Aalto University School of Science Master's Programme in Mathematics and Operations Research

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Decision Support System for Hydropower Planning under Inflow Uncertainty

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Hydropower production planning is a complex task with several elements. Generally, many reservoirs and power plants, environmental constraints, the dynamics between short term and longer term decisions, as well as the uncertainties in inflow and electricity prices need to be simultaneously considered. The decision making is therefore often supported by optimization models with different scheduling horizons from one day to several years ahead.

In this thesis, a new decision support system is developed for mid-term production planning for a case company that operates in a deregulated Nordic electricity market. The scheduling horizon is one year with daily resolution, but the most important emphasis is on the upcoming month. The target is to improve the current decision making process by developing more detailed optimization model and providing increased awareness of the inflow uncertainty. This decision support system is developed for a specific river system in Finland, but can be rather easily altered to other systems as well.

The problem is formulated as a linear program that is based on a currently used model. The objective is to maximize revenue by allocating the production against the price forecast, while still taking into account the environmental constraints and the hydrological situation of the river system. This formulation is then solved using a commercially available solver, and the results are visualized in a web-based tool utilizing several inflow scenarios. The tool contains some user defined choices that enables choosing amongst alternative production plans and conducting quick what-if scenario analysis, thus providing interactive risk control with respect to the inflow uncertainty. Additionally, the feasibility of the implemented model and its improvements to the previous model are presented in order to verify that it works reasonably.

Keywords:	Hydropower, inflow, scenario, production planning, mid-term,
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Vesivoiman tuotannonsuunnittelu on monimutkainen tehtävä, jossa on useita elementtejä. Yleensä on huomioitava samanaikaisesti monia järviä ja voimalaitoksia, ympäristövaatimuksia, lyhyen ja pitkän aikavälin päätösten välistä dynamiikkaa sekä tulovirtaamien ja sähkön hintojen epävarmuuksia. Päätöksentekoa tuetaan siksi usein optimointimalleilla, joiden suunnitteluhorisontti voi olla yhdestä päivästä useisiin vuosiin.

Tässä työssä kehitetään uusi päätöksenteon tukijärjestelmä keskipitkän aikavälin tuotannonsuunnittelulle esimerkkiyhtiötä varten, joka toimii vapautuneilla Pohjoismaisilla sähkömarkkinoilla. Suunnitteluhorisontti on yksi vuosi päiväresoluutiolla, mutta tärkein painotus on tulevalla kuukaudella. Tavoitteena on parantaa nykyistä päätöksentekoprosessia kehittämällä yksityiskohtaisempi optimointimalli sekä tuottamalla lisää tietoisuutta tulovirtaamien epävarmuuksista. Tämä päätöksenteon tukijärjestelmä on kehitetty tiettyä jokisysteemiä varten, mutta pystytään muokkaamaan muihinkin systeemeihin varsin helposti.

Ongelma on esitetty lineaarisena optimointimallina mikä perustuu nykyisin käytettyyn malliin. Päämääränä on maksimoida tulot allokoimalla tuotanto sähkön hintaennustetta vasten, ottaen kuitenkin huomioon ympäristörajoitteet sekä jokisysteemin hydrologinen tilanne. Tämä tehtävä ratkaistaan kaupallisella optimointiohjelmistolla, ja tulokset visualisoidaan web-pohjaisessa työkalussa hyödyntämällä useita tulovirtaamaskenaarioita. Työkalu sisältää muutamia käyttäjän määrittämiä valintoja mikä mahdollistaa valinnan vaihtoehtoisten tuotantosuunnitelmien välillä sekä nopean skenaariopohjaisen analyysin, täten tuottaen interaktiivista riskien hallintaa tulovirtaamien epävarmuuksien suhteen. Lisäksi, toteutetun mallin soveltuvuus ja parannukset aikaisempaan malliin esitetään sen varmistamiseksi, että se toimii järkevällä tavalla.

