market

The purpose of the forward electricity market is to provide hedge against the volatile prices in the spot market in addition to attracting speculators to increase liquidity. Now we will look at how the forward market also can be be used as a tool for production scheduling.

Hydropower producers with storage possibilities have the ability and the motive to plan production ahead in time. They can benefit from the volatile electricity prices and use their production flexibility to produce at maximum level when prices are high and save the water when prices are low. The production scheduling problem described in chapter 3 can be summarized as follow; Given that you have a price forecast of future spot prices, establish a production plan that maximizes profit considering all relevant constraints (Fosso & Gjengedal 2006*b*). In general, the producers want to make a strategy so that the present value of future production is maximized, as explained in chapter 3.

4.3.1 Market Value Maximization vs. Profit Maximization

In (Fleten 2000) it is claimed that there are two possible objectives for the producer; one is to maximize profit while the other one maximizes the market value. The difference between the two is that when maximizing profit one will make use of a forecast of expected profit based on expected future spot prices, while the maximization of market value is done by using information which lies in the future/forward prices. Using the forward prices to find the value of future production is also known as the certainty-equivalent method. Forward prices can be denoted as certainty equivalents because they are the minimum fixed price at which you would agree today to sell your future commodity (Brealey, Myers & Allen 2006).

Both methods are consistent with maximizing the present value of future sales of a commodity. For simplicity, we divide equation (4.1) in two for the reader to easily understand the difference between the two methods of production scheduling;

$$PV_t = \frac{E_t(S_T)}{(1+\rho)^{(T-t)}} \tag{4.2}$$

$$PV_t = \frac{F_{t,T}}{(1+r)^{(T-t)}} \tag{4.3}$$

Equation (4.2) refers to the profit maximization method and equation (4.3) refers to the market value maximization method. It is important to notice that the two methods should provide the same present value as long as proper discount factors are applied.

Forward prices are settled in advance of delivery. Keep in mind that forward curves are not forecasts of spot price in the future. The clearing price of forwards are the result of demand and supply, which in turn are determined by the individual characteristics of the market players. In fact, the main motivation for participants to engage in forward contracts is that of risk aversion. Hence, the market risk is already embedded in the forward prices and no risk adjustment to the value is needed to cover the risk from spot price uncertainty. In general, future cash flows that are certain such as a signed forward contract should be discounted at a risk-free interest rate, r (Bierman & Smidt 1993).

The expected future spot prices must be discounted with a risk adjusted interest rate. By not adjusting for the market risk, one is left with prices that would occur in the electricity market if all market participants were risk neutral and price-taking. If one assumes that the participants in the electricity market is risk averse, the price forecasts from expected spot price models are not consistent with how the market value the electricity, i.e. the forecasts of expected spot prices are not congruent with the forward prices.

Risk adjusted interest rate and market risk premium

An important quantity is the market risk premium, $\Pi_{t,T}$. This is defined as the difference, calculated at time t, between the forward price $F_{t,T}$, at time t with delivery at T, and the expected spot price at a future time T (McDonald 2003).

$$\Pi_{t,T} = E_t(S_T) - F_{t,T} \tag{4.4}$$

Forward prices which are certain at any point in time will generally be different from the expected spot prices which are uncertain. This gives a risk premium, $\Pi_{t,T}$. Several studies such as (Bodie & Roskansky 1980) find empirical evidence that supports a theory of a positive risk premium in several commodity markets. (Fama & French 1987) also find evidence of a positive risk premium. However, their result is not strong enough to resolve the long-standing controversy about the existence of nonzero expected premiums. A risk premium results in that one must use risk-adjusted discount rates, ρ, on the expected spot prices so that they are financially equivalent to the forward prices. Hence, if there is a positive risk premium, ρ must be larger than the risk-free rate r which is used to discount forward prices. With a negative risk premium, ρ must be less than the risk-free rate r.

In general, it is difficult to measure the market risk. The market price of risk can be seen as a drift adjustment in the dynamics of an asset to reflect how investors are compensated for bearing risk when holding the commodity or asset. Comprehensive analysis of the price structure is needed to express the market risk. See (Benth, Cartea & Kiesel 2006) for an example.

One of the peculiarities of commodities markets is that the market risk may be either positive or negative depending on the time horizon considered (Benth et al. 2006). The market risk is also dependent on how risk averse the market participants are and whether there is market power or not. If there exists market power, either the consumer side or the producer side is more eager to hedge and this will affect the forward prices and the risk level in the market.

Market risk and market risk premium in the Nordic electricity market

The risk premiums are hard to deduce for a complex commodity such as electricity. They often differ depending on the volatility of the products. For example, winter forwards and summer forwards are distinct products that will have different volatilities and corresponding risk premiums (Niemeyer 2000). Hence, the risk-adjusted discount rate, ρ, will vary depending on which season the expected spot prices are in.

(Botterud et al. 2002) are of the opinion that a risk premium arise in the electricity forward market if either the number of participants on the supply side differs substantially from the number of participants on the demand side, or if the degree of risk averseness varies considerably between the two sides. Because of the store-ability on the producer side in the hydro-dominated Nordic electricity market, the generators can take advantage of the fluctuation in price by adjusting their generation. Therefore, it is not necessary for the producers to fix the price in the forward market for all planned future generation. The situation is different on the consumer side where the participants have adjusted demand according to price. Hence, it makes sense that the consumers participates in the forward market to make sure that the expected future demand will be covered, given that the participants on the demand side are risk averse. If the difference in flexibility on the demand and supply side leads to an excess demand for forward contracts, the forward price would exceed the expected future spot price and the risk premium, $\Pi_{t,T}$ in equation (4.4) will turn out to be negative. (Botterud et al. 2002) carried out a study of Nord Pool's futures market in 1997. Empirical evidence supports the theory of a negative risk premium. In the case of a negative risk premium in equation (4.4), the risk-adjusted interest rate, ρ, must be less than the risk-free rate r.

4.3.2 How do Norwegian Hydropower Producers cope with Production Scheduling?

Traditionally, the Norwegian electricity generators have based their production plans on expected future spot prices and profit maximization. The expected spot prices, $E_t(S_T)$, are often provided by bottom-up models such as the EMPS-model. The main drawback with the bottom-up models is that they cannot estimate or capture the risk premium or the risk adjusted rate determined by the market forces (Fleten & Lemming 2003). As pointed out in previous sections, it is difficult to adjust the interest rate for the market risk. Hence, ρ is often set to equal zero which gives an incorrect present value calculation. A better approximation would be to discount with the risk-free rate, r. Still, the market risk is not adjusted for and the present value would be incorrect.

4.3.3 Discussion of Approach used in Production Scheduling

There are big differences in the two approaches to find the present value of future sales of electricity. It is resource demanding to make a forecast of expected future spot prices. The bottom-up models which are tools for calculating expected spot prices are only models of the reality. A model can never be better than its' weakest point. Bottom-up models used in the Nordic market were created before the liberalization of the market. Hence, they are created to work well in a different environment than the today situation (Fleten & Lemming 2003). After the expected spot prices are estimated, the work of finding proper value of the market risk remains. As mentioned earlier, this is a difficult task.

Given that there exists a competitive and efficient market place, the obvious choice would be to use the information already existing in the market, namely the forward prices. The production planner saves time and money by discounting forward prices with the relevant time horizon, with the risk-free rate. One does not need to estimate the future spot prices, and one does not need to worry about the appropriate discount rate to adjust for risk. This is consistent with financial theory which says that one should always look first at the market value of an asset when pricing an asset or commodity. Seen from an investors point of view, the market value defines the profitability (Brealey et al. 2006).

On the other hand, forward products listed by Nord Pool differ not only in terms of time to maturity but also in terms of the length of the delivery period. This means that at any point in time the decision maker has only a partial picture of the forward price curve available for analysis. This may be a downside of the use of the forward curve in production scheduling. Nevertheless, one can assume that the easiest way to provide information of the expected future spot prices is to look at the forward prices in the market.

Chapter 5

Framework of Hypotheses

5.1 General Hypothesis

The objective in this chapter is to develop hypotheses regarding hydropower scheduling based on the theory in chapter 3 and 4. The main focus is to capture which factors influence the scheduling decisions of a hydropower producer. In later chapters the hypotheses will be tested empirically.

5.1.1 Prices

As explained in section 3.3 a profit maximizing producer participating in the spot market has the objective to maximize profit of future production of electricity. Hence, the market prices are important factors in the hydropower scheduling problem. Maximizing profit of future production is to produce and sell electricity when the spot prices are high. As mentioned earlier the spot price is stochastic and hence the producer needs information of future spot prices in addition to the spot price of today in order to plan production ahead in time. A reasonable line of action will be to produce if the spot price today is high compared to the forecast of the price at a future point in time. A simple way to provide information of future spot prices is to use information from the future/forward market as explained in section 4.3. The price of a selected forward product with delivery at a future point in time provides information of how the market value a MWh electricity at that particular future point in time. Hence, spot price relative to forward price might affect the hydropower scheduling decision.

The spot price relative to the forward price has a positive impact on the production decision.

5.1.2 Inflow

Water from inflow is the "fuel" in the hydropower production. From the Kuhn-Tucker conditions of the optimal scheduling solution in section 3.3 we know that the production decision is directly linked to the reservoir filling. Inflow to the reservoir is consequently a factor which influences the production scheduling. The filling level of the reservoir affects the water value which in turn affects the production scheduling. In general, the higher the reservoir filling, the lower is the water value. If the water value is lower than the spot price it is wise to increase production. From this we can anticipate a positive relationship between the inflow and the production decision.

The inflow has a positive impact on the production decision.

Although it is obvious that there is a strong connection between reservoir level and the production decision, we choose not to formulate this in the general hypothesis because reservoir level is a direct cause of production and inflow. In addition reservoir level in itself can be interpreted as a production decision. For example, a low reservoir level is a direct consequence of a high level of production.

5.1.3 Seasonal Variations

In the Norwegian hydropower system inflow is dependent on seasonal variation over the year. Because of the cold climate, inflow mainly occur during spring, summer and autumn. During the winter snow reservoir can be measured and provides information of the magnitude of inflow from melted snow which occur at spring time.

One can assume that it is preferable for the producer to never empty the reservoirs. By keeping the reservoir fairly filled the producer is more flexible to produce whenever the prices are high. In addition, the producers are often obligated by the authority to keep a certain minimum reservoir level. A third reason for keeping the reservoir filled is that the energy coefficient is a function of the head of water. More MWh can be produced per m^3, the higher head of water.

We anticipate that the producers fill up their reservoirs during seasons when the inflow is large and save some of it for production during seasons when the inflow is low. Hence, the producers act differently to inflow dependent on which season they are in at the moment. During the filling season the production decision is less affected by the inflow since it is not a scarce resource. During the drawdown season inflow is a scarce resource and the production is highly affected by inflow. Hence, high inflow during the drawdown season results in increased production, but high inflow during the filling season does not increase production by the same magnitude.

Before the deregulation the producers were obligated to cover a certain demand and it was more important to spread the reservoir content over the year to be able to meet demand. The demand was also regional dependent. In Norway, the demand of electricity is higher during the winter which gave even more incentive to save water for production during the dry winter season. Many producers still use scheduling tools which are developed before the deregulation and with that plan production similar to what was optimal before the deregulation. This gives even more incentive to believe that production decisions are seasonal dependent.

Seasonal variation affects how the production decision is dependent on the inflow.

5.1.4 Lag of Production

There are certain external factors that affect the production scheduling over a period of time. For example extreme weather situations, gas- and coal prices which are not captured by the spot prices or the political situation. Also internal factors such as start- and stop costs, break-downs, maintenance or a shift in management affect production over periods of time. In general, it is hard to get an overall impression of all the external and internal factors that affect production for a certain time lag. If it is likely that such factors affect production over a period of time, the only way to capture such effects is to look at last weeks production level. For example, if a generator breaks down and affect this weeks production, then it is likely that next weeks production is affected as well.

Lag of production affects this weeks production.

5.1.5 Formulation of General Hypothesis

From the discussion above one can sum up with that it is fair to anticipate that a high spot price has a positive impact on todays' production while a high forward price results in a lower production. High inflow results in a high production. Production is less dependent on inflow during filling seasons than during drawdown seasons. Production is positively dependent on last week's production. Hence, we can formulate our general hypothesis;

The hydropower production scheduling problem is dependent on prices, inflow, seasonal variations and lag of production.

5.2 Specific Hypotheses

In the previous section we defined a general hypothesis regarding which factors that affect the hydropower production. We are also interested in testing more specific features of how the producers plan production and act in different situations. To do this we develop more specific hypotheses regarding production scheduling.

5.2.1 Reservoir Level and Production Scheduling

The general hypothesis does not include reservoir as a variable. Although reservoir level can be interpreted as a consequence of the production decision in itself, we want to study how well the producers stick to their scheduled production by indirectly using the reservoir level as remedy.

The producers have made production schedules for periods at a time to maximize sales of production and manage the reservoirs at the best possible way. Based on the calculated water values they have a schedule for optimal production. This also includes a schedule for the reservoir level ahead in time. A high positive deviation from expected reservoir level indicates that they should produce more if they want to be on schedule.

Hypothesis 1: A positive deviation from expected reservoir results in an increase in production.

From section 3.3 we know that it is crucial for the hydropower scheduling when the reservoir is running empty and when it is running full. This problem is even more critical during periods when it is unexpected to have an empty or full reservoir. As mentioned in section 3.3 the Norwegian hydropower producers have due to the natural variations of inflow estimated with empty reservoirs in late April weeks and full reservoirs in November. These expectations are of course depending on geographical location of the power station. At every other time of the year whenever extreme reservoir levels occur, it is reasonable to anticipate that the market price is subordinate for the decision making of the production. The main priority is to avoid overstepping the restrictions of the reservoir. Hence, the producer is willing to sell at a lower price now to prevent overflow, contra selling at higher price in a later period. By formulating a hypothesis for further testing we expect the production to be less dependent on both the spot price and a future expectation of the spot price.

Hypothesis 2: When the reservoir is nearly full or nearly empty price is subordinate in the decision-making process of the production.

It is also interesting how the producer deals with inflow in situations where the reservoir is nearly full. A reasonable expectation is that inflow makes the producer more eager to produce in situations where the reservoir is almost full compared to situations with normal reservoir level. As with the first hypothesis, we expect this to be true only during parts of the year when the producers do not expect to be threaten by overflow.

Hypothesis 3: When the reservoir is nearly full the production decision is more dependent on inflow than otherwise.

5.2.2 Extreme Prices and Production Scheduling

In the general hypothesis we anticipate a linear relationship between the price and the production. One can discuss whether the relationship is linear for all magnitudes of prices. We want to test whether there is a jump in production when prices are extremely high.

Hypothesis 4: When spot prices are extremely high we expect a jump in production.

5.2.3 Volatile Prices and Inflow and Production Scheduling

Volatile prices and inflow increase the real option value of the water in the reservoirs. Hence, the water value increases by increased price and inflow volatility. When the water value exceeds the spot price the optimal production decision is to not produce as seen in equation (3.13) in section 3.3. By this one can assume that an increase in price and inflow volatility results in a decrease in production.

Hypothesis 5: Increased variance in prices and inflow results in a decrease in production.

5.2.4 Relative Regulation and Relative Time of Production

The relative regulation is mentioned in section 3.3.2 as a factor that affects the planning horizon of the production. A low relative regulation indicates that the reservoir can only store water for a short time period into the future at a time. Hence, the producer only has the ability to schedule production for a short time horizon at a time. Thus, given a low relative regulation the forward prices do not have a great impact on the production decision of today.

Hypothesis 6: Producers with a low relative regulation will be less affected by the forward prices.

The relative time of production states how long time it takes to produce electricity from all the yearly inflow given that the station run at maximum capacity. We let Γ denote the relative time of production, $\overline{w}$ is the expected annual inflow and C is the installed capacity of the power station.

$$\Gamma = \frac{\overline{w}}{C} \tag{5.1}$$

Producers with a low relative time of production have a reduced risk of overflow. This gives a producer with a low relative time of production a higher flexibility compared to other producers caring a high relative time of production. The flexibility provides a possibility to produce in accordance with the market movements. Thus, one can expect that producers with a low relative time of production are more affected by prices but less by inflow.

Hypothesis 7: Producers with a low relative time of production are more affected by prices and less affected by inflow in the production decision.

5.2.5 Forward Prices and Production Scheduling

The forward volume traded at Nord Pool has increased since it first was introduced in 1993 and until today. The traded volume decreased between 2002 and 2003, but rose again after this (Nord Pool 2006*a*). The number of transactions of financial contracts was at its highest in 2006 compared to earlier years and rose by 13,4% from the year before (Statnett 2006). From this it is clear that there has been an increasing interest in the financial market. The more market transactions, the more efficient is the market expected to be. This might have affected the producers to rely more on the market and use the forward prices as forecasts of expected future spot prices.

Hypothesis 8: There has been a maturation during the years in the hydropower producers willingness to let the forward price affect the production decision.

Chapter 6

Data Description

6.1 Assumptions and Selection Criteria

The empirical analysis presented in this paper are mainly based on data collected from thirteen Norwegian hydropower producers. Based on the following assumptions, some criteria regarding the producers taking part in the analysis were decided in advance.

- All the producers are price takers. This is discussed in section 2.3.1 and it is a consequence of our assumption that the Nordic power market is sufficient competitive.
- None of the producers have bilateral contracts that obligate them to deliver power to a contracted price. Hence, we assume that all power produced is sold at Elspot. This assumption can be justified by the fact that if the producers have these contracts they may purchase the contracted volume at the spot market. Due to this, the scheduling problem does not change.

To comply with the assumption that the producers act as price takers we disregard the largest producers in Norway such as Statkraft and Hydro. The producers should participate in the Nordic electricity market, hence industrial companies that produce for own consumption are not of interest. Since producers with reservoirs are more flexible to schedule production, we disregard river plants. In addition, to keep the focus on external factors the power stations should not have water connections to other stations that affect the production considerably. The chosen hydro producers fulfill these requirements and as illustrated in Figure 6.1 the hydropower stations are situated all over the country to give a best possible representation of a Norwegian hydropower producer.

6.1.1 Descriptive Data of the Hydropower Stations

Although the power stations meet the criteria mentioned above, they are all different in respect to production capacity, reservoir size and other physical conditions. This is clearly seen from Table 6.1 where some descriptive data is presented.

Table 6.1: Descriptive data from the thirteen hydropower plants. Some notion require clarification; Inflow is the expected yearly inflow, relative regulation is defined as reservoir size divided by annual expected inflow (see section 3.3.2) and relative production time is defined as annual expected inflow divided by capacity (see section 5.2.4). Here the relative production time is denoted as the percentage of a year.

	Rated Capacity	*Energy Coefficient*	*Reservoir Size*	*Annual Inflow*	*Relative Regulation*	*Relative time of Production*
1	128 MW	1,16 kWh/m^3	228,1 GWh	641,2 GWh/yr.	0,356 yr.	57,2 %
2	120 MW	1,32 kWh/m^3	624,4 GWh	380,8 GWh/yr.	1,640 yr.	36,2 %
3	30 MW	1,15 kWh/m^3	47,1 GWh	106,6 GWh/yr.	0,442 yr.	40,5 %
4	40 MW	1,27 kWh/m^3	51,8 GWh	139,9 GWh/yr.	0,370 yr.	39,9 %
5	28 MW	0,67 kWh/m^3	118,9 GWh	87,8 GWh/yr.	1,350 yr.	35,8 %
6	23 MW	0,16 kWh/m^3	14,0 GWh	153,0 GWh/yr.	0,092 yr.	76,0 %
7	68 MW	1,25 kWh/m^3	255 GWh	272,3 GWh/yr.	0,937 yr.	45,7 %
8	167 MW	1,09 kWh/m^3	272,5 GWh	414,4 GWh/yr.	0,642 yr.	28,3 %
9	210 MW	1,46 kWh/m^3	1270 GWh	1250,5 GWh/yr.	1,015 yr.	68,0 %
10	62,1 MW	1,50 kWh/m^3	142 GWh	231,8 GWh/yr.	0,613 yr.	42,6 %
11	41 MW	0,95 kWh/m^3	42,6 GWh	81,3 GWh/yr.	0,953 yr.	22,6%
12	29 MW	0,91 kWh/m^3	12,4 GWh	147,2 GWh/yr.	0,084 yr.	57,9%
13	140 MW	1,36 KWh/m^3	380,8 GWh	662,9 GWh/yr.	0,574 yr.	54,0 %

6.2 Producer Panel Data

The data has a time solution of one week and a time horizon spanning from week 5 in 2000 until week 52 in 2006. This is a total of 361 time periods, hence 2004 is assumed to have 53 weeks while the other years have 52 weeks. The weekly data bring a lot of information about the short-term adjustments in the market and the long time horizon shows the long-term structures. Since the data from the different producers have the same time horizon, our data set is a balanced panel data set.