Asiasanat:	Vesivoima, tulovirtaama, skenaario, tuotannon suunnittelu, keskipitkä aikaväli, lineaarinen optimointi, päätöksenteon tu-		
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Helsinki, May 16, 2018

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Abbreviations and Acronyms

Energy markets and hydropower

DU	Day Unit
FCR	Frequency Containment Reserves
FCR-D	Frequency Containment Reserve for Disturbances
FCR-N	Frequency Containment Reserve for Normal operation
MW	Megawatt
MWh	Megawatt hour
RoR	Run-of-River hydropower plant
TSO	Transmission System Operator

Optimization and modelling

CCP	Chance-Constrained Programming
DM	Decision Maker
DP	Dynamic Programming
DSS	Decision Support System
ESO	Explicit Stochastic Optimization
ISO	Implicit Stochastic Optimization
LDR	Linear Decision Rule
LP	Linear Programming
MILP	Mixed Integer Linear Programming
NLP	Nonlinear Programming
RP	Reliability Programming
SDP	Stochastic Dynamic Programming
SLP	Stochastic Linear Programming

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Chapter 1

Introduction

Reservoirs and river systems in different areas of the world may have various purposes and objectives, such as hydropower production, water supply, irrigation and flood control. Vast amount of optimization models with different objectives and time horizons have been developed in order to enhance the operational planning of water resources. Regardless of the objective, the planners all around the world face one common challenge: the inherent uncertainty of inflow, which is a measure describing the incoming amount of water into the reservoirs. For the most part, it consists of precipitation, but in the Nordic countries the melting of snow has also a huge impact. On the other hand, in semi-arid regions such as Brazil's northeast region, evaporation rates might play a big role (Celeste et al., 2009). As the amount of water in a reservoir is a scarce resource, the inflow uncertainty should be taken into account in the planning procedure in order to enable efficient management of water resources, and to mitigate the risk of flooding or draining. This is important especially in the longer time horizon, because the accuracy of inflow forecasts naturally decreases towards the end of the forecasting horizon.

This thesis proposes a model-driven Decision Support System (DSS) for mid-term hydropower planning in the presence of inflow uncertainty. We aim to provide more information and enable better risk control for the current planning process used by a case company, which is based solely on a deterministic optimization. Additionally, we describe the relevant background, e.g., a short description of the Nordic electricity market, the basics of hydropower and a literature review of reservoir optimization methods.

1.1 Focus and Assumptions

The business environment of the case company is the Nordic electricity market, where the electricity price is freely determined and thus constitutes another uncertain variable, in addition to inflow. Therefore, the fundamental objective of the hydropower producer is to maximize the revenue by optimizing the production against the price of the electricity, while still taking into account the environmental constraints, hydrological situation and inflow risk. The uncertain variables can be generally accounted by utilizing multiple scenarios and forecasts. However, generating these scenarios is not in the scope of this thesis. Several inflow scenarios are provided by an external source, but by the time of writing, only one viable electricity price forecast is available. For this reason, the price uncertainty is not considered in this thesis. Moreover, the case company is assumed to be a *price taker*, meaning that it is not large enough to exercise market power by influencing the prices with its production decisions.

The optimization models that are used to solve water allocation problems can be divided into long-term, mid-term and short-term horizons. This thesis considers mid-term optimization in a specific river system with a time horizon of one year. The reservoirs in question are relatively small, so that the most important focus in the operational planning is the upcoming month. The proposed concept and optimization model can be rather easily altered to different river systems as well. Optimization in general, studies the following (Berg, 2017):

- 1. Modelling: assumptions, simplifications, choices for functions
- 2. Optimization theory: existence, uniqueness, characterization with optimality conditions, duality
- 3. Computation: methods, complexity

This thesis focuses only on the modelling part. The implemented optimization model should be formulated such that it describes the river system accurately enough for its purposes, while still maintaining computational feasibility and usefulness in practical usage. The computation part, i.e., what kind of algorithms are used to solve different problems, goes partly together with model formulations. For instance, linear optimization models are usually solved with different algorithms as nonlinear models. In this thesis, we formulate a linear model which is then solved with a commercially available solver. A few mentions of algorithms are very shortly addressed in the literature review, along with modelling approaches, but the detailed descriptions on how the algorithms actually work are left out of the scope of this thesis. Furthermore, optimization theory is not addressed in this thesis.

1.2 Research Objectives

The main objective is to *improve the mid-term hydropower planning process* by taking the uncertainty of inflow better into account. The way of doing this should be compatible with the current way of production planning that the case company uses. From this perspective, we aim to develop a rather pragmatic Decision Support System, which enriches the existing planning procedure by providing more information, alternatives and increased awareness of inflow risk. This is achieved by implementing an optimization model, using several inflow scenarios, and visualizing the results in a web-based tool with some user defined choices. Ultimately, the Decision Maker (DM) decides the final production plan with the help of the optimization model and visualizations.

The optimization model is built based on an existing model, but it is still implemented from scratch with a few updates and improvements. For instance, we include the possibility to participate in the Frequency Containment Reserve -markets (FCR), which may have an effect on the optimal production plans. Thus, another objective in this thesis is to study the effects of these improvements and also verify that the implemented model works as it should in different situations.

In addition to the implemented concept and modelling choices, we also aim to introduce alternative approaches that could be possibly considered in future development directions in terms of the entire planning procedure. As of now, more or less fixed production plans are used, but research has established several methods that would provide more strategy based plans, i.e., more flexibility with respect to the realizations of uncertainties.

1.3 Structure of the Thesis

The rest of the thesis is organized as follows. Chapter 2 briefly introduces the Nordic electricity markets with the emphasis on the physical market, as well as the frequency containment reserves. Chapter 3 describes the basics of hydropower, the role of inflow in the Nordics and the concept of marginal water value. Chapter 4 reviews literature on reservoir operation methods, with the main focus on the modelling of uncertainties. Chapter 5 presents the case river system, the implemented optimization model and the decision support framework in terms of considering the inflow risk. Chapter 6 presents and discusses the results and visualizations, and Chapter 7 finally concludes the thesis and suggests avenues for future developments. Figure 1.1 indicates how these chapters relate to each other.



Figure 1.1: Structure of the thesis.

Chapter 2

The Nordic Electricity Market

The Nordic electricity market was established during the 1990s as the individual countries deregulated their electricity industries and integrated them into a common market. Later on, the Baltic countries joined in 2010-2013. Prior to deregulation, the state was running the markets and the objective of a power producer was to adjust the supply to meet demand at minimum cost. Nowadays, the deregulated market has introduced free competition in order to increase the market efficiency. Consequently, the electricity prices are freely determined and the objective has changed to profit maximization. (Nord Pool, 2017c; Kinnunen, 2013)

This chapter briefly introduces the Nordic electricity market, as it is, the business environment of the hydropower producer considered in this thesis. Section 2.1 explains the principle behind price formation on a high level, and Section 2.2 introduces price areas. Section 2.3 breaks down the different markets in which the power producers can participate in.

2.1 Fundamentals of Price Formation

On a general level, the price of electricity is determined separately for each hour by the intersection of demand and supply curves, as illustrated in Figure 2.1. Since electricity is non-storable commodity, supply and demand have to be in equilibrium at all times. The supply curve is constructed in an increasing order of marginal costs of different production types, i.e., the *merit order*. Hence, the electricity price ideally equals the marginal cost of the most expensive production type that is dispatched, such that the total supply meets the demand (Kännö, 2013). Note that Figure 2.1 is only a simplified illustration because power plants from same production type can have different marginal costs in reality. Wind and Run-of-River (RoR) hy-



Figure 2.1: Conceptual price formation of electricity (Kinnunen, 2013).

dropower comes first in the merit order, since they are the cheapest sources and cannot be regulated. On the other hand, the most expensive gas and oil turbines are taken into use only when demand is high or when there is a significant lack of capacity of the cheaper production types. Kännö (2013) points out that reservoir hydropower is somewhat special production type, because it has very low marginal costs and the possibility to regulate the production with high flexibility. The production is then typically allocated to periods of high prices, when the opportunity cost of saving the water for later use is high.

Both supply and demand curves are subject to many uncertainties, such as weather conditions. Consumption is driven by temperature, whereas hydro and wind power capacities are dependent on precipitation and wind conditions, respectively. In addition, the marginal costs of thermal production are affected by fuel prices. Power plant outages and maintenances also affect to the general availability of production capacity. For the aforementioned reasons, the electricity prices can be volatile and difficult to forecast (Kinnunen, 2013). The price changes according to the changes in supply and demand. For instance, during high precipitation period, the hydropower production tends to increase, i.e., its production bar, as shown in Figure 2.1, widens. This moves the supply curve to the right which lowers the equilibrium point. An opposite effect happens when hydro production decreases. In the Nordics, the amount of hydropower capacity may have a significant effect on the prices, since hydropower covers approximately half of the total demand in a normal situation (Nord Pool, 2017c). The changes in demand side or in other production types also move the location of the equilibrium point in a similar way.