The producer data includes historical time series regarding production, reservoir level and inflow. Some of the producers do not directly measure inflow, but calculate it using alteration in reservoir level, production and spill. Nevertheless, the data provides the information the individual producer has available.

The data from the thirteen producers was gathered through electronic correspondence. We have as much as possible avoided to alter the time series we received. In some of the inflow time series a few data were negative. Since this is clearly unrealistic and caused by error in measurements or calculation, these figures were set equal to zero. A transformation of the reservoir level data with denomination Mm^3 to MWh using the average energy equivalent was for some producers required. In addition, some of the data we received was on hourly or daily basis. It was necessary to aggregate the data such that it has the form MWh/week or MWh.

6.2.1 Production Data

In Figure 6.2 the relative production, i.e. the weekly production divided by the maximum weekly production, for every producer is plotted against time. From the quite chaotic figure one sees that the relative production varies considerably. A tendency of a periodical trend can be noticed.

Quite often the data shows none production over the week. This may be the result of at least two situations; the producer finds it unfavorable to generate or the production stop is caused by maintenance or a breakdown. Unfortunately, information concerning planned and unplanned production stops is not available for the analysis.

Descriptive statistics for the production data is presented in Table 6.2 and from there one can notice that the maximum observed values are high. Actually, for most of the producers the maximum value is higher than the theoretical maximum based on the rated capacity presented in Table 6.1. This indicates that within a short period of time the producer has the possibility to producer more than the rated capacity. From the table one may also notice that the only producer who does not have minimum production of zero is producer 9.

Table 6.2: Descriptive statistics for production data. All data are in terms of MWh/week. ADF is the Augmented-Dickey-Fuller test value which have a critical value of -2,87 at a 5% sign. level in this testing.

	Mean	*Minimum*	*Maximum*	*Std. Deviation*	*ADF*
Producer 1	11058,72	0	21829,10	5899,87	-7,583
Producer 2	7754,59	0	18959,00	7198,81	-4,441
Producer 3	1697,31	0	5096,63	1642,10	-3,820
Producer 4	2447,82	0	5582,13	1610,47	-5,333
Producer 5	1734,37	0	4789,00	1807,73	-3,949
Producer 6	2141,32	0	3674,00	1039,14	-6,539
Producer 7	5327,13	0	11464,30	4771,38	-4,132
Producer 8	7963,45	0	26344,00	7059,42	-6,086
Producer 9	23834,78	1984,60	36651,30	10130,35	-4,744
Producer 10	4662,45	0	10652,70	3090,06	-6,465
Producer 11	1447,67	0	6576,30	1669,48	-7,242
Producer 12	2616,00	0	4686,00	1343,21	-6,769
Producer 13	11862,88	0	26286,15	7176,20	-6,380

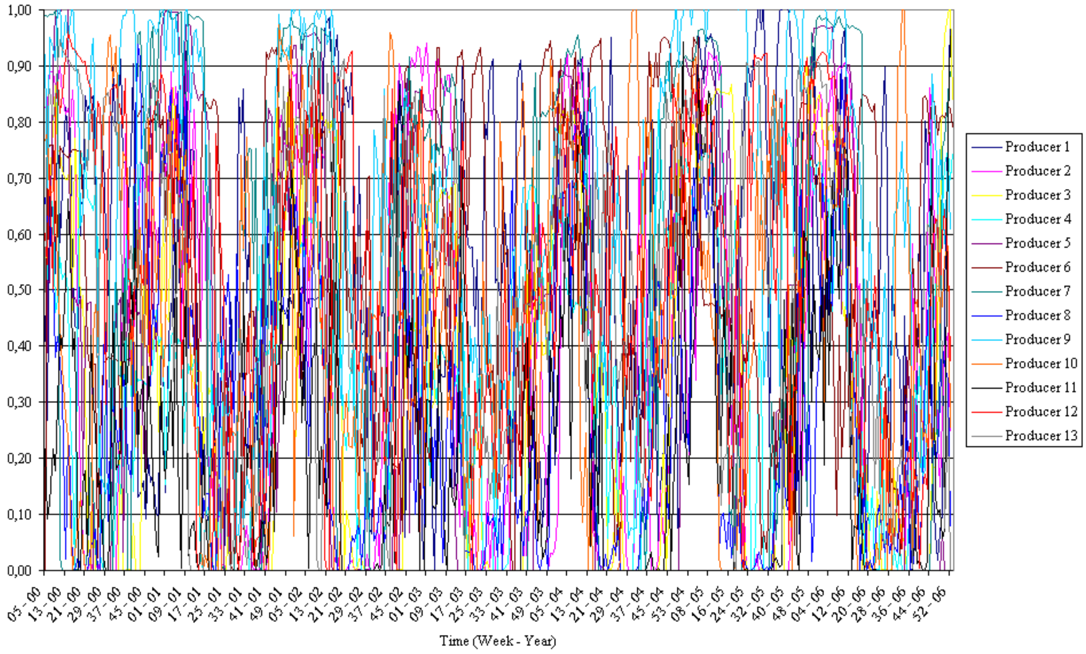

Figure 6.2: Relative production for all producers from week 5 in 2000 until week 52 in 2006. The figure is quite messy, but the purpose of presenting it is to illustrate that the relative production varies considerably over time and between producers.

6.2.2 Reservoir Data

Figure 6.3 illustrates the relative reservoir content, i.e. reservoir content as a share of the maximum reservoir capacity. A clear periodical variation can be seen. Since many of the reservoirs are emptied once a year, it may be argued that the producers only need a scheduling horizon until these dates. This agrees with the fact that all of the producers in our sample have a rather low relative regulation.

If there are more than one reservoir connected to the power stations, we have aggregated the reservoirs to one equivalent reservoir. This was done for producer 1, 4 and 13 and may cause that the flexibility of the producers seems greater than it really is. An additional weakness of the data is the lack of snow reservoir data. Descriptive statistics for the reservoir data are presented in Table 6.3.

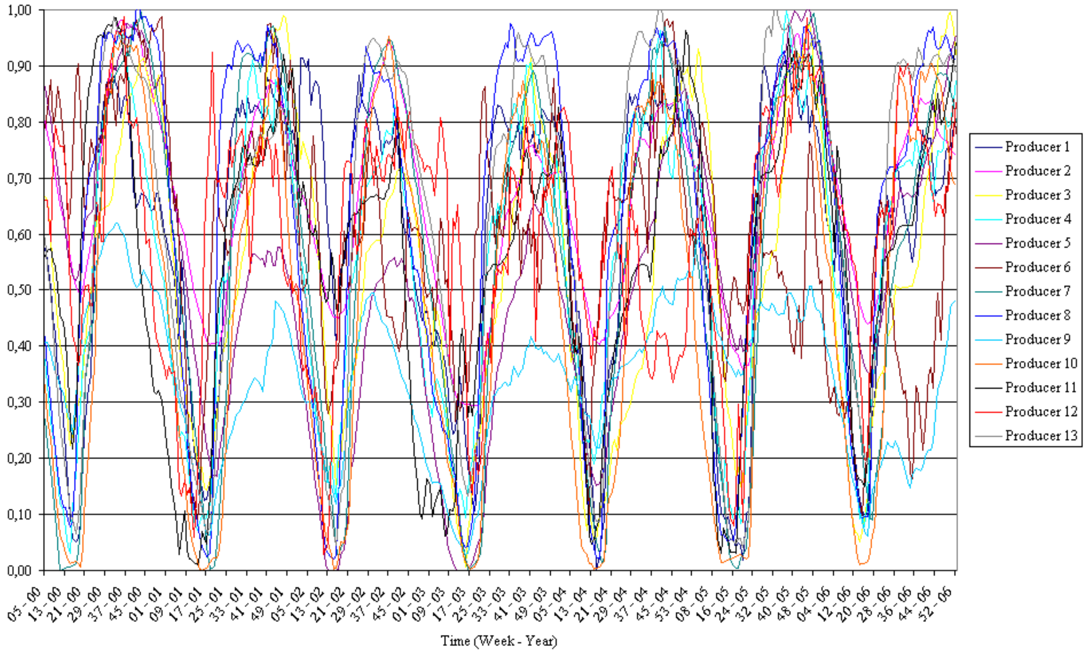

Figure 6.3: Reservoir content for all producers from week 5 in 2000 until week 52 in 2006.

6.2.3 Inflow Data

The expected yearly inflow for the hydropower plants in our sample are very dissimilar. To be able to say something general about the variation in inflow over the sample period, the relative inflow is calculated. Relative inflow is illustrated in Figure 6.4 and is defined as weekly inflow divided by the expected yearly inflow. The calculation of expected yearly inflow is presented in Appendix D.3.

Table 6.3: Descriptive statistics reservoir data. All data are in terms of MWh. ADF is the Augmented-Dickey-Fuller test value which have a critical value of -2,87 at a 5% sign. level in this testing.

	Mean	*Minimum*	*Maximum*	*Std. Deviation*	*ADF*
Producer 1	135517,08	557,76	208346,60	58218,85	-1,923
Producer 2	412735,88	183561,84	612497,16	109436,06	-1,334
Producer 3	25229,33	300,00	46900,00	12264,39	-1,180
Producer 4	28829,16	1616,74	51720,75	13620,42	-1,537
Producer 5	63145,45	0	119112,60	31007,76	-0,7387
Producer 6	8338,29	1241,76	13822,70	2897,50	-3,172
Producer 7	141293,56	50,00	253800,00	81100,69	-1,368
Producer 8	171572,58	5380,01	276220,65	87366,87	-1,570
Producer 9	433929,22	37500,00	786100,00	173833,97	-1,212
Producer 10	67641,27	100,00	135200,00	46670,28	-1,346
Producer 11	23490,98	399,91	41955,77	11203,10	-1,550
Producer 12	7358,68	0	12266,40	2620,86	-3,786
Producer 13	236639,39	15616,60	388839,39	114488,91	-1,328

As expected it seems like there are some seasonal variations over the year but it is difficult to see if there are variations between the years, hence if any of the years are "wetter" than the others. It appears to be large differences of the spread of inflow during the year. Some of the producers have evenly spread inflow, while others have periods with extremely high or low inflow. This is also evident from Table 6.4 where descriptive statistics for the inflow data is presented.

6.3 Price Data

All data concerning prices are obtained from the Nord Pool's FTP server files.

6.3.1 Spot Prices

The spot prices used in the analysis are weekly system prices denominated in Euro/MWh. These prices are weekly averages of the hourly system prices and are calculated and published by Nord Pool. In the first row of Table 6.5 descriptive statistics of the spot price are presented. When using the weekly average system price one loses the price variation within the day and between the days. This reduces the variance and may be the reason why the standard deviation of the spot price is quite similar to those of the forward prices.

In Figure 6.5 the development of the spot price in the sample period is shown. The winter 2002/2003 and the late summer of 2006 stand out as periods with particular high

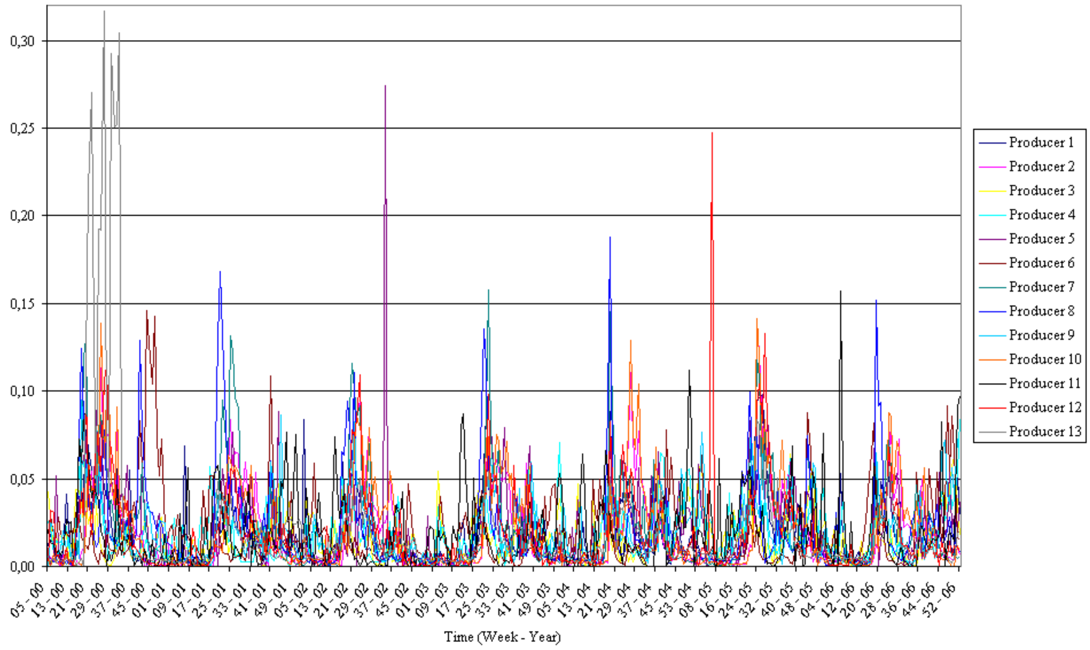

Figure 6.4: Relative inflow for all producers during the sample period

Table 6.4: Descriptive statistics inflow data. All data are in terms of MWh/week. ADF is the Augmented-Dickey-Fuller test value which have a critical value of -2,87 at a 5% sign. level in this testing.

	Mean	*Minimum*	*Maximum*	*Std. Deviation*	*ADF*
Producer 1	11638,63	0	63125,10	12375,56	-8,820
Producer 2	7312,65	0	50556,00	9151,31	-6,058
Producer 3	1743,28	0	6860,34	1437,45	-11,25
Producer 4	2709,79	0	12063,05	2318,80	-8,951
Producer 5	1872,45	0	24083,89	2193,93	-12,98
Producer 6	2967,86	0	22342,42	3250,55	-8,376
Producer 7	5575,83	0	43000,00	7542,10	-6,666
Producer 8	8413,89	0	77892,03	11601,80	-7,876
Producer 9	24149,50	0	118600,00	22266,42	-9,825
Producer 10	4795,54	0	32790,00	6077,11	-6,456
Producer 11	1577,18	0	12780,18	1785,31	-11,73
Producer 12	2784,34	0	36409,64	3762,68	-9,312
Producer 13	13779,56	0	209859,60	27271,23	-7,281

prices, which one may expect will affect the analysis. There seems to be no particular seasonal trend in the spot price. This is probably due to the relative short time period.

Table 6.5: Descriptive statistics for spot prices, forward week, forward season and forward year prices. All prices are in terms of Euro/MWh. ADF is the Augmented-Dickey-Fuller test value which have a critical value of -2,87 at a 5% sign. level in this testing.

	Mean	*Minimum*	*Maximum*	*Std. Deviation*	*ADF*
Spot Price	29,63	4,78	103,65	14,01	-2,928
Forward Week	30,44	5,70	114,56	14,89	-3,446
Forward Season	31,16	10,48	83,25	13,56	-2,890
Forward Year	28,54	15,57	57,80	9,73	-2,025

6.3.2 Forward Prices

The financial market at Nord Pool, Eltermin, has gone through considerably changes in our sample period. There has been a gradually introduction of new products and at the same time products have been phased out. In 2000 all products were listed in Norwegian kroner (NOK) and the product list was based upon a seasonal division of the year. The new products introduced are based upon the calender year and is listed in Euro. Hence, through the sample period seasonal and block products have been replaced with quarterly and monthly products and the prevailing currency has changed.

Based on the fact that the producers in the sample have a quite short relative regulation products with a time to maturity less than a year were considered. Secondly it is favorable to select different products with a spread in time to maturity. Therefore three different forward products were considered initially; a weekly forward with delivery next week, a seasonal forward with delivery next season and a yearly forward with delivery next year. Because of the changes in the product list at Nord Pool the seasonal forward product had to be constructed. The seasonal forward product consists of the seasonal product with delivery next season until week 40 in 2005 and from this week it consists of the quarterly product with delivery next quarter. The forward week and the forward year product have not gone through any changes in the sample period.

Forward products are traded continuously during a trading day, but for consistency with the other data, "weekly" forward prices is required. The closing prices at Wednesday which is at least likely to be a non-trading day, is selected to represent weekly closing prices. To allow for the change in currency we use historical yearly average currency spot rates published by Norges Bank (the central bank of Norway).

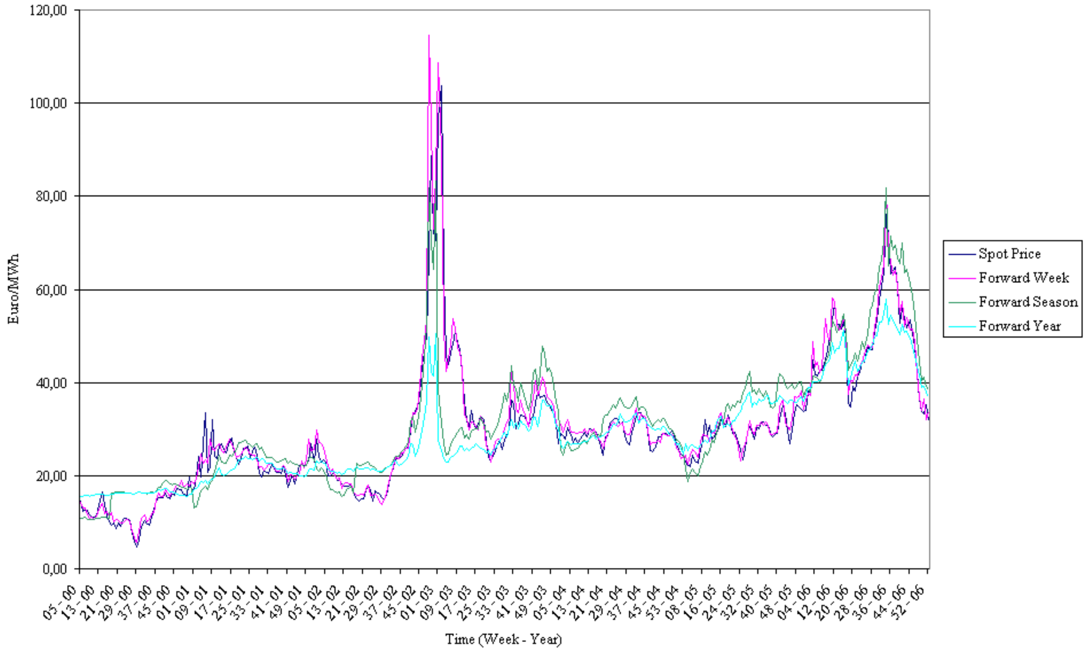

Figure 6.5: Spot and selected forward price development from week 5 in 2000 until week 52 in 2006.

6.4 Total Reservoir Content in the Market

Data regarding the total reservoir content in the market is obtained from Nord Pool and it is shown in Figure 6.6. Total reservoir content equals the aggregated reservoir contents of those reservoirs in Norway and Sweden that are recorded by Nord Pool.

In (Bruøygard & Larsen 2003) the authors found that the correlation between the deviation from expected reservoir level and the system price was -0,74. This indicates that a total reservoir level that deviates negatively from the normal level increases the prices.

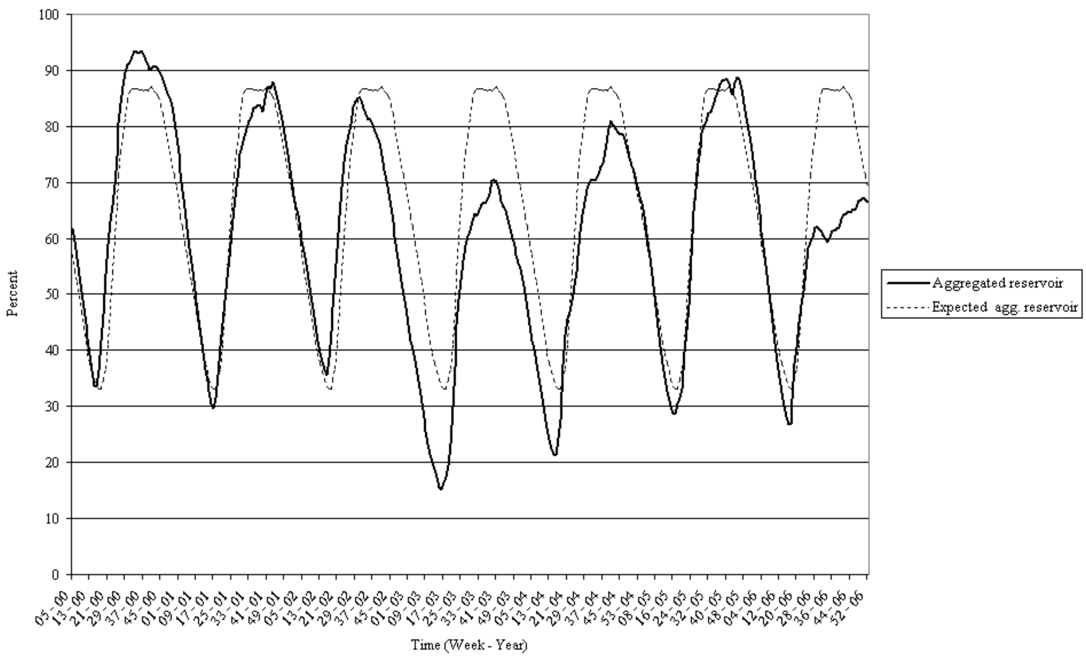

Figure 6.6: Aggregated reservoir content in the market. The difference between the solid-drawn and the dotted line is the deviation from expected reservoir level.