2.2 Price Areas

An integrated market enables the transmission of power between the countries, which leads to more secure electricity supply and more efficient use of the available power capacity (Nord Pool, 2017a). For instance, hydro dominated regions such as Norway might need imported electricity during low precipitation periods, when the need for thermal production increases (Kinnunen, 2013). However, the transmission capacity of the power grid is limited, which is why the Nordic and Baltic countries are divided into price areas by the transmission system operators (TSOs) in order to handle possible bottlenecks (Nord Pool, 2017d). TSOs own the national main grids, and are responsible for secure supply of electricity in their own area, as well as coordination between producers and consumers (Flatabo et al., 2003). The TSO of Finland is Fingrid. Finland and the Baltic countries form their own price areas, whereas Sweden, Norway and Denmark are divided into several price areas each.

In case supply and demand in a certain price area are not in balance, electricity will be either imported or exported to other areas, depending on whether there is a deficit or surplus of electricity. If the grid capacity is sufficient for the needed power flow between areas, the price will be the same for all areas. Otherwise, the area prices will be different such that exporting areas have lower price than importing areas. This way, the prices reflect the market situation in each area, i.e., higher price in importing areas lowers the demand by an amount that will match the available supply within the capacity limits (Nord Pool, 2017d). Nevertheless, the prices are still cheaper compared to the situation where the transmission of power between areas would not be possible. Figure 2.2 shows the hourly electricity price in Finland for three different weeks (from Monday to Sunday) in February, June and September, in 2017. The demand for electricity is commonly higher during the day hours of weekdays as opposed to nights and weekends, which increases the price accordingly. Figure 2.3 shows the areas, their corresponding prices $(in \in MWh)$ and the power flow between them (in MW) on November 13th 2017. In addition to Nordics and Baltics, nowadays electricity can also be exchanged between other European countries and Russia.



Figure 2.2: Hourly electricity prices in Finland for three different weeks in 2017. In addition to hourly variation, seasonal differences can be seen too, e.g., due to increased consumption during cold winter.



Figure 2.3: Area prices (\in /MWh) and flow of power (MW) between price areas on 13th of November 2017. Adapted from Statnett (2017).

2.3 Market Structure

As the previous section presented the price formation on a general level, we now present how the balance between supply and demand is accomplished in practice, via different markets. The structure of the Nordic electricity market as a whole is summarized in Table 2.1. Nord Pool Spot electricity exchange provides the markets for current day and the following day, where the area prices are determined. These are presented in Section 2.3.1. The financial market is provided by Nasdaq OMX Commodities, and is shortly described in Section 2.3.2. Finally, Section 2.3.3 introduces the markets for the power balance management provided by the TSOs, which ensure the balance between supply and demand close to real time.

	Physical contracts				Financial contracts
Provider	TSOs		Nord pool		Nasdaq OMX Commodities
Market	Reserves	Regulating market	Intraday market	Day-ahead market	Financial market
Time scale	Seconds	15-60 minutes	Minutes Hours	Hours next day	daily weekly monthly quarterly annually

Table 2.1: The structure of the Nordic power market (Kinnunen, 2013)

2.3.1 Physical Market

Physical markets consist of day-ahead (Elspot) and intraday markets (Elbas), which are markets leading to the actual physical delivery of electricity. On the Elspot, area prices, i.e., *spot prices*, are calculated for each hour of the following day based on an auction. Market participants place their orders by 12:00 (CET), specifying the volume in MWh/h they are willing to buy or sell at specific price levels in \in /MWh, for each hour in the following day. These orders are then aggregated into supply and demand curves which determine the next days prices according to the principles explained in Section 2.2. In addition to area prices, Nord Pool calculates the so-called system price or the reference price, which corresponds to the price level where the grid capacities between the price areas would be infinite. Therefore, if bottlenecks do not occur in the grid, all area prices are equal to the system price. This kind of price formation process produces electricity at the lowest possible cost for every hour of the day. (Flatabo et al., 2003; Nord Pool, 2017c)

Elspot market balances supply and demand for the most part. However, imbalances may still occur between the closing of Elspot and the delivery next day due to unexpected incidents, such as plant outages or strong winds. The intraday market Elbas functions as an aftermarket to Elspot that provides a possibility to handle these imbalances (Flatabo et al., 2003). Volumes can be traded every day around the clock until 30 minutes before delivery (in Finland). According to Nord Pool (2017b), Elbas is becoming increasingly important with an increasing amount of wind power and its unpredictable nature.