6.5 Stationarity Test

A Dickey-Fuller test has been conducted for all the time series. With a 5% significance level the critical value is -2,87. The production and inflow series as well as the spot, the forward week and forward season price series are all stationary. The forward year price series and the reservoir time series are non-stationary. However, the first difference of the time series are all stationary with a 5% significance level.

Stationarity is an important property for the empirical analysis presented in later chapters. Due to this, the non-stationary forward year variable is disregarded. This is a simplification that could be justified by the fact that most of the producers in our sample have a shorter scheduling horizon than one year. The other non-stationary variables are employed further but to allow for the testing, only as first differences.

The results of the test for the production, reservoir, inflow and prices are reported in Table 6.2, 6.3, 6.4 and 6.5 respectively. For results of the stationary tests on the other variables, see Appendix B.1

6.6 Correlation between Variables

A high correlation in absolute value between variables indicates collinearity, i.e. a linear relationship among the variables. The result of collinearity among independent variables in a regression model is biased estimators. To avoid collinearity a rule of thumb, is to not include two variables with at correlation coefficient higher than 0,8 or 0,9 in absolute value in the same regression model (Hill, Griffiths & Judge 2001). In Table 6.6 the correlation matrix for the stationary variables is presented. All variables are presented thoroughly in next chapter. The highest correlation is found between the prices. Particularly the correlation between S and FW and $\frac{S}{F}$ and $(\frac{S}{F})^2$ with a correlation coefficient of respectively 0,9755 and 0,9847 are very high. In Table B.2 the correlation matrix for the differenced variables are shown. Two problematic high correlation coefficients should be noted, the correlation between Δw and $\Delta w - E[w]$ equal to 0,9439 and the correlation between $\Delta(\frac{S}{F})$ and $\Delta(\frac{S}{F})^2$ at 0,9675. These results are regarded for later in chapter 7 where different formulations of models are discussed.

Table 6.6: Correlation coefficient between all stationary variables. Production and inflow are denoted with p and w, respectively. Spot, forward season and forward week are denoted S, FS and FW. The variables will be discussed thoroughly later. The problematic high correlation between S and FS and $\frac{S}{F}$ and $(\frac{S}{F})^2$ should be noted.

	p	w	w_{t+1}	$w - E[w]$	S	FW	FS	$\frac{S}{F}$	$(\frac{S}{F})^2$
p	1								
w	0,3133	1							
w_{t+1}	0,2900	0,7559	1						
$w - E[w]$	0,1139	0,7029	0,4017	1					
S	-0,0196	-0,1444	-0,1273	-0,1266	1				
FW	-0,0194	-0,1412	-0,1297	-0,1205	0,9755	1			
FS	-0,1033	-0,0440	-0,0421	-0,0976	0,8368	0,8568	1		
$\frac{S}{F}$	0,1509	-0,2417	-0,2063	-0,1163	0,3429	0,2340	-0,1258	1	
$(\frac{S}{F})^2$	0,1452	-0,2183	-0,1848	-0,0957	0,3402	0,2277	-0,1460	0,9847	1

Chapter 7

Mathematical Formulation of Models

7.1 Introduction

In chapter 5 the framework of the hypotheses was presented. In order to test the general hypothesis empirically, we present several models with different formulations of the dependent and independent variables. All the models have in common that they describe hydropower generation.

7.2 Dependent Variables

7.2.1 Production, p

The simplest way to formulate the dependent variable is as production, p. Then all producer specific variables are expressed in MWh. The drawback with this formulation is that producer specific effects become evident.

To cope with the undesirable producer specific effects we add a producer specific production capacity dummy, D_{cap}, as an intercept along with the constant. This is simply done by dividing all the producers into groups with respectively "high production capacity" and "low production capacity". Producer 1,2,8,9 and 13 have a remarkably higher installed capacity than the other producers. See Table 6.1. It is reasonable to believe that producers with a high capacity compared to the other producers are able to produce at a higher level than the others.

The capacity dummy equals one for producers with a large production capacity, and zero for producers with a small capacity. By this, the model is adjusted for the proper production level for each producer;

We let D_{cap} denote the capacity dummy which is producer dependent

$$D_{cap} = \begin{cases} 1 & \text{if the station has a large installed capacity} \\ 0 & \text{else} \end{cases} \tag{7.1}$$

Notice that the dummy is producer dependent and should be indexed according to producers. For notational ease we skip indexes on all dummies introduced in this and in later chapters.

7.2.2 Relative Production, $\frac{p}{p_{max}}$

Another way to avoid some of the producer specific effects is to formulate the dependent variable as production relative to production capacity, $\frac{p}{p_{max}}$. Instead of adding a capacity dummy as an independent variable in the model we use the actual capacity to adjust for producer specific effects in the dependent variable. This method is less rough than adding an intercept dummy. Hence, the producer specific effects are better taken care of. When the dependent variable is formulated as relative production it makes sense to also formulate the producer specific independent variables as relative numbers. The only producer specific independent variable defined in the general hypothesis in chapter 5 is inflow. All the formulations of the inflow variable introduced later are given relative to expected yearly inflow, $\overline{w}$, when the dependent variable is relative production.

7.2.3 Deviation from Expected Reservoir Level, $R - E[R]$

From chapter 3 we know that the main focus in scheduling production is to decide how much to produce at every point in time and simultaneously make sure that the reservoir level is within its restrictions. These two decision variables are closely linked and it may be argued that the management of the reservoir and the production scheduling amount to largely the same issue. The link has already been formulated in hypothesis 1 in section 5.2.1.

The expected reservoir level expresses the producers anticipations of the inflow and how to optimally manage the water in order to avoid overflow or scarcity. Depending on the time of the year the expected reservoir level for each producer varies. If the producers choose to deviate from the expected reservoir it is probably because of the circumstances i.e. prices and inflow make it favorable. Hence, the deviation from the expected reservoir, $R - E[R]$, may be seen as an indirect measure of production. A high deviation from the expected reservoir indicates a low production. An advantage of using deviation from expected reservoir level as a dependent variable instead of production or relative production is that one may expect less noise due to maintenance or breakdowns. The calculation of expected reservoir curves is fully explained in Appendix D.1.

From the stationarity tests in 6.5 we know that the time series of deviation from expected reservoir level is non-stationary. However, the differenced time series of deviation from expected inflow is stationary. In the models with deviation from expected reservoir level as dependent variable we have chosen to let all the independent variables also be differenced. This is to simplify the interpretation of the model. A model with both differenced and not differenced variables may be harder to interpret.

7.3 Independent Variables

As with the dependent variable, the independent variables can also be formulated in different ways. We present three alternatives to formulate price and three alternatives to formulate inflow.

7.3.1 Price

Spot, S and Forward Season, FS

In the general hypothesis we want to see how the production is affected by the spot price and forward prices. One way to handle this is to include both the spot price and one or several forward products. From the stationarity and correlation analysis in section 6.5 one knows that forward year is non-stationary and cannot be included in the model. Further one sees that forward week is highly correlated with spot price and forward season. Hence, some choices have to be made regarding which prices to include in the model. It is necessary to include spot price since we want to test how the price of today compared to some future price affects production. The average of the selected producers' relative regulation is approximately eight months, which suits the time horizon of forward season. In addition, forward season with delivery the next season is the most frequently traded forward product (SKM 2007). Hence, we find it suitable to include forward season, FS in the model in addition to spot price, S.

Spot Relative to the Average of Forwards, $\frac{S}{\bar{F}}$

An alternative to including spot and forward separately in the model is to include spot price relative to the average of forward prices, $\frac{S}{\bar{F}}$. By introducing spot relative to the average of forward prices one captures the dynamics of the prices in the market. One can argue that producers are not interested in the spot price and the forward price separately but in relation with another. When the producers decide whether to produce today or to save water for future production, they want to consider the spot price in relation to the forward prices. Even though the spot price is high and indicates that there should be a high production, as long as the forward prices are high as well it might hinder a high production. The average forward price is an average of forward week and forward season.

Square of Spot relative to Forward, $(\frac{S}{\bar{F}})^2$

A third way, is to anticipate that there is a polynomial relationship between spot relative to forwards and the production, $(\frac{S}{\bar{F}})^2$. The larger gap between spot and forward, the more influenced is production.

7.3.2 Inflow

Inflow, w

The most intuitive way to include inflow, w, in the model is at level i.e in MWh. Producer specific effects are conspicuous since inflow is dependent on geographical location and the hydrological situation at the power plant. In models where the dependent variable is $\frac{p}{p_{max}}$ we introduce inflow relative to expected inflow, $\frac{w}{\bar{w}}$, in order to avoid producer specific effects in the relative models.

Deviation from Expected Inflow, $w - E[w]$

As described in section 3.4 most Norwegian power producers have quite good forecasts based on long time series of historical inflow. Hence, one can assume that the producers have knowledge of expected future inflow in their minds when they schedule production so that expectation of inflow is already embedded in their plans. Because of this one can argue that it is the deviation from expected inflow, $w - E[w]$, rather than the inflow alone that has a positive impact on production. To estimate the expected inflow the average inflow for each week over the years for each producer is calculated. For further details of the calculation, see Appendix D.3.

Lead of Inflow, w_{t+1}

Another approach is to assume that the producers cannot respond to inflow on the very same day as the production decision is carried into effect. It is rather the anticipation of next week's inflow that affect production today. Our data set does not include forecasts of inflow. However, if one can assume that the hydropower producers have very good inflow forecasts for the next week, one can use the actual inflow data of the next week as "expected inflow" that is available to the producer one week in advance. In practice one introduces the lead of next week‘s inflow, w_{t+1}, into the model.

7.3.3 Other Independent Variables

Filling- and Drawdown Seasonal Dummy, D_s

The seasonal effect is included by a dummy which states whether the production takes place during the drawdown season or during the filling season, D_s.

$$D_s = \begin{cases} 1 & \text{in week 18 - 39} \\ 0 & \text{in week 40 - 17} \end{cases} \tag{7.2}$$

As expressed in section 5.1.3 one expects that seasonal variations has an effect on how the producer is affected by inflow in the production decision. One expects a high inflow to increase production less during filling seasons. Hence, the dummy is included as a slope dummy in combination with inflow, i.e. $D_s \times w$. If the inflow variable has the form; "deviation from expected inflow", the seasonal variation is already regarded for by subtracting the expected inflow. Here we choose to include the seasonal dummy as an intercept for the purpose to still be able to separate between filling- and drawdown season. Although inflow is taken care of, we expect the production to be lower in the filling season because inflow affects production less.

Lag of Production, p_{t-1}

Earlier production affect the production today as stated in the general hypothesis in 5.1.4. To test this relationship we have included last weeks production, p_{t-1}, to be an independent variable in the regression models. For the relative production model we naturally get $(\frac{p}{p_max})_{i,t-1}$ and for the deviation from expected reservoir; $\Delta(R-E[R])_{i,t-1}$.

7.4 Model Formulations

All the different designs of the dependent and independent variables constitutes different linear regression models that are tested in later chapters. We find all the different model formulations logical and consistent with theory in earlier chapters.

7.4.1 Dependent Variable: Production

Deviation from Expected Inflow

$$p_{i,t} = \alpha + \beta_1 D_s + \beta_2 (w - E[w])_{i,t} + \beta_3 (\frac{S}{\overline{\overline{F}}})_{i,t} + \beta_4 p_{i,t-1} + \epsilon_{i,t} \tag{7.3}$$

$$p_{i,t} = \alpha + \beta_1 D_s + \beta_2 (w - E[w])_{i,t} + \beta_3 (\frac{S}{\bar{F}})^2_{i,t} + \beta_4 y_{i,t-1} + \epsilon_{i,t} \tag{7.4}$$

$$p_{i,t} = \alpha + \beta_1 D_s + \beta_2 (w - E[w])_{i,t} + \beta_3 S_{i,t} + \beta_4 FS_{i,t} + \beta_5 y_{t-1} + \epsilon_{i,t} \tag{7.5}$$

Inflow

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 (\frac{S}{\bar{F}})_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.6}$$

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 (\frac{S}{\bar{F}})^2_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.7}$$

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 S_{i,t} + \beta_5 FS_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \tag{7.8}$$

Lead of Inflow

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t+1} + \beta_3 D_s w_{i,t+1} + \beta_4 (\frac{S}{\bar{F}})_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.9}$$

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t+1} + \beta_3 D_s w_{i,t+1} + \beta_4 (\frac{S}{\bar{F}})^2_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.10}$$

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t+1} + \beta_3 D_s w_{i,t+1} + \beta_4 S_{i,t} + \beta_5 FS_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \tag{7.11}$$

7.4.2 Dependent Variable: Relative Production

Deviation from Expected Inflow

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2 (\frac{w - E[w]}{E[w]})_{i,t} + \beta_3 (\frac{S}{\bar{F}})_{i,t} + \beta_4 (\frac{p}{p_{max}})_{i,t-1} + \epsilon_{i,t} \tag{7.12}$$

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2 (\frac{w - E[w]}{E[w]})_{i,t} + \beta_3 (\frac{S}{\bar{F}})^2_{i,t} + \beta_4 (\frac{p}{p_{max}})_{i,t-1} + \epsilon_{i,t} \tag{7.13}$$

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2 (\frac{w - E[w]}{E[w]})_{i,t} + \beta_3 S_{i,t} + \beta_4 FS_{i,t} + \beta_5 (\frac{p}{p_{max}})_{i,t-1} + \epsilon_{i,t} \tag{7.14}$$

Inflow

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2(\frac{w}{\overline{w}})_{i,t} + \beta_3 D_s(\frac{w}{\overline{w}})_{i,t} + \beta_4(\frac{S}{\overline{F}})_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.15}$$

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2(\frac{w}{\overline{w}})_{i,t} + \beta_3 D_s(\frac{w}{\overline{w}})_{i,t} + \beta_4(\frac{S}{\overline{F}})^2_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.16}$$

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2(\frac{w}{\overline{w}})_{i,t} + \beta_3 D_s(\frac{w}{\overline{w}})_{i,t} + \beta_4 S_{i,t} + \beta_5 FS_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \tag{7.17}$$

Lead of Inflow

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2(\frac{w}{\overline{w}})_{i,t+1} + \beta_3 D_s(\frac{w}{\overline{w}})_{i,t+1} + \beta_4(\frac{S}{\overline{F}})_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.18}$$

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2(\frac{w}{\overline{w}})_{i,t+1} + \beta_3 D_s(\frac{w}{\overline{w}})_{i,t+1} + \beta_4(\frac{S}{\overline{F}})^2_{i,t} + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{7.19}$$

$$(\frac{p}{p_{max}})_{i,t} = \alpha + \beta_1 D_s + \beta_2(\frac{w}{\overline{w}})_{i,t+1} + \beta_3 D_s(\frac{w}{\overline{w}})_{i,t+1} + \beta_4 S_{i,t} + \beta_5 FS_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \tag{7.20}$$

7.4.3 Dependent Variable: Deviation from Expected Reservoir

Deviation from Expected Inflow

$$\Delta(R - E[R])_{i,t} = \beta_1 D_s + \beta_2 \Delta(w - E[w])_{i,t} + \beta_3 \Delta(\frac{S}{\overline{F}})_{i,t} + \beta_4 \Delta(R - E[R])_{i,t-1} + \epsilon_{i,t} \tag{7.21}$$

$$\begin{aligned}\Delta(R - E[R])_{i,t} = {} & \beta_1 D_s + \beta_2 \Delta(w - E[w])_{i,t} + \beta_2 \Delta(\frac{S}{\overline{F}})^2_{i,t} + \beta_3 D_s \Delta(w - E[w])_{i,t} \\ & + \beta_4 \Delta(R - E[R])_{i,t-1} + \epsilon_{i,t}\end{aligned} \tag{7.22}$$

$$\begin{aligned}\Delta(R - E[R])_{i,t} = {} & \beta_1 D_s + \beta_2 \Delta(w - E[w])_{i,t} + \beta_2 \Delta S_{i,t} + \beta_3 \Delta FS_{i,t} \\ & + \beta_4 D_s \Delta(w - E[w])_{i,t} + \beta_5 \Delta(R - E[R])_{i,t-1} + \epsilon_{i,t}\end{aligned} \tag{7.23}$$

Inflow

$$\Delta(R-E[R])_{i,t} = \beta_1 \Delta w_{i,t} + \beta_2 D_s w_{i,t} + \beta_3 \Delta(\frac{S}{F})_{i,t} + \beta_4 \Delta(R-E[R])_{i,t-1} + \epsilon_{i,t} \quad (7.24)$$

$$\Delta(R-E[R])_{i,t} = \beta_1 \Delta w_{i,t} + \beta_2 D_s w_{i,t} + \beta_3 \Delta(\frac{S}{F})^2_{i,t} + \beta_4 \Delta(R-E[R])_{i,t-1} + \epsilon_{i,t} \quad (7.25)$$

$$\begin{aligned}\Delta(R-E[R])_{i,t} &= \beta_1 \Delta w_{i,t} + \beta_2 D_s w_{i,t} + \beta_3 \Delta S_{i,t} + \beta_4 \Delta FS_{i,t} \\ &+ \beta_5 \Delta(R-E[R])_{i,t-1} + \epsilon_{i,t}\end{aligned} \quad (7.26)$$

Lead of Inflow

$$\Delta(R-E[R])_{i,t} = \beta_1 \Delta w_{i,t+1} + \beta_2 D_s w_{i,t+1} + \beta_3 \Delta(\frac{S}{F})_{i,t} + \beta_4 \Delta(R-E[R])_{i,t-1} + \epsilon_{i,t} \quad (7.27)$$

$$\Delta(R-E[R])_{i,t} = \beta_1 \Delta w_{i,t+1} + \beta_2 D_s w_{i,t+1} + \beta_3 \Delta(\frac{S}{F})^2_{i,t} + \beta_4 \Delta(R-E[R])_{i,t-1} + \epsilon_{i,t} \quad (7.28)$$

$$\begin{aligned}\Delta(R-E[R])_{i,t} &= \beta_1 \Delta w_{i,t+1} + \beta_2 D_s w_{i,t+1} + \beta_3 \Delta S_{i,t} + \beta_4 \Delta FS_{i,t} \\ &+ \beta_5 \Delta(R-E[R])_{i,t-1} + \epsilon_{i,t}\end{aligned} \quad (7.29)$$

7.5 Data Snooping

Trying many variables in a regression without basing the selection of the candidate variables on an economic theory is known as "data mining" or "data snooping". The result in such cases is that the true significance level will be considerably greater than the nominal significance level assumed (Brooks 2002).

We have kept our models simple to avoid the charge that we have tested a wide variety of models. There might be other alternative formulations of the variables for instances logarithmic transformation of the prices and lag of independent variables. However, since the best models are going to be used in testing of further hypotheses such transformations would complicate the interpretation of the results. We want to remain the reader that the purpose with this thesis is not to find the "best model", but to find a model that is well suited to test qualitative aspects of the scheduling decisions. Due to that, we limit the analysis to the 27 models presented.

Some initial testing was required to avoid testing too many models. For example we tested for lag of the dependent variable initially to find out whether it was necessary to include lag as a variable at all. It is meaningless to test all combinations of variables unless they are logically consistent together in a model. Therefore we have avoided using software methods such as stepwise regression which mechanically search through all possible combinations of models without evaluating the logical composition of the variables.

Data snooping is a common problem in empirical research. The phenomenon is especially a problem in the analysis of time-series data, as typically only a single history measuring a given phenomenon is available for analysis (White 2000). One way to avoid data snooping is to cross validate the data. Then one tests the forecast performance of the model in an out-of-sample data set. The idea is essentially that a proportion of the data is not used in the model estimation, but is retained for model testing. A relationship observed in the estimation period that is solely a result of data snooping, and is therefore spurious, is very unlikely to be repeated in the out-of-sample testing. Therefore, models that are the product of data snooping are likely to fit poorly and give very inaccurate forecasts for the out-of-sample period (Brooks 2002). Out-of-sample testing will be accomplished in section 8.3 where the results of the general hypothesis are presented.

7.5.1 Testing Hypotheses Suggested by the Data

By defining variables based on theory of hydropower and the forward market and not defining hypotheses based on trends in the data set, we hope to avoid the problem of data snooping. Both the general and specific hypotheses are tested with evidence that were not used in constructing the hypotheses. This is because every data set must contain some chance patterns which are not present in the population under study. Studying the data sample and search for evidence which are formulated as hypotheses is spurious and must be avoided. When testing a data set on which the hypothesis is known to be true, the data set is by definition not a representative data set, and any resulting significance levels are meaningless.

Chapter 8

General Hypothesis Testing

8.1 Estimation Method

8.1.1 Dynamic Panel Data

As mentioned in section 6.2 the data gathered is on the form of balanced panel data. The use of panel data provides less collinearity among the variables, more degrees of freedom and more efficiency. In general, panel data is better able to identify and measure effects that is not detectable in pure cross-section or pure time-series data (Baltagi 2005).

The models presented in section 7.4 are due to the lagged dependent variable, dynamic panel models. The models do not include dummies for each producer or each time periods, and must therefore be characterized as dynamic random effects models (See Appendix A.5). Since the objective of the analysis is to investigate how Norwegian hydropower producers schedule production, i.e. we want to make inferences about the population of Norwegian hydropower producers, a random effects models is suited (Baltagi 2005). Notice that quite strict criteria are applied in the selection of the producers. Therefore, inference may only be made to other hydropower producers that fulfill these assumptions.

Data with both a cross-section and time-series dimension does not usually display the properties that standard econometric techniques require. Although care has been taken in the choice of which producers to include in the sample, they are of varying size and other physical conditions. As a result, one may expect that the producers exhibit different variation. Hence, they will probably not fulfill the homoskedasticity assumption. White's test for heteroskedasticity is presented in section 10.2.

8.1.2 Generalized Method of Moments Estimator

Models have to be estimated by methods that handle the problems afflicting them. The GMM estimator is suited for dynamic model estimation. The method does not require the usual assumptions that the variables are independent and identically distributed and that the error components are homoskedasctic and non-autocorrelated. The assumptions required that are relevant for this analysis, are stationarity and non-collinearity. The results of the stationary test and the collinearity test are presented in section 6.5 and section 6.6, respectively. When allowing for these results the GMM estimator is suited for our analysis. In Appendix A.2 more information regarding GMM is provided.

Based on the above discussion, to estimate the regression models 1-step GMM estimator using dynamic panel data and robust standard errors implemented in OxPack 3.1 PcGive is applied.

8.2 Cross-validation of Models

In order to find which of the alternative model formulations in section 7.4 that best predicts the production decision and to avoid data snooping, the models are cross-validated. Partitioning the sample of data into subsets makes it possible to consider how well the model predicts response values from data that were not used in building the candidate models (Walpole, Myers, Myers & Ye 2002). The estimation of the models is performed on the in-sample data, while the out-of-sample data is retained for subsequent use in confirming and validating the initial analysis.

The data set in our analysis is a panel data set. It is therefore possible to cross-validate either over time or individuals. Since it is reasonable to expect larger differences between individuals than over time, cross-validation over time has been chosen. The full sample data is divided in two; an in-sample and an out-of-sample period. The in-sample period consists of 257 time periods and lasts from week 5 in 2000 until week 53 in 2004. The out-of-sample period is from week 1 in 2005 until week 52 in 2006, a total of 104 time periods. Hence, the in-sample is a larger sample and therefore the main sample in our analysis. The disadvantage with a cross-validation over time is that historical events that occur only in one of the sample period may disturb the analysis.

Using the definition presented in (Campbell & Thompson 2007), the out-of-sample R^2 is calculated and used as a criteria to select between the alternative models.

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(p_t - \widehat{p_t})^2}{\sum_{t=1}^{T}(p_t - \overline{p_t})^2} \tag{8.1}$$

where $\widehat{p_t}$ is the predictive production in the out-of-sample period using the estimates obtained from the regression on the in-sample data. The $\overline{p_t}$ denotes the weekly average production calculated from the in-sample data. The out-of-sample R^2 for the relative production models and the deviation from expected reservoir models are calculated similarly.

8.3 Discussion of Results from the Model Estimation

8.3.1 In-sample Estimation

The results of the estimation of the nine production models are presented in Figure C.1 in Appendix C.1. For these models, all variables have significant t-statistics and signs that are consistent with our general hypothesis presented in chapter 5. A high installed capacity leads to an increase in production. The inflow and the lead of inflow influence the production positively and during the filling season this impact is less, but still positive. The estimated coefficient of the deviation from the expected inflow variable is positive and the estimations of the models including these variables indicate that the production is lower during the filling season than else. Likewise, the signs of the price coefficients are as anticipated; a high spot price increases production, while a high forward season price decreases production. In absolute value, the coefficient of the forward is higher than that of spot which indicates that a marginal increase of the forward price reduces the production more than a marginal increase in the spot price increases production. Spot relative to forward and the square of spot relative to forward have a positive coefficients which is also in accordance with our expectations. In addition, the lagged dependent variable is significant with a positive coefficient for all production models.

Three of the estimated production models have an insignificant constant, but since our general hypothesis does not require a non-zero constant these models are still included in the out-of-sample validation. For the models with spot relative to forward and the square of spot relative to forward, some of the estimated constants are negative. Since production cannot be negative this implies that these models are invalid for some values of the independent variables, for instance if all independent variables equals zero. This is a limitation of the models.

The in-sample R^2 for all production models are above 87%. Model (7.6) has the highest in-sample R^2 of 87,37%. In Figure 8.1 the residuls, i.e. the difference between the actual and the fitted production for model (7.6) are plotted. As expected, the residual plot illustrates that the producers have different variation in regression disturbance. Moreover, it indicates that the error components in the model are heteroscedastic. For further discussion of heteroskedacity in the model, see section 10.2.

The results of the estimation of the relative production models are presented in Figure C.2 and the results are quite similar to those of the production models. The coefficients of the variables have the expected sign as discussed above, and all have significant t-statistics. The estimated constant in model (7.16) and (7.18) do not have significant

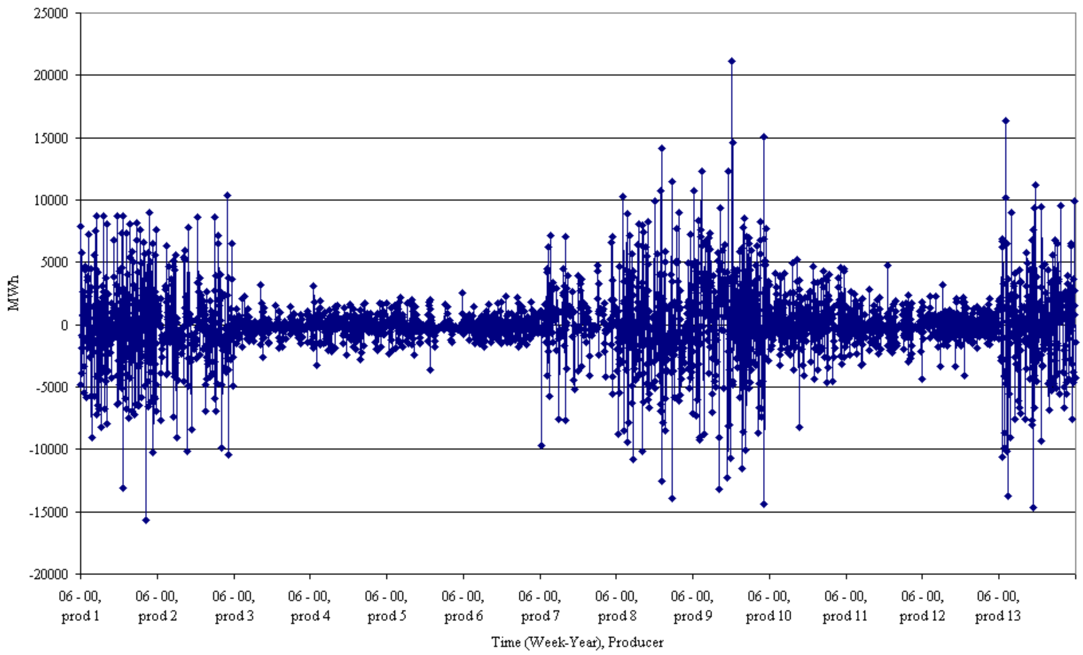

Figure 8.1: Residual plot for model 7.6

t-statistics, but since a non-zero constant is not required by the general hypothesis, this does not affect the out-of-sample validation. Model (7.17) has the highest in-sample R^2 among the relative production models.

In Figure C.3 results of the in-sample estimation of the deviation from expected reservoir models are shown. The results from the estimation of these models are less satisfactorily then for the other models discussed above. Only two of the deviation from expected reservoir models; model (7.24) and (7.25) fulfill the requirement of logical and significant coefficients. In the models including spot and forward season prices, the coefficient belonging to the forward price has the wrong sign compared to what is expected. The other models that are excluded from the out-of-sample validation have insignificant t-statistics. The highest in-sample R^2 among the accepted models is achieved by model (7.24).

8.3.2 Out-of-sample Validation

Out-of-sample R^2 is calculated for the candidate models that fulfill the in-sample requirements of logical and significant coefficients. The results are listed in the last columns of Figure C.1, C.2 and C.3. Clearly, the production models with an out-of-sample R^2 at approximately 88% perform much better than the relative production and deviation from expected reservoir models with an out-of-sample R^2 of about 69% and 53%, respectively. Although the production models have one more variable than the two other model classes because of the capacity dummy, it is clear that the production models better predict the out-of-sample values.

The very highest out-of-sample R^2 is equal to 88,56% and is achived by model (7.6). Model (7.7) and (7.8) follow close behind with an out-of-sample R^2 equal to 88,549% and 88,547%. Hence, based on the out-of-sample R^2 model (7.6) is the best model of those 27 presented, and will therefore be used in the specific hypotheses testing. Figure 8.2 illustrates the predicted production for the out-of-sample period using model (7.6) from the in-sample data. In the same figure the actual production in the out-of-sample period is plotted and one notices that the fit is quite good.

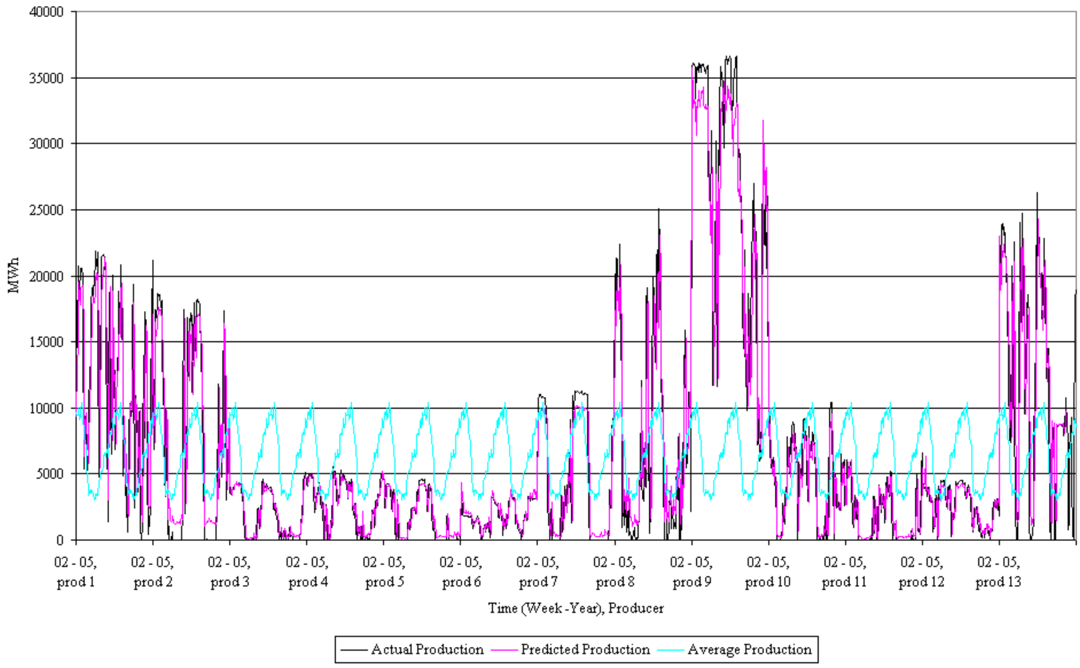

Figure 8.2: Actual production and predicted production using model (7.6) for the out-of-sample period.

8.3.3 Results of the General Hypothesis

From the discussion above we state that model (7.6) is the best model based on the out-of-sample R^2 criteria. Since this model fulfills our anticipations from the general hypothesis, we can conclude that the hypothesis is accepted. Below, model (7.6) is presented with its estimated coefficients.

$$p_{i,t} = -1045,25 + 913,35D_{cap} + 0,07w_{i,t} - 0,05D_s w_{i,t} + 1361,90(\frac{S}{\overline{\overline{F}}})_{i,t} + 0,87p_{i,t-1}$$

The general hypothesis states that inflow has a positive impact on production and that this impact is less during the filling season. During the drawdown season the model estimates that an increase in inflow of 1 MWh/week increases production with 0,07 MWh/week. Moreover, in the filling season the marginal increase is 0,02 MWh/week. Further, the general hypothesis state that spot relative to forward is positively affecting production. Production is dependent of spot relative to forward multiplied with a factor of 1361,9 MWh/week. Hence, if the current spot price is higher than the forward price, the rise in production is higher than 1361,9 MWh/week. This is a result deserving notice since it indicates that the forward market provides information applicable in the production scheduling. Given that these results are valid for other forward products as well, the forward curve can replace price forecasts based upon resource-demanding bottom-up models as discussed in chapter 4.

The lag of production is important in the estimated model. We see that this week's production can be explained by 87% of last weeks production. This finding is consistent with the general hypothesis. Finally, given that the producer has a high installed capacity, the production level rises with 913,35 MWh.

The constant is negative, which is unexpected and a limitation of the model. However, only in 23 of the 3328 weeks in the in-sample period and 2 of the 1339 weeks of the out-of-sample period, the production is respectively estimated and predicted to be negative.

Some of the hypotheses presented in chapter 5 require that spot and forward prices are modeled explicitly. Due to this we will test the price related hypotheses with model (7.8), which is the best model including S and FS separately. Model (7.8) is given with its estimated coefficients below and we see that it supports the general hypothesis.

$$p_{i,t} = 389,94 + 926,45D_{cap} + 0,07w_{i,t} - 0,06D_s w_{i,t} + 23,57S_{i,t} - 27,62FS_{i,t} + 0,87p_{i,t-1}$$

Again, notice that FS has the anticipated negative coefficient. Hence, the forward season product provides information of whether to save the water for production next season or not. This decision is not solely based on the forward season price but in combination with the spot price. In this model the spot price and the forward season are modeled separately unlike in model (7.6). Nevertheless, the negative sign of the forward coefficient and the positive sign of the spot coefficient support that a spot price has a positive impact on present production while the forward price affects present production negatively.

The out-of-sample R^2 of model (7.8) is slightly lower than that of model (7.6). Nevertheless, both models are assumed to perform well due to the high out-of-sample R^2 and are suitable for further hypotheses testing. The in-sample residual plot and the out-of-sample predicted production plot for model (7.8) are presented in Appendix C.2. As with model (7.6) the residual plot strongly indicates heteroskedasticity and the predicted production for the out-of-sample period fits the actual production well.

Chapter 9

Specific Hypotheses Testing

9.1 Introduction

We require a valid model for hydropower production as a foundation for the testing of the specific hypotheses. The specific hypotheses are mostly aimed at specific conditions of the variables. Hence, we have to create new variables that capture the qualitative aspects of the hypotheses. More specificly, we create dummy variables that are included in the model from the general hypothesis testing. The purpose behind the inclusion of dummies is not to improve the overall model, but to test the specific hypotheses.

Standard procedure in econometric hypothesis testing is to find out if the variable of interest, i.e. the dummy variable, has a significant t-statistics (See Appendix A.3.4). For the usual t-test to be valid the homoskedasticity assumption must hold (Wooldridge 2003). To allow for this, we have used robust standard errors which correct for heteroskedasticity in the estimation.

In 8.3.3 we argued that model (7.6) and model (7.8) were selected for testing of the specific hypotheses. Depending on which hypothesis is tested, the adequate model of the two is applied. For example, hypotheses which directly aim at how producers respond to different prices require model (7.8) which contain spot and forward prices separately, while model (7.6) is for the other hypotheses. All the hypotheses are tested on both in-sample and out-of-sample data separately. The out-of-sample testing is not required in the hypothesis testing. Still the same, we test the hypotheses using out-of-sample as well to assure against overfitting. As with testing of the general hypothesis, the specific hypotheses is tested by applying 1-step GMM estimator using dynamic panel data and robust standard errors implemented in OxPack 3.1 PcGive.

9.2 Hypothesis 1

The hypothesis states that deviation from expected reservoir results in an increase in production. One can argue that it would make sense to include reservoir as an independent variable to test the hypothesis. Unfortunately, this is not an option since the time series of reservoir is non-stationary (see section 6.5). The testing procedure is to add a dummy intercept for each producer with a positive deviation from expected reservoir, D_{dev}. By adding the dummy as an intercept one tests whether the production rises to a higher level as a consequence of a positive deviation from expected reservoir.

We let D_{dev} be;

$$D_{dev} = \begin{cases} 1 & \text{if the deviation from reservoir is positive} \\ 0 & \text{else} \end{cases} \tag{9.1}$$

By applying this dummy we can only test how the producer act to the scenario when the reservoir is above the expected level contra when it is not. Model (7.6) is applied in the testing of the hypothesis.

Model (7.6) including the intercept dummy, D_{dev};

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 D_{dev} + \beta_3 w_{i,t} + \beta_4 D_s w_{i,t} + \beta_5 (\frac{S}{F})_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \tag{9.2}$$

The null hypothesis states that the intercept dummy is not significant given that the other independent variables are included in model (9.2);

$$H_0 : \beta_2 = 0, \qquad H_1 : \beta_2 > 0 \tag{9.3}$$

Since D_{dev} is the only variable to be tested in the model, it is sufficient to check whether the t-probability of D_{dev} is significant given the other independent variables.

9.2.1 Results Hypothesis 1

The results from in-sample and out-of-sample testing are respectively listed in Table 9.1 and Table 9.2. What is interesting is the coefficient and t-probability of D_{dev}. The null hypothesis is rejected at a 5% significance level. Hence, we accept the hypothesis that deviation from expected reservoir is affecting the production. The chance of committing a type I error by rejecting the null hypothesis is approximately zero, see Appendix A.3.1. Further we notice that the coefficient of D_{dev} has a positive sign which is in according with the hypothesis; A positive deviation from expected reservoir increases production. In the in-sample data testing, a positive deviation from expected reservoir increases production with 386,90 MWh which is an increase of about 6 % of the average production. In the out-of-sample testing a positive deviation from expected reservoir increases production with 632,03 MWh which correspond to a 10 % increase of the average production. The producers reluctance to deviate from expected reservoir level might also indicate that the production is restricted by concession laws regarding reservoir levels. Due to estetic and environmental reasons, these restrictions state that the producer has to keep the water level within a certain range during specific periods of the year.

For both samples, the t-statistics prove that all independent variables are significant. Hence, the model is still valid. There has been a slight increase in in-sample R^2 due to the inclusion of the new variable. A R^2 of 87,43% implies that the overall model is a good fit.

Table 9.1: Results hypothesis 1 from in-sample data

	α	D_{cap}	D_{dev}	$w_{i,t}$	$D_s w_{i,t}$	$(\frac{S}{F})_{i,t}$	$p_{i,t-1}$	R^2
coef.	-1462,38	933,92	386,90	0,0667	-0,0525	1616,30	0,8651	0,8743
t-prob.	0,001	0,000	0,000	0,000	0,001	0,000	0,000	

Table 9.2: Results hypothesis 1 from out-of-sample data

	α	D_{cap}	D_{dev}	$w_{i,t}$	$D_s w_{i,t}$	$(\frac{S}{F})_{i,t}$	$p_{i,t-1}$	R^2
coef.	-4685,82	819,25	632,03	0,0882	-0,0520	4768,27	0,8705	0,8976
t-prob.	0,001	0,000	0,000	0,000	0,033	0,001	0,000	

9.3 Hypothesis 2

The hypothesis states that when the reservoir is nearly full or nearly empty the market price is subordinate in the decision-making process of the production. We want to test how the producer act to prices at different reservoir levels in situations where it is not expected to have nearly full or nearly empty reservoir levels. It is reasonable to apply model (7.8) to test the hypothesis. To test how the producers act with respect to prices when the reservoir is at unexpectedly high and low levels we have added a dummy to present these situations. First one has to exclude the weeks of the year when it is expected to have a high or low reservoir filling. Although all the producers are expecting a low reservoir level during spring and a high reservoir level during late autumn, it is difficult to generalize. Hence, each producer experiences high and low filling level at different points in time. For each producer we have anticipated three weeks during spring and three weeks during autumn that are expected to have respectively low and high reservoir filling. These weeks are the expected minimum and maximum reservoir level ± 1 week. See Appendix D.2 for more information.