2.3.2 Financial Market

Physical markets provided by Nord Pool only cover the present and the following day. However, the electricity prices can be volatile and uncertain especially in the long run. Therefore, power producers may want to secure a certain amount of revenue even if the prices would drop. Similarly, big industrial consumers may want to fix their purchase price for certain volume in order to avoid unexpectedly large costs if the price level increases. Financial trading enables this kind of longer term hedging against price risks through variety of financial contracts, such as futures, forwards and options. These contracts can have a time horizon up to ten years, covering daily, weekly, monthly, quarterly and annual contracts (NASDAQ OMX Commodities, 2018; Nord Pool, 2017c). Contrary to the physical market, the financial contracts do not result in physical delivery of electricity. Instead, only cash settlements take place throughout the time horizon of a contract or only at end of it, depending on the contract type. These contracts often use the system price as the reference for settlement (Flatabo et al., 2003). Deeper explanation of the financial market is left out of scope in this thesis.

2.3.3 Power Balance Management

Even though the orders settled in day-ahead and intraday markets achieve the balance between supply and demand for the most part, real time imbalances still occur due to unexpected plant failures and inaccurate forecasts for generation or consumption. This causes fluctuations in the frequency of the power grid, which is why the power balance in the grid must be maintained continuously, in even shorter time scale than intraday market. Under normal circumstances, the power grid frequency is ideally 50 Hz, and it is allowed to vary between 49.9-50.1 Hz (Fingrid, 2017a). When there is less production than consumption in the grid, the frequency is smaller than 50 Hz, whereas production surplus leads to a frequency greater than 50 Hz. In order to secure the continuous supply of eletricity, the TSOs control the power balance by offering products and markets which attempt to maintain the frequency in real time. These markets generally consist of manually activated regulation power market, and automatically activated Frequency Containment Reserves (FCR). In this section, we focus on FCR since it is more relevant from the point of view of this thesis.

The frequency containment reserves are used for continuous frequency control in the grid, and they are further divided into Frequency Containment Reserve for Normal operation (FCR-N) and Frequency Containment Reserve for Disturbances (FCR-D). The aim of FCR-N is to keep the frequency within the normal range 49.9 - 50.1 Hz, so it activates in both directions. On the other hand, FCR-D attempts to maintain the frequency at least in 49.5 Hz in case it drops below the normal range. (Fingrid, 2017a)

The Nordic TSOs have agreed to constantly maintain a total of 600 MW of FCR-N, which is divided annually between Finland, Sweden, Norway and East Denmark in relation to the consumption of each country. The obligation of Finland is about 140 MW. The total amount of FCR-D is set each week, such that the steady state frequency deviation would not exceed 0.5 Hz even if a large production unit in the power system would suddenly get disconnected. Normally, the amount of maintained FCR-D in the joint Nordic system is 1200 MW, of which Finland has an obligation of 220-265 MW. The national TSOs acquire the needed reserves mostly by organizing both yearly and hourly markets for FCR, and by trading the reserve capacities between countries. In the hourly markets, it is possible to participate in the middle of calendar year, and the prices for each day are determined by bidding. In the yearly markets, a bidding competition is organized in the fall, after which it is not possible to join the market later on during the year. A fixed price holds throughout the year, which is determined according to highest accepted offer. (Fingrid, 2017a)

From the point of view of a power producer, adjustable power capacity can be offered to FCR markets given that the power source satisfies certain technical conditions, which are presented in Table 2.2. Automatic activation must take place within seconds and minutes after frequency changes in the grid. In FCR-D, the activation must start already when frequency is 49.9 Hz. The maximum FCR capacities that a power source can offer within these activation conditions are measured by control experiments. (Fingrid, 2017b)

Now consider a power producer that can produce power within $P_{min} \leq P \leq P_{max}$, and has maximum FCR capacities of P_{FCR-N} and P_{FCR-D} . These

Table 2.2: Technical requirements for participating in FCR markets (Fingrid, 2017b).

	Minimum size	Full activation time
FCR-N	0.1 MW	In 3 min after frequency
		step change of ± 0.1 Hz
		50~% in 5 s
FCR-D	1 MW 100 % in 30 s, with frequency 49.50 Hz	100 % in $30 s$, with
		frequency 49.50 Hz

maximum amounts can be offered to their full extent only when P is not too close to P_{min} or P_{max} , i.e., when there is enough room to adjust the production based on the frequency changes. Figure 2.4 shows the principles of calculating the available reserve capacities in all situations. These four



Figure 2.4: Calculation of reserve capacities in different power areas (Fingrid, 2017b).

situations are further explained below (Fingrid, 2017b):

- 1. When P is close to P_{min} , the amount for normal reserve P_{FCR-N} is calculated to the extent there is adjustable power within P_{min} .
- 2. When $P_{max} P \ge P_{FCR-N} + P_{FCR-D}$, both reserves are calculated to their full extent.
- 3. When P gets closer to P_{max} , the normal reserve is first calculated to its full extent, and after that the disturbance reserve to the extent there is adjustable capacity left.
- 4. When P is almost equal to P_{max} , the amount of P_{FCR-N} is calculated to the extent there is available power within P_{max} .