We let D_{res} represent when the reservoir is at minimum 90% or maximum 10% filling level;

$$D_{res} = \begin{cases} 1 & \text{if the reservoir is at minimum 90\% or maximum 10\% filling level} \\ 0 & \text{else} \end{cases} \tag{9.4}$$

To test how these extreme situations affect the prices the dummy is multiplied with respectively the spot price and the forward price to form slope dummies. A slope dummy operates by changing the slope of the regression line, but leaves the intercept unchanged. The dummies are added to model (7.8) to be able to test the hypothesis as expressed in equation (9.5);

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 S_{i,t} + \beta_5 D_{res} S_{i,t} + \beta_6 FS_{i,t} + \beta_7 D_{res} FS_{i,t} + \beta_8 y_{i,t-1} + \epsilon_{i,t} \tag{9.5}$$

The null hypothesis states that the variables $D_{res}S_{i,t}$ and $D_{res}FS_{i,t}$ do not affect production given that the other variables are included in model 9.5;

$$H_0 : \beta_5 = \beta_7 = 0, \qquad H_1 : \beta_5 < 0 \quad \text{and} \quad \beta_7 > 0 \tag{9.6}$$

The null hypothesis contains more than one variable and therefore the f-statistic is required to test this hypothesis, (see Appendix A.3.5);

$$f_{obs} = \frac{SSR(\beta_5, \beta_7 | \beta_1, \beta_2, \beta_3, \beta_4, \beta_6)/2}{SSE/(N-k)} \sim F[2, (N-k)] \tag{9.7}$$

9.3.1 Results Hypothesis 2

The f_{obs}-statistic equals 4,02 for the in-sample testing which is larger than the critical value of $F[2, \infty]$ which equals 3,00 at a 5 % significance level. Hence, the null hypothesis is rejected on the in-sample testing. The p-value is approximately 0,0196 which states the probability of commiting a type I error. The f_{obs}-statistic for the out-of-sample testing equals 2,93 and the critical value is still 3,00 as for the in-sample testing. Hence, the null hypothesis is not rejected based on the out-of-sample data. Since the in-sample testing is superior to the out-of-sample testing, and the fact that the hypothesis is on the verge of being significant also in the out-of-sample testing, the hypothesis is doubtfully accepted. Nevertheless, to verify this conclusion the hypothesis should be tested on another sample. Table (9.3) and Table (9.4) below provides information of the coefficients and t-probabilities of the models respectively for the in-sample testing and the out-of-sample testing. The signs of the coefficients in both models are in accordance with the hypothesis that prices are less important to the hydropower producers when the reservoirs are nearly full or empty. Both the coefficients of the spot price and the forward price are reduced in absolute value when the reservoir is at an unexpected high or low filling level.

All the variables have significant t-statistics and when the model is tested using the in-sample data, R^2 equals 87,40%. Hence, the tested dummies contribute with an increase in R^2 of 0,03%.

Table 9.3: Results hypothesis 2 from in-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$D_{res}S_{i,t}$	$FS_{i,t}$	$D_{res}FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	404,71	918,86	0,0693	-0,0563	26,96	-54,61	-30,48	44,28	0,8666	0,8740
t-prob.	0,002	0,000	0,000	0,001	0,000	0,003	0,000	0,027	0,000	

Table 9.4: Results hypothesis 2 from out-of-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$D_{res}S_{i,t}$	$FS_{i,t}$	$D_{res}FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	688,17	745,14	0,0904	-0,0541	74,15	-126,49	-79,21	114,93	0,8705	0,8970
t-prob.	0,006	0,000	0,000	0,031	0,001	0,002	0,001	0,002	0,000	

9.4 Hypothesis 3

Here, we want to test whether the production decision is more dependent on inflow than otherwise in situations where the reservoir is nearly full. This hypothesis does not involve the prices so we choose to test it on model (7.6). Likewise hypothesis 2, we only test the hypothesis on data when the producer does not expect the reservoir to have a high filling level. The dummy is constructed as in hypothesis 2. The only difference is to not add data when the reservoir has a low filling level;

We let $D_{high,res}$ represent when the reservoir is at minimum 90% filling level;

$$D_{high,res} = \begin{cases} 1 & \text{if the reservoir is at minimum 90\% filling level} \\ 0 & \text{else} \end{cases} \tag{9.8}$$

The hypothesis aim at testing how the producers respond to inflow. Hence, the dummy is included as a slope dummy by multiplying it with inflow. Model (7.6) including the slope dummy is given below

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 D_{high,res} w_{i,t} + \beta_5 (\frac{S}{F})_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \tag{9.9}$$

The null hypothesis is to test the significance of the included slope dummy given the other independent variables in model (9.9);

$$H_0 : \beta_4 = 0, \qquad H_1 : \beta_4 > 0 \tag{9.10}$$

9.4.1 Results Hypothesis 3

The t-probabilities of $D_{high,res}w_{i,t}$ in Table 9.5 and Table 9.6 show that the hypothesis is significant at a 5 % significance level for both the in-sample data and the out-of-sample data. The probability of rejecting the null hypothesis when it is actually true is 0,045 for the in-sample testing. This is close to the critical significance level of 0,05. The p-value for the out-of-sample testing is approximately zero. In addition one sees that the positive signs of the coefficients of the variables $D_{high,res}w_{i,t}$ are consistent with the hypothesis that the producer wants to increase production with an unexpected increase in inflow.

The overall model has a R^2 equal to 87,37% when using the in-sample data. This is an increase of 0,007% from the R^2 without the dummy. Since including a new variable usually improves R^2, this increase is marginal.

Table 9.5: Results hypothesis 3 from in-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$D_{high,res}w_{i,t}$	$(\frac{S}{F})_{i,t}$	$p_{i,t-1}$	R^2
coef.	-1074,33	911,20	0,0685	-0,0549	0,0160	1390,78	0,8669	0,8737
t-prob.	0,002	0,000	0,000	0,001	0,045	0,000	0,000	

Table 9.6: Results hypothesis 3 from out-of-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$D_{high,res}w_{i,t}$	$(\frac{S}{F})_{i,t}$	$p_{i,t-1}$	R^2
coef.	-4226,71	602,73	0,0865	0,1205	0,1205	4622,03	0,8794	0,8976
t-prob.	0,002	0,002	0,000	0,000	0,000	0,002	0,000	

9.5 Hypothesis 4

Hypothesis 4 states that when spot prices are extremely high we expect a jump in production. To test whether there is an increase in production caused by high spot prices we include an intercept dummy to declare when extremely high spot prices occur. It is not an easy task to define a high spot price. To avoid testing hypothesis suggested by the data we do not study the spot curve in the sample period to find patterns that might only be typically for this sample period. Instead we sort the data in descending order and define the 5 % highest prices as "exremely high prices".

We let D_{spot} represent the 5 % highest spot prices;

$$D_{spot} = \begin{cases} 1 & \text{if the spot price is among the 5\% highest} \\ 0 & \text{else} \end{cases} \tag{9.11}$$

The hypothesis is tested on model (7.8) with the dummy intercept included. This model is better suited than model (7.6) since the hypothesis is price related;

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 D_{spot} + \beta_3 w_{i,t} + \beta_4 D_s w_{i,t} + \beta_5 S_{i,t} + \beta_6 FS_{i,t} + \beta_7 y_{i,t-1} + \epsilon_{i,t} \quad (9.12)$$

The null hypothesis is to test the significance of the high price intercept dummy given that the other independent variables in model (9.12) are included in the model;

$$H_0 : \beta_2 = 0, \qquad H_1 : \beta_2 > 0 \quad (9.13)$$

9.5.1 Results Hypothesis 4

From Tables 9.7 and 9.8 one sees that the t-probability of the extreme price dummy is significant at 5 % significance level for the in-sample data testing but not for the out-of-sample data testing. Although the hypothesis is significant for the in-sample testing, the negative sign of the coefficient is not consistent with the hypotehsis that high prices increases production. Instead the result tells us that there is a decrease in production caused by extremely high spot prices. Hence, the null hypothesis is not rejected and one cannot conclude that extremely high spot prices results in an increase in production from this test. The overall model using the in-sample data has a R^2 equal to 87,38%. All the other variables are significant, although the hypothesis is rejected.

However, it is interesting to investigate the reason for the rejection of the hypothesis. From theory in chapter 5 one knows that the objective of the hydropower producers is to maximize income from sales of power which undoubtedly mean to produce and sell as much as possible to a high price. The result from the testing of hypothesis 1 shows that the producers want to produce in accordance with a desired or expected reservoir level. Given that there is a positive deviation from expected reservoir the production increases in order to reach for the desired reservoir level. With knowledge of this, it is interesting to find out how the producer's reservoir level is situated when the extremely high spot prices occur. Firstly, we take a look at the aggregated reservoir level in Norway and Sweden which is available at Nord Pool‘s FTP server. During times of extremely high spot prices the aggregated reservoir level is well situated below the expected reservoir level for this time of the year. Hence, it seems like that the aggregated reservoir level is reflected in the prices. A more comprehensive check for the producers in the sample proves that eleven out of thirteen producers had a reservoir level below their expected reservoir level at that time of the year. Hence, when the reservoirs are below the expected reservoir level for a given time of the year, the producers are unwilling to increase production even though extreme high spot prices occur. Another reason for the aversion of increased production might be that there is a delay in detecting when high prices occur because spot prices are volatile. This leads us to the testing of the hypothesis which deals with uncertainty in prices and production decision.

Table 9.7: Results hypothesis 4 from in-sample data

	α	D_{cap}	D_{spot}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	286,15	920,54	-474,34	0,0689	-0,0554	30,36	-29,56	0,8674	0,8738
t-prob.	0,015	0,000	0,021	0,000	0,001	0,000	0,000	0,000	

Table 9.8: Results hypothesis 4 from out-of-sample data

	α	D_{cap}	D_{spot}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	703,68	793,50	-79,76	0,0898	-0,0560	59,24	-65,64	0,8710	0,8966
t-prob.	0,012	0,000	0,769	0,000	0,038	0,003	0,001	0,000	

9.6 Hypothesis 5a

Here we test whether increased volatility in spot price results in a decrease in production. Unlike hypothesis 2 were both spot price and forward price related effects were tested in the same hypothesis using an f-test, we want to test the specific effect of respectively the spot price and the forward price in this hypothesis. Hence, we have to test the increased volatility of spot price and forward price separately in two hypotheses, 5a and 5b.

The spot prices are stochastic and the hydropower producer is familiar with this. The purpose with this hypothesis is to test how the producers react to an extreme increase in volatility of spot prices. To test this we select the spot prices with an extremely high volatility and make dummies for these prices. Again it is a problem to define what is extremely volatile prices. The variance for each week in the time series is calculated from the present week including the two previous weeks. The spot prices are available on a daily basis which makes it possible to calculate the variance based on 21 data points in total. The variance data is sorted in descending order and the 5 % highest variances are defined as "extremely high variances". An intercept dummy for these spot prices is made;

We let $D_{var,S}$ represent the 5 % most volatile spot prices;

$$D_{var,S} = \begin{cases} 1 & \text{if the spot price is among the 5\% with highest volatility} \\ 0 & \text{else} \end{cases} \tag{9.14}$$

Model (7.8) is used for the testing since the hypothesis is price related;

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 D_{var,S} + \beta_3 w_{i,t} + \beta_4 D_s w_{i,t} + \beta_5 S_{i,t} + \beta_6 FS_{i,t} + \beta_7 y_{i,t-1} + \epsilon_{i,t} \tag{9.15}$$

The null hypothesis is to test the significance of the high volatility intercept dummy given that the other independent variables in model (9.15) are included in the model;

$$H_0 : \beta_2 = 0, \qquad H_1 : \beta_2 < 0 \tag{9.16}$$

9.6.1 Results Hypothesis 5a

The t-probabilities of $D_{var,S}$ in Table 9.9 and Table 9.10 show significance at 5% level in both the in-sample testing and the out-of-sample testing. Hence, the null hypothesis is rejected with a probability of 0,006 in the in-sample data and 0,007 in the out-of-sample data of committing a type I error. The negative signs of the coefficients of $D_{var,S}$ shows that the production decreases when the spot price volatility is exremely high. This is consistent with the hypothesis. In addition, there as been a slight increase in R^2 and the other variables are still significant.

The testing of hypothesis 4 provided unexpected results indicating that extremely high spot prices leads to a decrease in production. Inspired by the testing result of hypothesis 5a we check if extremely high spot prices occur at the same time as the spot prices are very volatile. In seven out of thirteen cases the spot price is both extremely high and volatile at the same time. This might indicate that even though spot prices are extremely high the producer is reluctant to produce because the spot prices are very volatile at the same time.

Table 9.9: Results hypothesis 5a from in-sample data

	α	D_{cap}	$D_{var,S}$	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	325,41	918,96	-475,65	0,0694	-0,0560	29,91	-30,56	0,8675	0,8738
t-prob.	0,008	0,000	0,006	0,000	0,001	0,000	0,000	0,000	

Table 9.10: Results hypothesis 5a from out-of-sample data

	α	D_{cap}	$D_{var,S}$	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	552,82	785,23	-807,82	0,0903	-0,0538	62,38	-64,07	0,8700	0,8970
t-prob.	0,036	0,000	0,007	0,000	0,046	0,002	0,001	0,000	

9.7 Hypothesis 5 b

This part of hypothesis 5 tests whether increased volatility in forward price results in a decrease in production. As with spot prices, forward prices are also stochastic. The purpose with this hypothesis is to test how the producers react to increased volatility in forward prices. The volatility of forward prices is calculated the same way as for spot prices as they also are available on a daily basis. The variance data is sorted in descending order and the 5 % highest variances are defined as "extremely high variances". An intercept dummy for these forward prices is made.

We let $D_{var,FS}$ represent the 5 % most volatile forward season prices;

$$D_{var,FS} = \begin{cases} 1 & \text{if the forward price is among the 5\% with highest volatility} \\ 0 & \text{else} \end{cases} \tag{9.17}$$

Model (7.8) is applied for the testing since the hypothesis is price related;

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 D_{var,FS} + \beta_3 w_{i,t} + \beta_4 D_s w_{i,t} + \beta_5 S_{i,t} + \beta_6 FS_{i,t} + \beta_7 y_{i,t-1} + \epsilon_{i,t} \tag{9.18}$$

The null hypothesis is to test the significance of the high volatility intercept dummy given that the other independent variables in model (9.18) are included in the model;

$$H_0 : \beta_2 = 0, \qquad H_1 : \beta_2 < 0 \tag{9.19}$$

9.7.1 Results Hypothesis 5b

The t-probability of $D_{var,FS}$ in the in-sample testing in Table 9.11 shows insignificance at a 5% level. The out-of-sample testing in Table 9.12 shows significance. Since the in-sample is superior to the out-of-sample, the null hypothesis is not rejected at a 5% level. However, it is interesting to test the hypothesis on a larger sample to validate the result. In the in-sample testing the R^2 has not increased by including the dummy.

Table 9.11: Results hypothesis 5b from in-sample data

	α	D_{cap}	$D_{var,FS}$	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	381,26	925,85	-33,80	0,0692	-0,0561	23,89	-27,54	0,8671	0,8737
t-prob.	0,003	0,000	0,852	0,000	0,001	0,000	0,000	0,000	

Table 9.12: Results hypothesis 5b from out-of-sample data

	α	D_{cap}	$D_{var,FS}$	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	620,47	790,16	-705,64	0,0905	-0,0542	62,95	-66,26	0,8696	0,8969
t-prob.	0,012	0,000	0,013	0,000	0,045	0,002	0,001	0,000	

9.8 Hypothesis 5c

The third part of hypothesis 5 is related to extreme increase in variance of inflow. We test whether an increased volatility in inflow results in a decrease in production. As with spot price, inflow is also stochastic. Inflow data is only available on a weekly basis, hence the inflow variance is calculated over a longer time period than the spot price variance. The variance for each week is calculated from data from the present week including eleven weeks into the past. The variance data is sorted in descending order and the 5% highest inflow variances are defined as "exremely high inflow variances." An intercept dummy for these variances is made;

We let $D_{var,w}$ represent the weeks with the 5 % most volatile inflows;

$$D_{var,w} = \begin{cases} 1 & \text{if the inflow is among the 5\% with highest volatility} \\ 0 & \text{else} \end{cases} \tag{9.20}$$

Model (7.6) is applied in the testing since this hypothesis is not price related;

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 D_{var,w} + \beta_3 w_{i,t} + \beta_4 D_s w_{i,t} + \beta_5 (\frac{S}{F})_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \tag{9.21}$$

The null hypothesis is that the inflow volatility intercept dummy is not significant given that the other independent variables in model (9.21) are included;

$$H_0 : \beta_2 = 0, \qquad H_1 : \beta_2 < 0 \tag{9.22}$$

9.8.1 Results Hypothesis 5c

The t-probabilities of $D_{var,w}$ on both the in-sample testing and the out-of-sample testing shows that the null hypothesis is not rejected on a 5% significance level. Hence, we cannot conclude that a high increase in variance in inflow results in less production. The R^2 has also decreased by including $D_{var,w}$ in the model. The reason for this might be that the reservoir function as a buffer that smooths out high variance in inflow. Thus, our results indicate that the producers is more affected by variation in prices than of variation in inflow.

Table 9.13: Results hypothesis 5c from in-sample data

	α	D_{cap}	$D_{var,inflow}$	$w_{i,t}$	$D_s w_{i,t}$	$(\frac{S}{F})_{i,t}$	$p_{i,t-1}$	R^2
coef.	-1042,89	903,73	-1,40e-07	0,0706	-0,0530	1371,36	0,8646	0,8689
t-prob.	0,001	0,000	0,252	0,000	0,001	0,000	0,000	

9.9 Hypothesis 6

Hypothesis 6 states that producers with a low relative regulation will be less affected by the forward prices. For the testing of the hypothesis, all the producers are categorized

Table 9.14: Results hypothesis 5c from out-of-sample data

	α	D_{cap}	$D_{var,w}$	$w_{i,t}$	$D_s w_{i,t}$	$(\frac{S}{F})_{i,t}$	$p_{i,t-1}$	R^2
coef.	-3616,68	606,28	2,9925e-07	0,0946	-0,0572	4059,26	0,8666	0,8825
t-prob.	0,011	0,002	0,622	0,000	0,050	0,007	0,000	

according to their relative regulation. In Table 6.1 the relative regulation for all the producers are listed. Producer 6 and 12 have a low relative regulation compared to the other producers and are selected to present "low relative regulation" in the data sample. What is interesting is how the low relative regulation affects how the producer is influenced by the forward price in the production decision. Hence, we construct a slope dummy that state the relationship between low relative regulation and the forward price. Firstly, the dummy for low relative regulation is defined.

We let $D_{low,reg}$ represent if the producer has a low relative regulation;

$$D_{low,reg} = \begin{cases} 1 & \text{if the producer is among the ones with a low relative regulation} \\ 0 & \text{else} \end{cases} \tag{9.23}$$

Model (7.8) is applied in the testing since this hypothesis is price related;

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 S_{i,t} + \beta_5 FS_{i,t} + \beta_6 D_{low,reg} FS_{i,t} + \beta_7 y_{i,t-1} + \epsilon_{i,t} \tag{9.24}$$

The null hypothesis states that the slope dummy for low relative regulation is not significant in model (9.24) given that the other independent variables are included;

$$H_0 : \beta_6 = 0, \qquad H_1 : \beta_6 < 0 \tag{9.25}$$

9.9.1 Results Hypothesis 6

The t-probabilities of $D_{low,reg}FS_{i,t}$ shows that the null hypothesis is not rejected at a 5% significance level on both in-sample and out-of-sample testing. Hence, we cannot conclude that a low relative regulation makes the producer less dependent on the forward price in the decision process of the production scheduling. This may be due to our choice of forward product. In addition, the R^2 has not changed impling that the dummy does not contribute to the fit of the model.

Table 9.15: Results hypothesis 6 from in-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$D_{low,reg}FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	395,27	395,27	0,0693	-0,0562	23,57	-27,31	-2,05	0,8670	0,8737
t-prob.	0,002	0,000	0,000	0,001	0,000	0,000	0,518	0,000	

Table 9.16: Results hypothesis 6 from out-of-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$D_{low,reg}FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	728,88	792,77	0,0898	-0,0562	58,14	-65,30	-0,0806	0,8711	0,8966
t-prob.	0,005	0,000	0,000	0,034	0,002	0,001	0,955	0,000	

9.10 Hypothesis 7a

Hypothesis 7 is related to relative time of production, which is a characteristic of producers. The first part of the hypothesis states that producers with a low relative time of production are more affected by prices in the production decision. The producers with a low relative time of production is selected to be producers who distinctly have a lower relative time of production than the other producers. In our sample, producer 8 and 11 fulfill these requirements. A slope dummy is made to test whether the dependence of spot and forward prices change when the producer has a low relative time of production.

We let D_Γ represent producers with a low relative time of production;

$$D_\Gamma = \begin{cases} 1 & \text{if the producer is among the ones with a low relative time of production} \\ 0 & \text{else} \end{cases} \tag{9.26}$$

Model (7.8) is applied in the testing since this hypothesis is price related.

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 S_{i,t} + \beta_5 D_\Gamma S_{i,t} + \beta_6 FS_{i,t} + \beta_7 D_\Gamma FS_{i,t} + \beta_8 y_{i,t-1} + \epsilon_{i,t} \tag{9.27}$$

We want to test how the interaction of spot price and the forward price affect production. The null hypothesis states that the added slope coefficients, $D_\Gamma S_{i,t}$ and $D_\Gamma FS_{i,t}$, is not significant in the model given that the other variables are included;

$$H_0 : \beta_5 = \beta_7 = 0, \qquad H_1 : \beta_5 > 0 \quad \text{and} \quad \beta_7 > 0 \tag{9.28}$$

The null hypothesis contains more than one variable and therefore the f-statistic is required to test this hypothesis.

$$f_{obs} = \frac{SSR(\beta_5, \beta_7|\beta_1, \beta_2, \beta_3, \beta_4, \beta_6)/2}{SSE/(N-k)} \sim F[2,(N-k)] \quad (9.29)$$

9.10.1 Results of Hypothesis 7a

The f_{obs}-statistic of the in-sample testing equals 0,4270 which is lower than the critical value of $F[2,\infty]$ which equals 3,00 at a 5% significance level. The out-of-sample f_{obs}-statistic equals 0,1631 and is also lower than the critical value of 3,00. In addition, the t-probabilities of $D_\Gamma S_{i,t}$ and $D_\Gamma FS_{i,t}$ in Tables 9.17 and 9.18 show that the coefficients are both insignificant. Hence, the null hypothesis is not rejected on a 5% significance level allthough the R^2 shows a slight increase by including the dummy.

Table 9.17: Results hypothesis 7a from in-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$D_\Gamma S_{i,t}$	$FS_{i,t}$	$D_\Gamma FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	401,88	990,20	0,0691	-0,0568	21,64	13,50	-24,28	-24,79	0,8633	0,8740
t-prob.	0,002	0,000	0,000	0,000	0,000	0,492	0,000	0,281	0,000	

Table 9.18: Results hypothesis 7a from out-of-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$D_\Gamma S_{i,t}$	$FS_{i,t}$	$D_\Gamma FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	821,62	885,52	0,0893	-0,0573	59,60	-406,52	-67,28	-0,0986	0,8662	0,8968
t-prob.	0,010	0,000	0,000	0,034	0,002	0,202	0,001	0,990	0,000	

9.11 Hypothesis 7b

The second part of hypothesis 7 states that producers with a low relative time of production are less affected by inflow in the production decision. To test whether this is true, one combines the dummy for low relative production with inflow to form a slope dummy. Model (7.6) is applied in the testing since the hypothesis is not related to price.

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 (\frac{S}{F})_{i,t} + \beta_5 D_\Gamma w_{i,t} + \beta_6 p_{i,t-1} + \epsilon_{i,t} \quad (9.30)$$

The null hypothesis states that the slope dummy for low relative time of production is not significant in model (9.30) given that the other independent variables are included in the model;

$$H_0 : \beta_5 = 0, \qquad H_1 : \beta_5 < 0 \quad (9.31)$$

9.11.1 Results of Hypothesis 7b

The t-probabilities show insignificance of $D_\Gamma w_{i,t}$ in the in-sample testing in Table 9.19 and significance in the out-of-sample testing in Table 9.20. Hence, the null hypothesis is not rejected at 5% level. The R^2 does not change by inclusion of the dummy. Nevertheless, further testing on another sample is required to validate the hypothesis.

Table 9.19: Results hypothesis 7b from in-sample-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$(\frac{S}{F})_{i,t}$	$D_\Gamma w_{i,t}$	$p_{i,t-1}$	R^2
coef.	-1041,19	946,85	0,0707	-0,0551	1363,80	-0,0145	0,8648	0,8737
t-prob.	0,002	0,000	0,000	0,001	0,000	0,072	0,000	

Table 9.20: Results hypothesis 7b from out-of-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$(\frac{S}{F})_{i,t}$	$D_\Gamma w_{i,t}$	$p_{i,t-1}$	R^2
coef.	-3599,6	819,01	0,0904	-0,0534	4012,72	-0,0445	0,8722	0,8966
t-prob.	0,004	0,000	0,000	0,041	0,002	0,008	0,000	

9.12 Hypothesis 8

The last hypothesis tests whether there has been a maturation during the years in the hydropower producers willingness to let the forward price affect the production decision. To test this hypothesis the in-sample period is divided in two. The first 2,5 years are denoted "early period" and the second 2,5 years are denoted "late period". A dummy for the second half of the in-sample period is defined as D_{late} to create a slope dummy with the forward prices;

$$D_{late,} = \begin{cases} 1 & \text{late period} \\ 0 & \text{else} \end{cases} \tag{9.32}$$

Model (7.6) is applied in the testing since this hypothesis is related to the forward price. A slope dummy consisting of D_{late} multiplied with forward season is included in the model;

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 S_{i,t} + \beta_5 FS_{i,t} + \beta_6 D_{late} FS_{i,t} + \beta_7 y_{i,t-1} + \epsilon_{i,t} \tag{9.33}$$

The null hypothesis states that the slope dummy for late forward prices is not significant in model (9.33) given that the other independent variables are included in the model;

$$H_0 : \beta_6 = 0, \qquad H_1 : \beta_6 > 0 \tag{9.34}$$

9.12.1 Results Hypothesis 8

The t-probability of the slope dummy, $D_{late}FS_{i,t}$, shows that the null hypothesis is not rejected on a 5% significance level for the in-sample testing. The out-of-sample data is not applied in the testing of the hypothesis since it belongs to another time period than the time period of interest in the hypothesis. This is a common problem when cross-validating models of time-series data, see section 8.2. Nevertheless, the in-sample testing shows that one cannot conlude that there has been an increased willingness among the hydropower producers to use information in the forward market. In addition, the R^2 does not change when including $D_{late}FS_{i,t}$ in the model. The reason for the rejection of the hypothesis might be that the in-sample period is to short.

Table 9.21: Results hypothesis 8 from in-sample data

	α	D_{cap}	$w_{i,t}$	$D_s w_{i,t}$	$S_{i,t}$	$FS_{i,t}$	$D_{late}FS_{i,t}$	$p_{i,t-1}$	R^2
coef.	510,64	927,04	0,0691	-0,0559	22,80	-34,55	4,92	0,8668	0,8737
t-prob.	0,007	0,000	0,000	0,001	0,000	0,001	0,255	0,000	

Chapter 10

Discussion of Applied Methods

10.1 Shortcomings with the Data

In panel data analysis it is of importance to have enough individuals for the regression results to be valid (Yaffee 2003). With thirteen producers, our analysis would stand stronger if the data set consisted of more cross-sectional individuals. Due to the poolability assumption (see section 10.3), the regression would also improve if the producers in the sample were more alike. This could be achieved by imposing even stricter assumptions criteria in the selection of the producers. However, by imposing stricter selection criteria one may not get a large enough sample.

There are some shortcomings with the gathered data set which may have influenced the analysis. Data regarding maintenance and snow reservoir are two variables already mentioned that could have contributed to better understanding on how hydropower producers schedule production. With maintenance data available, production stops caused by maintenance could have been excluded from the analysis. If snow reservoir data was available we would have a more proper picture of the water resource situation the producer act according to. Weather and temperature data could have contributed in the analysis similarly. The producer's inflow forecast is also an interesting variable to include in the regression. In general, introducing more independent variables may explain the scheduling decision better. However, it is a trade-off between accuracy and keeping the models simple. A higher resolution time would also enhance the accuracy since this would imply more data.

Time dependent restriction due to esthetical or environmental reasons are important in the scheduling of generation (SKM 2007). Unfortunately, data regarding other restriction than maximum and minimum production capacity and reservoir level were not available.

The time span considered include very different market situations. In 2000 the hydropower production in Norway was at a historical high level with a production of 142

TWh, while in 2003 the electricity production from hydropower was only 106 TWh due to extremely low inflow (NVE 2006*c*). The low supply of power caused very high prices in the same period. These peculiar circumstances are unfavorable for the analysis because we might draw inference based on data affected by very special incidents.

10.2 Testing for Heteroskedasticity: White's test

White's test for heteroskedasticity (see Appendix A.4.2) is conducted for the two models used in the hypotheses testings; model (7.6) and (7.8). For model (7.6) the square of the residuals were regressed against 18 variables, while for model (7.8) 25 non-redundant squares and cross-products of the original dependent variables were used. The results of the White's tests are summarized in Table 10.1 and since the observed χ^2 value for both models are higher than the critical χ^2 values the null hypothesis of homoskedasticity is rejected.

Hence, our assumption of heteroskedastic regression errors made in section 8.1.1 are verified. It is therefore reasonable to say that our choice of GMM as regression estimator seems proper.

Table 10.1: Results of the White's test conducted for model (7.6) and (7.8). In the right column $\chi^2_{0,05}$ presents the critical value of acceptance of the test.

	R^2 *auxiliary regression*	χ^2_{obs}	$\chi^2_{0,05}$
Model (7.6)	0,1698	565,12	28,869
Model (7.8)	0,1811	602,76	37,652

10.3 Test of Poolability: Chow test

In the estimation of the models it is assumed that the parameters i.e. the β's are the same across producers and over time. Due to this, it is natural to check if the data can be pooled together. In the case of the thirteen power producers it is natural to expect larger differences between the individuals than over the time periods. Hence, a poolability test over individuals is therefore conducted.

(Baltagi 2005) suggests using the Chow test to test if it is reasonable to pool the data. The poolability test is taken under the assumption of $\epsilon \sim N(0, s^2 I_{NT})$. Hence, that the error components are homoskedastic. Although, the White's test accomplished in section 10.2 shows that the error components from model (7.6) and (7.8) do not fulfill this assumption the test is still undertaken and used as a basis of discussion.

The Chow test (see Appendix A.5.4) is conducted for a revised version of the two models used in the hypothesis testing. To be able to accomplish the testing the producer specific dummy, D_{cap}, was removed. The results are listed in Table 10.2.

Table 10.2: The results of the poolability tests. An F_{obs} greater than the critical value results in rejection of the null hypothesis that the data is poolable.

	F_{obs}	*Critical F value*
Revised model (7.6)	4,57	1,320
Revised model (7.8)	4,04	1,295

We see that the Chow test for poolability of cross-section data is rejected at a 5 % significance level for both the models. Hence, by applying a restricted i.e. a pooled regression model, bias may be introduced into the regression result. However, (Toro-Vizcarrondo & Wallace 1968) discuss that "if one is willing to accept some bias in trade for a reduction in variance, then even if the restriction is not true one might still prefer the restricted model." One of the motives behind pooling of cross-sections is to widen the database in order to get better and more reliable estimates of the parameters of the regression model. Although the Chow test of poolability is rejected, one might still pool the data to reduce variance in the data. Since the objective of this paper is to find out what drives production sheduling for Norwegian hydropower producers in general, pooling of the data is a necessary consequence. If more strict assumption criterias were applied in the selection of producers as discussed in section 10.1, the poolability assumption may have been fulfilled.

Chapter 11

Conclusion

In this master thesis we present data from thirteen adequate Norwegian hydropower producers. The data gathered is relevant to the production scheduling problem and is applied in testing of the hypotheses which are proposed based on theory of hydropower schdeuling and electricity forward markets.

Our findings show that hydropower production is dependent on inflow, spot- and forward prices, seasonal variation and lag of production. This is consistent with our general hypothesis. Based on our knowledge of the hydropower industry, it is common to construct price forecasts based on bottom-up analysis. Due to this, perhaps our most interesting result is the significance of the forward price in production. This indicates that forward prices are adequate as input in the production scheduling. Hence, the information from the forward market can be used in the scheduling instead of conducting price forecasts from the prevailing bottom-up models. However, since only weekly and seasonal forward products are considered in our regression, further research should try to avoid the correlation problem and include other products to capture the dynamics of the forward curve. The purpose behind such an analysis would be to confirm our results.

Other interesting results are that a positive deviation from expected reservoir results in increased production. This indicates that producers find it favorable to keep the reservoir level close to expectations based on earlier years. This might also indicate that local restrictions which are not included in the available data material affect production strongly. When the reservoir is unexpectedly nearly empty or nearly full, the prices affect production less than otherwise. When the reservoir is unexpectedly nearly full, the production decision is more dependent on inflow than normal. Hence, when the reservoir is nearly bound by its restrictions, the production scheduling is more affected by the physical factors such as inflow, while price is subordinate. Further, the analysis reveals that extremely high spot prices do not give a rise in production as anticipated. Increasing variance in the spot price gives a lower production. By further investigation we see that during time-periods when prices were high they were also very volatile. Hence, producers are rational and defer to produce because of the volatility. Increasing variance in inflow does not decrease production. This was not expected prior to the analysis. However, it can be explained by the reservoir functioning as a buffer for volatile inflow. Producers with a low relative regulation were assumed to be less dependent on the forward price in the production decision. This hypothesis is rejected. Likewise, it was assumed that producers with a low relative time of production are flexible and should be more dependent on prices and less dependent on inflow. Testing did not give any acceptance of this hypothesis either. Further we expected that there has been a maturation during the years in the hydropower producers willingness to let the forward price affect the production decision. This hypothesis is also rejected. A longer time horizon in the data might give the wanted results.

The empirical analysis shed light on how the scheduling is performed and it provides important information about how the producers act in specific situations. The results of most of the hypotheses testings indicate that hydropower scheduling is performed in accordance with theory. The usefulness of the empirical analysis is to better understand the dynamics of the scheduling problem.

The conclusion of an empirical analysis is strengthened by testing the hypotheses using other sets of data. Hence, testing our hypotheses on data from other producers is suggested for further research.

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Appendix A

Statistical Concepts

A.1 Linear Regression

The concept of linear regression analysis deals with finding the best relationship between the dependent variable, Y, and the independent variables, x_i, and quantifying the strength of that relationship. In simple linear regression we have only one independent variable, x, in multiple linear regression we have n independent variables, x_i, where $i = 1, .., n$. A multiple regression structure might be

$$Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \epsilon \tag{A.1}$$

The parameters α and β are unknown and must be estimated from the data. One can never observe the actual ϵ values in practice and thus one can never draw the true regression line but only an estimate of the true regression line. The estimated or fitted regression line is given by

$$\hat{y} = \hat{\alpha} + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 \tag{A.2}$$

One important concept in regression analysis is the residuals. The residuals are errors in the fit of the model; $e_i = y_i - \hat{y}_i$, $i = 1, .., n$. If the size of the residuals is large, then the model is clearly not good.

A.1.1 SSE, SSR, SST

The total sum of squares, SST, is the total sum of squares of the dependent variable, y.

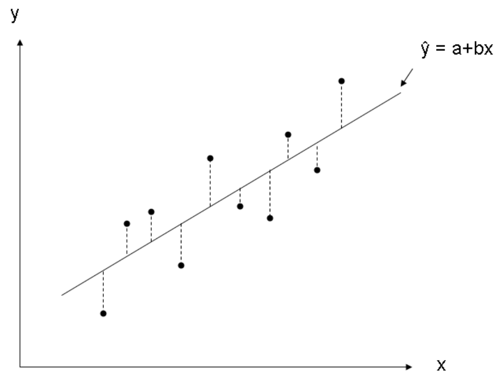

Figure A.1: Residuals as vertical deviations. The dots are the actual observations, and the dotted lines are the deviations from the actual observations and the fitted line, $\hat{y}$.

$$SST = \sum_{i=1}^{n} (y_i - \overline{y})^2 \tag{A.3}$$

The regression sum of squares, SSR, reflects the amount of variation in the y-values explained by the regression model

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \overline{y})^2 \tag{A.4}$$

The residual sum of squares of the errors about the regression line are denoted by SSE and reflects variation about the regression line.

$$SSE = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{A.5}$$

Finally, SST can be divided into two components, SSR and SSE respectively;

$$SST = SSR + SSE \tag{A.6}$$

A.1.2 R-squared

R^2 is a measure of the proportion of variability explained by the fitted regression model. This can be calculated from the total sum of squares SST and the error sum of squares SSE. The SSE value is the variation due to error or variation unexplained by the regression model. The variation which is explained by the regression is $SSR = SST -$

SSE. The expression for R^2 can be derived as; $R^2 = 1 - \frac{SSE}{SST}$. The higher the value of R^2, the more variance is explained by the regression model, i.e. the better is the model (Walpole et al. 2002).

A.2 GMM

The basic idea of GMM is to obtain estimates of parameters of statistical models. Let y_t denote the dependent variable and $\boldsymbol{X}$ a $K \times T$ matrix of the K independent variables. The model specified for the dependent variable implies certain expectations, for example

$$E[y_t] = E[\boldsymbol{\beta X}] \tag{A.7}$$

The models in section 7.4 fit into this framework. The most natural way to check this expectation is to examine sample averages, i.e. to calculate

$$\frac{1}{T}\sum_{t=1}^{T} y_t \qquad \text{and} \qquad \frac{1}{T}\sum_{t=1}^{T}(\boldsymbol{\beta X}) \tag{A.8}$$

GMM estimates the parameters, i.e. $\boldsymbol{\beta}$, by making the sample averages in equation (A.8) as close to each other as possible. GMM then works out a distribution theory for the estimates and suggests that we evaluate the model by looking at how close the sample averages of the dependent and "weighted" independent variables are to each other. This is equivalent to looking at the production errors. GMM gives a statistical test of the hypothesis that the underlying population means are in fact zero (Cochrane 2005).

A.3 Hypotheses Testing

Hypothesis testing is a statistical inference procedure which is based on constructing a statistic from a sample that will enable the analyst to decide whether or not the data in the sample would have been generated by a hypothesized population. In general one makes a statement of the hypothesis in form of a "null" hypothesis or maintained hypothesis, and an "alternative" hypothesis. Respectively denoted H_0 and H_1. The sample data indicates whether the null hypothesis should be rejected or not. The classical or Neyman-Pearson methodology involves partitioning the sample space into two regions. If the sample data fall in the critical region, then the null hypothesis is rejected; if they fall in the acceptance region, then it is not (Greene 2000).

A.3.1 Type I error

The testing of the hypothesis lead to a rejection of the null hypothesis when it is actually true.

A.3.2 Type II error

The testing of the hypothesis fail to reject the null hypothesis when it is false.

A.3.3 p-value

The probability of committing a type I error is often denoted the p-value. A p-value is the lowest level of significance at which the observed value of the test statistic is significant. If we observe a value t of a random variable T used as a test statistic, then the p-value of t is the probability that T will assume a value as or more unfavorable to the null hypothesis as the observed value t. The p-value can be used to reject or not reject the null hypothesis. For example, if we go through with a test with 5% significance level, then we would reject the null hypothesis if the p-value is lower than 0,05. Traditionally one does not want the type I error to be greater than 0,05 or 0,01. We have chosen the significance level of 0,05 for the testing of our hypotheses.

A.3.4 Testing on single variables: *t*-statistics

The t-statistics is a test whether the means of two normally distributed populations are equal. This test is often used to decide whether a single regression coefficients is significant in a model. One tests the difference between the mean of the estimated regression coefficient and the "true" regression coefficient, divided by the standard deviation. A common test is whether a regression coefficient β is significantly different from zero. The test statistic is can then be expressed as

$$t = \frac{\hat{\beta}_i - \beta_i}{SE(\hat{\beta}_i)} \tag{A.9}$$

The null hypothesis then formulates;

$$H_0 : \beta_i = 0, \qquad H_1 : \beta_i < 0 \tag{A.10}$$

Since $\hat{\beta}_i = 0$, the test statistics in A.9 collapses to

$$t = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)} \tag{A.11}$$

This is standard output in most computer programs and the belonging p-value can easily show whether the coefficient is significantly different from zero or not (Greene 2000).

A.3.5 Testing on subsets of variables: f-statistics

The f-test is often used in testing of hypotheses when it is of interest to test more than one coefficient simultaneously. For instance, one want to test the significance of β_1 and β_2 simultaneously in a regression model estimated from N data and with k variables. The f-test statistic for testing multiple hypotheses about the coefficient estimates is given by

$$f = \frac{[SSR(\beta_1, \beta_2|\beta_3, \beta_4, ..., \beta_k)]/2}{SSE/(N-k)} = \frac{[SSR - SSR(\beta_3, \beta_4, ..., \beta_k)]/2}{SSE/(N-k)} \tag{A.12}$$

Note that two regression models are tested; one containing all the regression coefficients and one containing all but the two variables which is tested (β_1 and β_2) (Walpole et al. 2002). The first model is often referred to as the "restricted model" and the second is referred to as the "unrestricted model" and (Brooks 2002). The p-value of the f-statistics determines if the hypotheses are rejected or not.

A.4 Assumptions and Requirements for Regression Variables

A.4.1 Stationary Time Series

The usual property of a regression using the time-series data is dependent on the assumption that the time-series variables are stationary stochastic processes. A time series y_t is stationary if the criteria below is true for all variables

$$E(y_t) = \mu \tag{A.13}$$

$$var(y_t) = \sigma^2 \tag{A.14}$$

$$cov(y_t, y_{t-s}) = \gamma_s \tag{A.15}$$

where equation (A.15) implies that the covariance depends on s, not t.

Series which can be made stationary by taking the first difference are said to be integrated of order 1, and denoted $I(1)$. In general, if series must be differenced d times to be made stationary it is denoted $I(d)$. The consequences of nonstationarity can be quite severe, leading to estimators, test statistics and predictors that are unreliable. Many of variables studied in macroeconomics and finance are nonstationary time series and it is therefore import to test for stationarity (Hill et al. 2001).

Tests for Stationarity : the Dickey-Fuller Tests

The stationarity of a time series can be tested using the Dickey-Fuller (DF) test.

Assuming that y_t follows

$$y_t = \alpha_0 + \rho y_{t-1} + \upsilon_t \tag{A.16}$$

y_t is stationary if $|\rho| < 1$. Thus we can test for nonstationarity by testing the null hypothesis that $\rho = 1$. The test is put into a convenient form by subtracting y_{t-1} from both sides of (A.16) to obtain

$$y_t - y_{t-1} = \alpha_0 + \rho y_{t-1} - y_{t-1} + \upsilon_t \tag{A.17}$$
$$\Delta y_t = (\rho - 1) y_{t-1} + \upsilon_t \tag{A.18}$$
$$\Delta y_t = \gamma y_{t-1} + \upsilon_t \tag{A.19}$$

Then the hypothesis can be formulated as

$$H_0 : \rho = 1 \leftrightarrow H_0 : \gamma = 0 \tag{A.20}$$
$$H_0 : \rho < 1 \leftrightarrow H_0 : \gamma < 1 \tag{A.21}$$

To test the hypothesis we estimate (A.17) and examine the t-statistics. But if the null hypothesis is true y_t follows a random walk, hence the t-statistics no longer has a t-distribution. Consequently one has to compare the statistics with specially constructed critical values.

The augmented Dickey-Fuller (ADF) test derives from the DF test by adding lagged differences. The general modified model for the ADF(s) is

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \sum_{i=1}^{s} \gamma \Delta y_{i-1} + \upsilon_t \tag{A.22}$$

A.4.2 Heteroscedasticity

Heteroscedasticity is when the variance of the error term are not constant across observations. That is; $var(e_i) \neq \sigma^2$. When applying the least squares estimator one important assumption is that the error term has constant variance across all the observation, i.e. the model is homoskedasticic. In the case of heteroscedasticity the least square estimator is still a linear and unbiased estimator, but it is no longer the best linear unbiased estimator. When the error term is heteroskedastic, the standard errors computed for the least squares estimator are incorrect. This implies that other estimators than the least squares estimators should be applied. GMM is a proper estimator to be applied in case of heteroskedasticity (Hill et al. 2001).

Test for Heteroskedasticity: White's test

White's test proposed in (White 1980) tests for the presence of heteroskedasticity due to one or more of the independent variables. The test is based on an auxiliary regression of the squared residuals i.e. $e_{i,t}^2$ on all squares and cross-products of the original regressors. Redundant variables like squares of dummy variables are left out.

Under the null hypothesis of homoskedasticity is

$$N \times R^2 \sim \chi^2_{df} \tag{A.23}$$

where N is the sample size, R^2 is from the auxiliary regression and the degrees of freedom for the χ^2 equals the number of regressors in the auxiliary regression. If the observed χ^2 value is higher than the critical χ^2 value the null hypothesis of homoskedasticity is rejected. Then the model has heteroskedastic regression errors.

A.4.3 Collinearity

Collinearity refers to any linear relationship among explanatory variables in a regression model. In case of collinearity, there is no guarantee that the data will be "rich in information", nor that it will be possible to isolate the parameters of interest. The consequences of collinearity is that the estimator is not defined, i.e. one cannot obtain estimates of β using standard estimators such as least squares and GMM. A rule of thumb is that a correlation coefficient between two explanatory variables greater than 0,8 or 0,9 in absolute value indicates a collinear relationship which is potentially harmful (Hill et al. 2001).

A.5 Panel Data

The term "panel data" refers to data sets where we have data on several individuals over several time periods. A panel data regression differs from a regular time-series or cross-section regression in that it has a double subscript on its variables

$$\boldsymbol{Y_{it}} = \boldsymbol{\alpha} + \boldsymbol{X_{it}^T}\boldsymbol{\beta} + \boldsymbol{u_{it}} \qquad i = 1, ..., N; t = 1, ..., T \tag{A.24}$$

where i denoting firms, individuals, countries, etc. and t denoting time. The i therefore denotes the cross-section dimension whereas t denotes the time-series dimension.

A.5.1 The Fixed Effect Model

This type of panel data model is an appropriate specification if we are looking at a specific set of N firms and our inference is restricted to the behavior of these set of firms. For instance if we look at all the countries in the EU or all the states in America (Baltagi 2005). The fixed effect model is a type of panel models that have constant slopes but intercepts that differ according to the cross-sectional unit or time. This is because there are significant individual or temporal effects respectively. This implies that a dummy for each individual or time period is added in the model (Yaffee 2003).

A.5.2 The Random Effects Model

The random effect model is an appropriate specification if we are drawing N individuals randomly from a large population. The individual effect is characterized as random and inference pertains to the population from which the sample was drawn. Unlike the fixed effect model, this model allows for random intercepts in addition to random slopes. Hence, no intercept dummies that differs according to cross-sectional units or time are added in the model (Yaffee 2003).

A.5.3 Dynamic Panel Models

In a dynamic panel model, a lagged dependent variable is introduced to either fixed effects or random effects models. By introducing a lag of the dependent variable one assumes that the number of temporal observations is greater than the number of regressions in the model (Yaffee 2003).

A.5.4 Test for Poolability: Chow Test

The Chow test is an econometric test of whether the coefficients in different linear regression models with different data are equal. One tests the validity of the null hypothesis that individual effects can be neglected. Imposing the restriction in the null hypothesis regardless of whether it is true or false will reduce the variance of the pooled estimator. If the restriction is false, bias may be introduced (Baltagi 2005).

The unrestricted model expresses that we have a regression equation y_i for each generator, hence the individual effects are taken into account

$$y_i = Z_i\delta_i + u_i, \qquad i = 1, .., N \tag{A.25}$$

where $y_i' = (y_{i1}, ..., y_{iT})$, $Z_i = [l_T, X_i]$ and X_i is $T \times K$, δ is $1 \times (K+1)$ and u_i is $T \times 1$. It is important to notice that the δ_i's are different for every generator equation. We want to test the hypothesis $H_0 : \delta_i = \delta$ for all i, so that under H_0 we can write the restricted model given in equation (A.25) as

$$y = Z\delta + u \qquad i = 1, .., N \tag{A.26}$$

where $Z' = (Z_1', Z_2', ..., Z_N')$ and $u' = (u_1', u_2', ..., u_N')$. In the restricted model, all the producer specific data is pooled together

Now, the Chow test can be expressed by a f-test on the difference in residual sum of squares of the unrestricted and the restricted model

URSS= unrestricted residual sum of squares
RRSS= restricted residual sum of squares obtained by imposing the restrictions of the hypothesis

$$f = \frac{(RRSS - URSS)/r}{URSS/(n-k-1)} \tag{A.27}$$

r is the number of restrictions imposed by the hypothesis, n is the total number of observations in the restricted model and k is the number of regressors in the restricted model. If the f-test is significant the restricted model is applicable (Maddala 2001).

Appendix B

Stationarity and Correlation Tests

B.1 Further Results from the Stationarity Tests

A Dickey-Fuller test has been conducted for all the variables. For the variables that are non-stationary, the first differences of the variables are tested as well. The results of the tests that are not reported in the thesis are reported in Table B.1.

Table B.1: ADF values from the stationarity test for Deviation from expected inflow, Deviation from expected reservoir, first differences of Deviation from expected reservoir and first differences of Reservoir for all producers. The critical value is -2,870 at a 5% significance levels. Hence, the Deviation from expected inflow time series is stationary for all producers as well as the differenced time series. Deviation from expected reservoir is non-stationary for all producers.

Producer i	$w_i - E[w_i]$	$R_1 - E[R_i]$	$\Delta(R_1 - E[R_i])$	ΔR_i
1	-12,54	-2,870	-14,68	-9,955
2	-12,87	-2,081	-10,87	-4,679
3	-12,47	-2,085	-13,50	-8,252
4	-10,39	-3,009	-14,82	-9,623
5	-16,41	-1,078	-12,62	-6,533
6	-9,000	-3,374	-15,72	-14,19
7	-11,26	-2,714	-11,76	-5,174
8	-11,30	-2,564	-12,24	-6,612
9	-12,09	-1,197	-11,20	-8,430
10	-14,28	-2,829	-13,77	-6,556
11	-6,994	-1,859	-11,60	-9,680
12	-14,38	-3,686	-16,18	-16,14
13	-3,654	-2,379	-10,95	-4,928

B.2 Correlation Matrix for Differenced Time Series

Table B.2: Correlation coefficients for differenced variables. A correlation higher than 0,9 indicate that collinearity may be a problem in the regression analysis. Due to the high correlation coefficient one should not include Δw and $\Delta(w - E[w])$ and $\Delta(\frac{S}{F})$ and $\Delta(\frac{S}{F})^2$ in the same model. The correlation between the other variables are not problematic.

	Δp	Δw	Δw_{t+1}	$\Delta(w - E[w])$	ΔR	$\Delta(R - E[R])$	ΔS	ΔFW	ΔFS	$\Delta(\frac{S}{F})$	$\Delta(\frac{S}{F})^2$
Δp	1										
Δw	0,0644	1									
Δw_{t+1}	-0,0616	-0,2160	1								
$\Delta(w - E[w])$	0,0749	0,9439	-0,2384	1							
ΔR	-0,0114	0,2538	-0,2290	0,2187	1						
$\Delta(R - E[R])$	-0,0134	0,3391	-0,3050	0,3527	0,5995	1					
ΔS	0,1170	-0,0790	0,0202	-0,0741	-0,0819	-0,1343	1				
ΔFW	0,0258	-0,0462	-0,0080	-0,0423	-0,0400	-0,0704	0,6167	1			
ΔFS	-0,0542	-0,0218	-0,0155	-0,0223	0,0024	-0,0618	0,0243	0,4275	1		
$\Delta(\frac{S}{F})$	0,1502	-0,0601	0,0428	-0,0528	-0,0766	-0,0901	0,5519	-0,1190	-0,4192	1	
$\Delta(\frac{S}{F})^2$	0,1476	-0,0547	0,0396	-0,0499	-0,0748	-0,0879	0,5684	-0,0910	-0,3818	0,9675	1

Appendix C

Models Estimated from General Hypothesis Testing

C.1 Coefficients and Statistics for Estimated Models

In Figure C.1, C.2 and C.3 are the estimated coefficients and the belonging t-probability of respectively the production, relative production and deviation from expected reservoir models presented. The figures are shown in the three next pages and for all figures the following applies; insignificant t-probabilities are marked with red, in the second column from the right is the in-sample R^2 presented and the last column reports the out-of-sample R^2.

Model equation		Constant	D_s	D_{cap}	Deviation from expected inflow	Inflow	D_s * Inflow	Lead of inflow	D_s * Lead of inflow	Spot Price	Forward Season	Spot relative to forward price	(Spot relative to forward price) ^{2}	Lag of production	In-sample R^2	Out-of-sample R^2
Eq. (7.3)	Coeff.	-419,058	-224,635	1072,4300	0,0255							890,257		0,8811	0,87231	0,88325
	t-prob.	0,218	0,036	0,000	0,000							0,004		0,000		
Eq. (7.4)	Coeff.	58,4871	-238,3730	1073,0900	0,0252								405,785	0,8810	0,87230	0,88320
	t-prob.	0,741	0,019	0,000	0,000								0,003	0,000		
Eq. (7.5)	Coeff.	550,782	-253,3080	1079,2000	0,0242					15,3168	-18,7544			0,8805	0,87235	0,88303
	t-prob.	0,000	0,016	0,000	0,000					0,006	0,014			0,000		
Eq. (7.6)	Coeff.	-1045,25		913,346		0,0694	-0,0546					1361,9		0,8670	0,87367	0,88555
	t-prob.	0,002		0,000		0,000	0,001					0,000		0,000		
Eq. (7.7)	Coeff.	-337,3820		915,6200		0,0696	-0,0554						635,8110	0,8671	0,87366	0,88549
	t-prob.	0,044		0,000		0,000	0,001						0,000	0,000		
Eq. (7.8)	Coeff.	389,9370		926,4480		0,0692	-0,0561			23,5709	-27,6177			0,8670	0,87371	0,88547
	t-prob.	0,002		0,000		0,000	0,001			0,000	0,000			0,000		
Eq. (7.9)	Coeff.	-808,4990		950,3670				0,0454	-0,0366			1129,7500		0,8753	0,87192	0,88238
	t-prob.	0,005		0,000				0,000	0,000			0,000		0,000		
Eq. (7.10)	Coeff.	-221,9330		952,1650				0,0455	-0,0371				528,0400	0,8754	0,87191	0,88237
	t-prob.	0,122		0,000				0,000	0,000				0,000	0,000		
Eq. (7.11)	Coeff.	413,6870		964,5930				0,0454	-0,0379	20,3733	-24,8815			0,8748	0,87202	0,88238
	t-prob.	0,002		0,000				0,000	0,000	0,000	0,001			0,000		

Figure C.1: Results from the estimation of production models where the estimated coefficients and their belonging t-probability are reported. For models found valid out-of-sample R^2 is calculated.

Model equation		Constant	D_s	Deviation from expected inflow	Inflow	D_s * Inflow	Lead of inflow	D_s * Lead of inflow	Spot Price	Forward Season	Spot relative to forward price	(Spot relative to forward price)^2	Lag of relative production	In-sample R^2	Out-of-sample R^2
Eq. (7.12)	Coeff.	0,0558	-0,0458	0,8340							0,0511		0,8097	0,7510	0,68861
	t-prob.	0,004	0,000	0,000							0,002		0,000		
Eq. (7.13)	Coeff.	0,0832	-0,0466	0,8294								0,0233	0,8096	0,7510	0,68851
	t-prob.	0,000	0,000	0,000								0,001	0,000		
Eq. (7.14)	Coeff.	0,1189	-0,0477	0,8094					0,0009	-0,0013			0,8076	0,7512	0,68822
	t-prob.	0,000	0,000	0,000					0,000	0,000			0,000		
Eq. (7.15)	Coeff.	-0,0398			2,0083	-1,7464					0,0950		0,8400	0,7490	0,69107
	t-prob.	0,035			0,000	0,000					0,000		0,000		
Eq. (7.16)	Coeff.	0,0103			2,0188	-1,7820						0,0437	0,8402	0,7490	0,69095
	t-prob.	0,365			0,000	0,000						0,000	0,000		
Eq. (7.17)	Coeff.	0,0625			2,0035	-1,8148			0,0016	-0,0020			0,8393	0,7492	0,69160
	t-prob.	0,000			0,000	0,000			0,000	0,000			0,000		
Eq. (7.18)	Coeff.	-0,0218					0,9886	-0,9440			0,0834		0,8459	0,7444	0,68083
	t-prob.	0,162					0,011	0,014			0,000		0,000		
Eq. (7.19)	Coeff.	0,0224					0,9964	-0,9732				0,0382	0,8462	0,7443	0,68080
	t-prob.	0,009					0,010	0,011				0,000	0,000		
Eq. (7.20)	Coeff.	0,0718					0,9773	-0,9976	0,0015	-0,0019			0,8445	0,7447	0,68111
	t-prob.	0,000					0,013	0,010	0,000	0,000			0,000		

Figure C.2: Results from the estimation of relative production models where the estimated coefficients and their belonging t-probability are reported. Notice that for these models are the inflow variables divided by the expected yearly inflow. For models found valid out-of-sample R^2 is calculated.

Model equation		D_s	Deviation from expected inflow	Inflow	D_s * Inflow	Lead of inflow	D_s * Lead of inflow	Spot relative to forward price	(Spot relative to forward price)^2	Spot Price	Forward Season	Lag of deviation from expected reservoir	In-sample R^2	Out-of-sample R^2
Eq. (7.21)	Coeff.	75,4793	0,3770					-5119,64				0,5767	0,42248	
	t-prob.	0,185	0,087					0,004				0,000		
Eq. (7.22)	Coeff.	77,1848	0,3771						-2229,43			0,5769	0,42224	
	t-prob.	0,178	0,087						0,002			0,000		
Eq. (7.23)	Coeff.	105,5990	0,3748							-131,992	-39,6687	0,5721	0,42334	
	t-prob.	0,096	0,088							0,003	0,067	0,000		
Eq. (7.24)	Coeff.			0,5869	-0,3355			-4366,57				0,5756	0,44519	0,5343
	t-prob.			0,000	0,008			0,005				0,000		
Eq. (7.25)	Coeff.			0,5872	-0,3356				-1930,59			0,5758	0,44516	0,5337
	t-prob.			0,000	0,008				0,003			0,000		
Eq. (7.26)	Coeff.			0,5843	-0,3340					-116,749	-35,8087	0,5717	0,44623	
	t-prob.			0,000	0,008					0,005	0,045	0,000		
Eq. (7.27)	Coeff.					-0,2715	0,1604	-5700,15				0,4020	0,24627	
	t-prob.					0,000	0,085	0,007				0,000		
Eq. (7.28)	Coeff.					-0,2709	0,1593		-2469,42			0,4021	0,24588	
	t-prob.					0,000	0,088		0,006			0,000		
Eq. (7.29)	Coeff.					-0,2736	0,1617			-173,587	-72,27	0,3967	0,25171	
	t-prob.					0,000	0,084			0,012	0,013	0,000		

Figure C.3: Results from the estimation of deviation from expected reservoir models where the estimated coefficients and their belonging t-probability are reported. Notice that for these models are all variables differenced. For models found valid out-of-sample R^2 is calculated.

C.2 Residual and Predicted Production Plots for model (7.8)

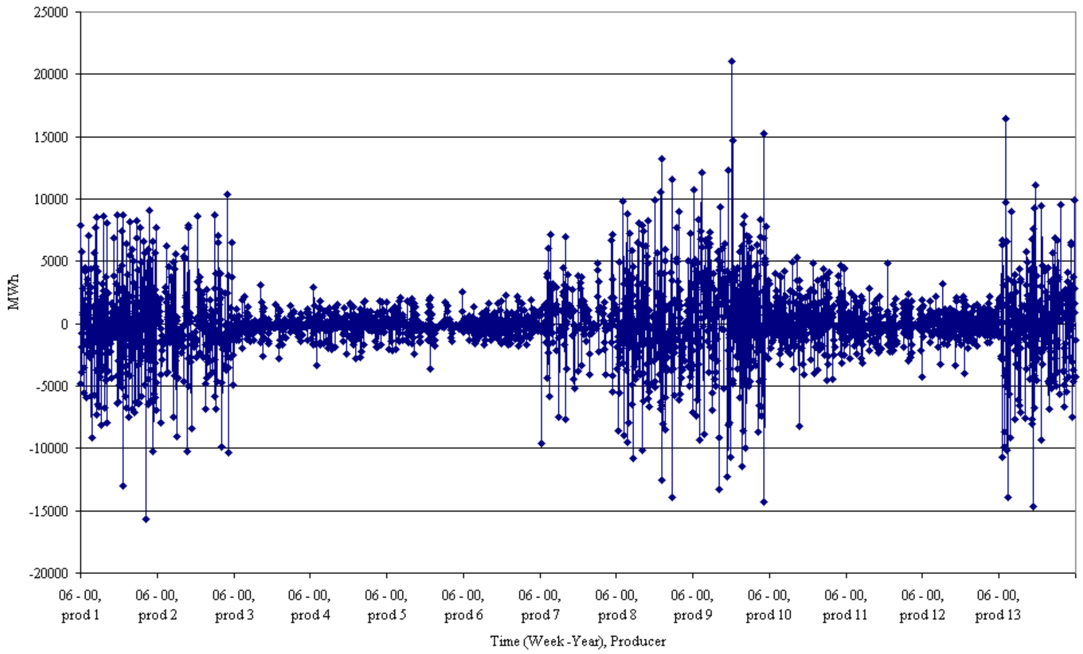

Figure C.4: Residual plot for model (7.8). Due to the clear variation in the size of the residuals between the producers the plot indicates that the error components are heteroskedastic.

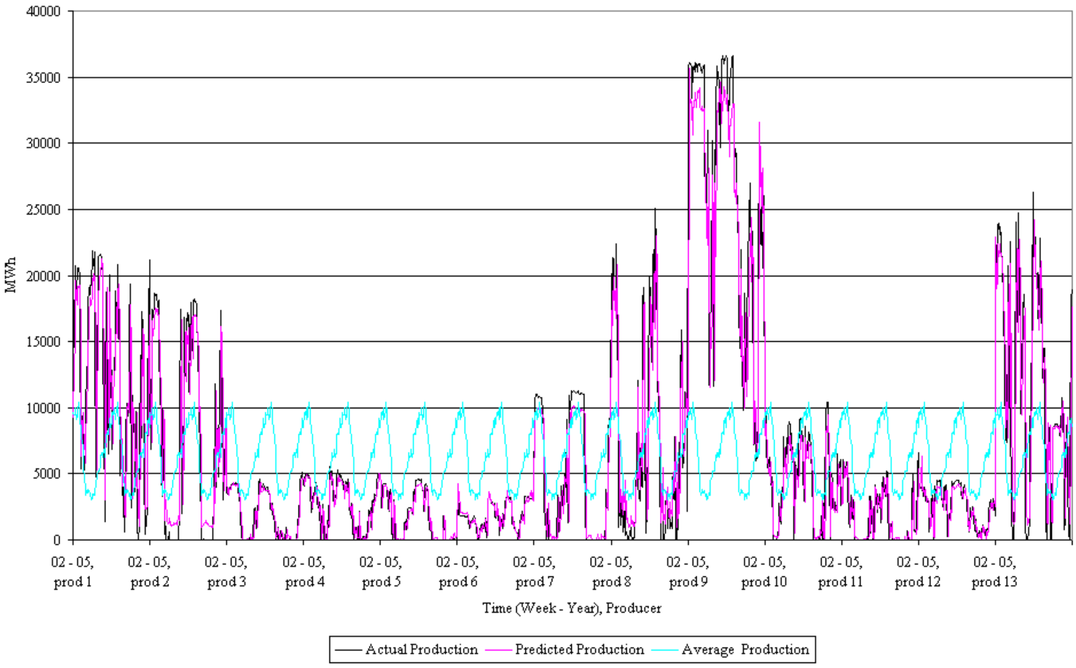

Figure C.5: Actual production and predicted production using model (7.8) for the out-of-sample period. The fit seems quite good which is also substantiated by the high out-of-sample $R^2 =$ 88,549%.

Appendix D

Various Calculations

D.1 Estimating Deviation from Expected Reservoir

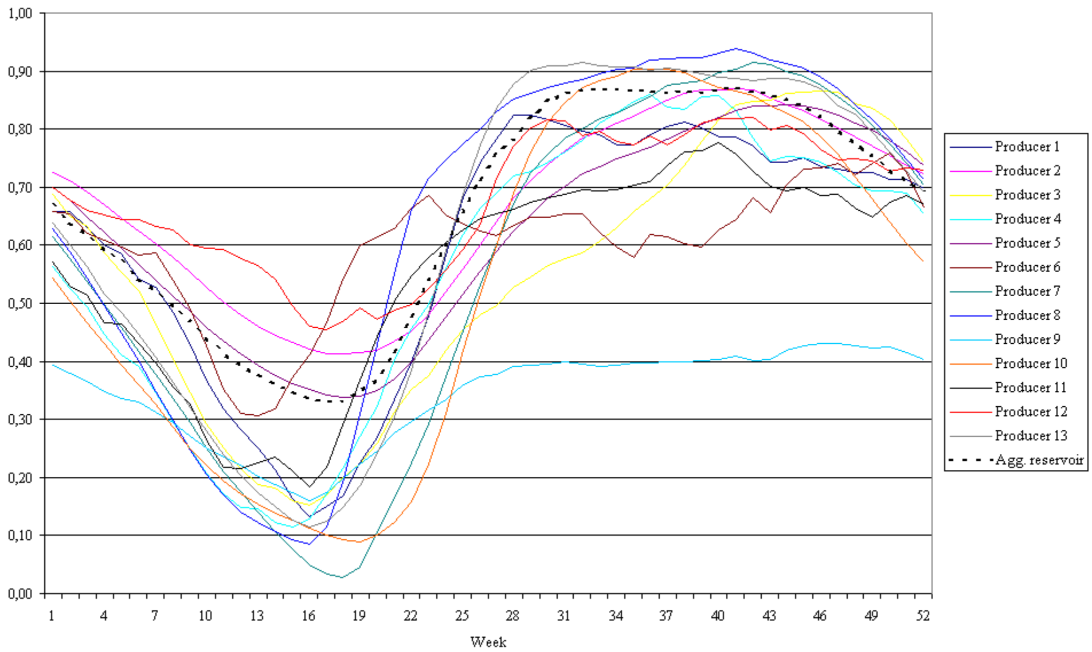

Figure D.1: The estimated expected reservoir levels

To estimate the expected reservoir curve a normal reservoir curve over the year is calculated for each producer based on the average reservoir level of each week. The estimated expected reservoir curves are illustrated in Figure D.1. For some of the producers, for instance producer 5, 7, 8 and 10, the normal curve is a smooth curve with the properties one expects i.e. a peak in the autumn and a valley in the spring. On the other hand, from Figure D.1 one sees that the normal curves for for instance producer 6 and 11, are jagged and do not at all resemble the expected aggregated reservoir which is shown with the dotted line.

The weekly average reservoir levels are calculated using the available data. For most of the producers this means only seven years of data, but for some producers longer time series were procured. Since quite few years are used, the error done when using the sample mean $\overline{x}$ as an estimate of the expected reservoir level μ is investigated.

Assuming that the weekly reservoir level for each producer is normal distributed [1], we can be $(1-\alpha)100\%$ confident that the error when $\overline{x}$ is used as an estimate of μ, will not exceed $t_{\alpha/2}\frac{s}{\sqrt{n}}$ where $t_{\alpha/2}$ is the t-value with $\upsilon = n-1$ degrees of freedom from the Student's t-distribution and s is the standard deviation.

Using a $0,05$ level of significance an error for every producer and week is calculated.

$$e_{i,t} = t_{\alpha/2,\upsilon}\frac{s_{i,t}}{\sqrt{n}}, \qquad i = 1...13, t = 1...52 \tag{D.1}$$

Table D.1: Minimum and maximum percentage error over the week for each producer when using the sample mean as the expected reservoir level

Producer	*No. of years*	$t_{\alpha/2,\upsilon}$	*Minimum error*	*Maximum error*
1	7	2,447	2,99%	77,08%
2	7	2,447	7,23%	18,59%
3	8	2,365	8,79 %	53,81%
4	7	2,447	6,81%	44,76%
5	47	2,015	5,31%	17,95%
6	7	2,447	9,79%	67,76%
7	7	2,447	5,55%	127,83%
8	17	2,120	3,14%	39,38%
9	7	2,447	18,43%	66,76%
10	23	2,074	2,82%	50,77%
11	7	2,447	8,34%	84,51%
12	22	2,080	6,55%	27,66%
13	16	2,131	4,53%	41,04%

In Table D.1 the minimum and maximum errors over the weeks for each producer are presented. To be able to compare the minimum and maximum errors better, the percentage error of the belonging mean $\overline{x}_{i,t}$ are shown. For producer 1 the best week, i.e. the week with the minimum error, has an error of 2,99%. This means that we can be

[1] For bell-shaped distributions of the random variables X_1, X_2,..., X_n the use of the t-distribution for confidence intervals is likely to be quite good even if the normal distribution assumption is not fulfilled (Walpole et al. 2002).

95% confident that the expected reservoir level lies within the interval $\overline{x}_{1,t} \pm 0,0299 \times \overline{x}_{1,t}$ for the best week t for producer 1. As seen from the table, the errors for some of the producers are considerably high. This indicates that the average weekly reservoir level is not a very good estimate of the expected reservoir level for a given week, at least not for the producers where only 7 years of data is available. With more years of data available, the errors tend to be less and one may expect that the producers have better forecasts for expected reservoir level to base their scheduling on. Nevertheless, with the data material gathered these are the only estimates based on merely the producer data set that could be calculated. In Figure D.2 the relative deviation from the expected reservoir, i.e. the deviation divided by the expected reservoir is shown.

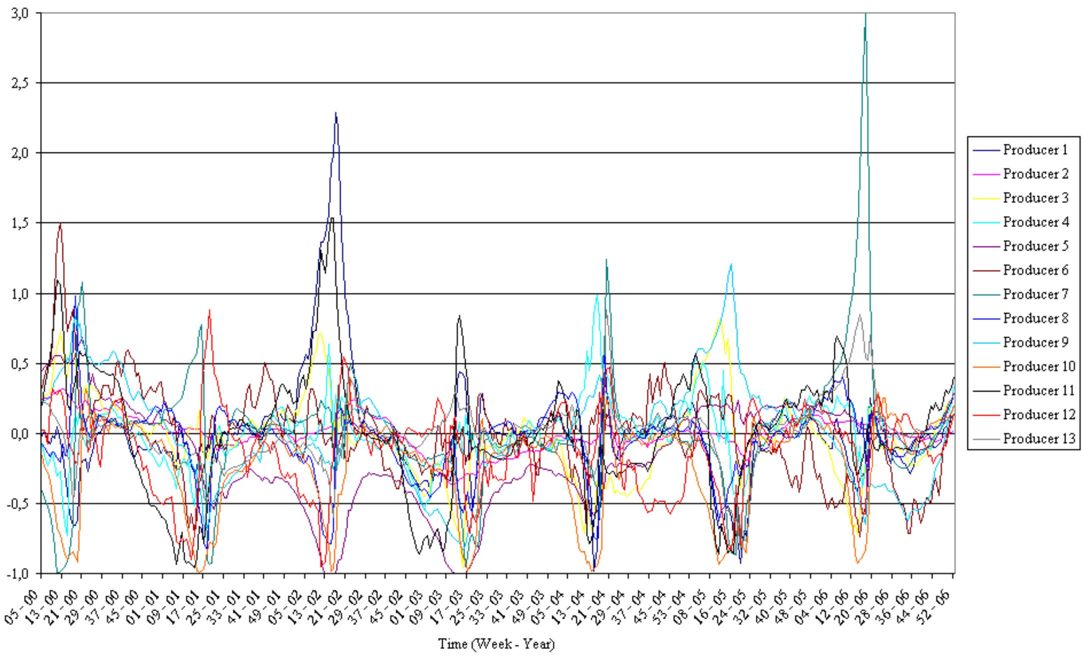

Figure D.2: Relative deviation from estimated expected reservoir

An alternative procedure on how to estimate expected reservoir curves is presented next. Both the procedures have their advantages and disadvantages. Since the method described in this section best consider the producer specific characteristics, this method is chosen.

Table D.2: Week of the year when the reservoir is at its expected minimum and maximum level. The values are used to develop dummies in hypothesis 1 and 3.

Producer	*week with min. reservoir*	*week with max. reservoir*
Producer 1	16	29
Producer 2	18	41
Producer 3	16	46
Producer 4	15	36
Producer 5	18	44
Producer 6	13	50
Producer 7	18	42
Producer 8	16	41
Producer 9	16	47
Producer 10	19	47
Producer 11	16	40
Producer 12	17	42
Producer 13	16	32

D.2 Estimating Deviation from Expected Reservoir - An Alternative Procedure

The normal reservoir curves calculated as described above have some weaknesses. Due to this, an alternative procedure using the normal reservoir level for the whole market is computed. In Figure D.1 the dotted line shows the normal level for the aggregated total reservoir in Norway and Sweden. This curve is much smoother than the producer specific curves and may be regarded as a good estimate of the expected total reservoir level.

Since the weekly averages are not so good estimates of the expected level we want to improve the normal reservoir curves based on the data of the aggregated reservoir. Hence, the goal is to use the normal level for the aggregated reservoir to smooth out the producer specific curves and at the same time keep some of the producers dependent characteristics.

To accomplish this, we first standardize the aggregated reservoir curve denoted by $Y = [y_1, y_2, ..., y_{52}]$. The mean $\bar{Y}$ and the standard deviation σ_Y from Y are calculated. Let the standard curve be expressed as

$$\omega_t = \frac{y_t - \bar{Y}}{\sigma_Y}, \qquad t = 1, ..., 52 \tag{D.2}$$

Hence, the standard curve $\Omega = [\omega_1, \omega_2, ..., \omega_{52}]$ fluctuates around 0 and has a standard deviation equal to 1.

From Figure D.1 one sees that the normal curves for each producer fluctuate around different levels and that some producers seem to have greater variations in reservoir level.

In order that the new normal curves Z_i, should have these producers specific properties as well, the average, $\bar{X}_i$, and the standard deviation, σ_{X_i}, of the normal curves for each producer X_i are calculated. Using the standard curve, Ω, a new normal reservoir curve for each producer is calculated

$$z_{i,t} = \omega_t \times \sigma_{X_i} + \bar{X}_i, \qquad i = 1...13, t = 1...52 \tag{D.3}$$

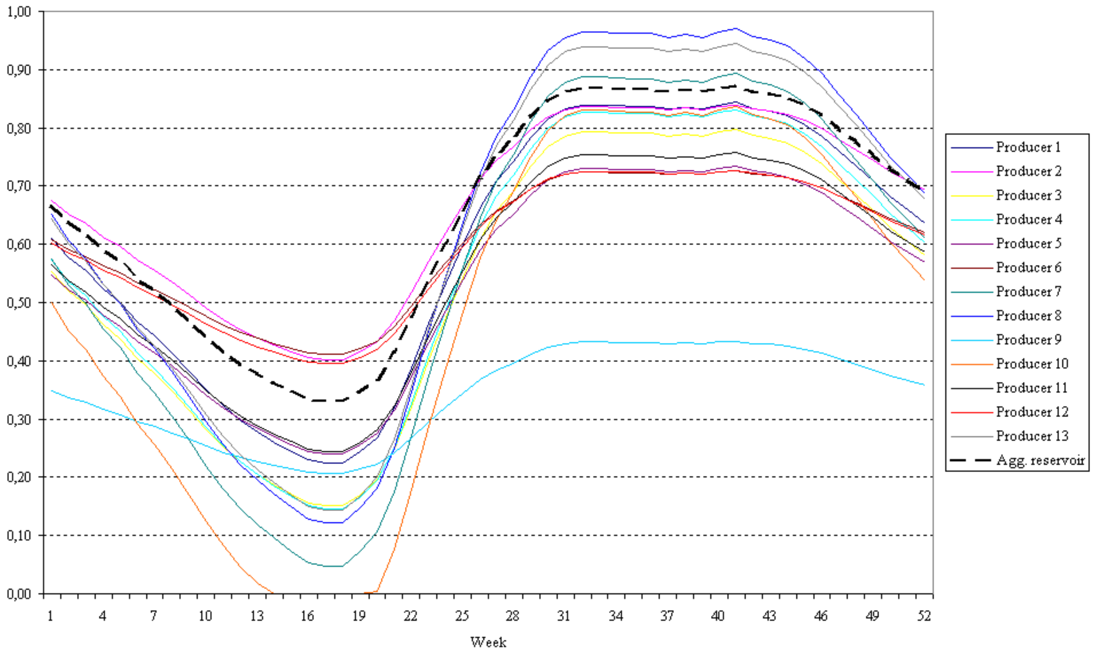

Figure D.3: The normal reservoir levels based on the normal aggregated reservoir curve

In Figure D.3 the normal reservoir curves based on the normal aggregated reservoir curve are shown. When constructing these curves some of the values turned out to be slightly negative. Since this is clearly unrealistic the figures are set to zero. One sees that the normal reservoir curves for the different producers have the same shape as the normal aggregated reservoir curve, but at the same time have kept some of its properties shown in figure D.1.

D.3 Estimating Deviation from Expected Inflow

The estimated expected inflow over the year for each producer is presented in Figure D.4. The averages are calculated from the data available and following the procedure presented in section D.1 the errors done when using the sample average as the expected inflow are calculated and shown in Table D.3. For some of the producers for instance producer 9,

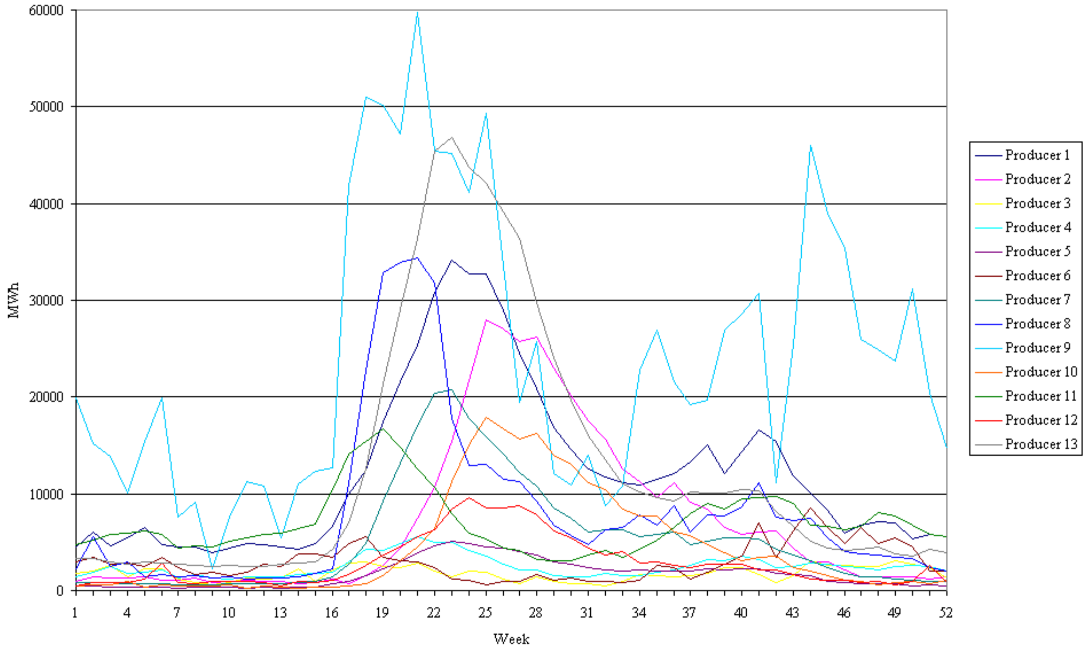

Figure D.4: Estimated expected inflow over the year

the expected inflow curve in Figure D.4 is jagged and do not show the properties one expects. This is probably due to that too few years have been used when calculating the weekly averages and this is seen from Table D.3.

Table D.3: Minimum and maximum percentage error over the week for each producer when using the sample mean as the expected inflow

Producer	*No. of years*	$t_{\alpha/2,\upsilon}$	*Minimum error*	*Maximum error*
1	76	1,995	8,25%	45,00%
2	23	2,074	11,97%	60,95%
3	8	2,365	16,09%	123,43%
4	44	2,018	9,92%	44,45%
5	98	1,988	7,69%	46,97%
6	7	2,447	22,16%	115,00 %
7	76	1,995	7,45%	29,73%
8	17	2,120	19,39 %	145,25%
9	7	2,447	29,43%	260,18%
10	24	2,068	12,85%	97,30%
11	76	1,995	12,84%	38,65%
12	22	2,080	12,32%	118,90 %
13	77	1,995	9,56%	21,39%