To summarize, the available FCR capacities depend on where the produced power P lies within its range $[P_{min}, P_{max}]$. Considering the yearly markets for FCR in Finland, the market participant needs to provide hourly reserve plan for the next day to Fingrid by 18:00 CET-time (Fingrid, 2017a). The market participant then gets paid simply by maintaining the offered capacities. For instance, if a hydropower producer has maximum capacities of $P_{FCR-N} = 1$ MW and $P_{FCR-D} = 2$ MW, and is planning to produce power in area 2 throughout the next day, both reserve capacities can be sold to their full extent. Assuming the prices of 2017, a compensation of 1 MW \cdot 24 h \cdot 13.0 \in /MWh + 2 MW \cdot 24 h \cdot 4.7 \in /MWh = 537.6 \in is paid by maintaining these reserve capacities. In comparison, if it would be necessary to produce at P_{max} through the next day, then it is not feasible to sell any reserve capacities to FCR market. If a power producer fails to maintain the offered reserve capacities, a compensation must be paid to Fingrid. Reservoir hydropower is well suited for participating in these markets due to its high degree of flexibility. As a new contribution to the previously used mid-term models by the case company, the optimization model implemented in this thesis takes into account the possibility to participate in the FCR markets.

These automatically activating power reserves provide momentary balancing to the grid in a time scope of some minutes, which gives time to fix the situation manually in case there are larger fluctuations in the grid. For this purpose, there is also manually activated regulation power market, where the technical participation requirement is to be able to change production or consumption at least 10 MW in 15 minutes. This manual regulation power then releases the already activated FCR capacities back into use for the next frequency fluctuations. Kinnunen (2013) provides quite thorough explanation of the regulation market, but in this thesis it is left out of scope.

To summarize this whole chapter, an overview of the price formation and the market structure was presented. It is worth noting that there are many details that were not covered here since the purpose was only to provide somewhat short introduction to the Nordic market. The most relevant markets are Elspot and FCR, in which the produced hydropower and the corresponding adjustable capacities are to be sold. Moreover, even though the amount of total hydropower can have a significant effect on the electricity prices in the Nordics, the river system considered in this thesis is not large enough to have an actual influence on the prices. Thus, the power producer is assumed to be a *price taker*. The Finnish area spot price forecast is then used as an input to the optimization model.

Chapter 3

Hydropower

This chapter presents the basics of hydropower in Section 3.1 and different kinds of hydropower plants in Sections 3.2-3.4. In addition, Section 3.5 introduces inflow and its yearly cycle in the Nordics together with reservoir levels, and Section 3.6 explains the concept of marginal water value.

3.1 Basics of Hydropower

Hydropower is the largest renewable energy source globally, contributing 71% of all renewable electricity (World Energy Council, 2016). In 2016, 16.4% of all global electricity was generated by hydropower. However, in the Nordic market, even half of all production comes from hydropower. The most hydro-dominated country is Norway, where 99% of its electricity production comes from hydropower (IRENA, 2017).

The principle of hydropower production is to utilize the potential energy of flowing water, such that water falling from higher to lower elevation is converted into electricity. This process is illustrated in Figure 3.1. The stored water in the reservoir is released through the penstock, which rotates the turbine. The generator then converts this mechanical energy into electricity, which is transmitted to consumers via power lines (Mäkiharju, 2012).

The potential energy E of the stored water can be written with basic physics as follows:

$$E = mgh = \rho Vgh, \tag{3.1}$$

where *m* is the mass of the water, ρ is the density of water ($\approx 10^3 \ kg/m^3$), *V* is the volume of water, *g* is the gravitational acceleration constant (9.81 m^2/s), and *h* is the height difference between the reservoir level and the tail water, i.e., the *head*. Since power can be defined as the rate of producing



Figure 3.1: A general hydropower plant (Tennessee Valley Authority, 2017)

energy, the power output of a turbine can be written as

$$P = \eta \rho g h q, \tag{3.2}$$

where η is the efficiency of the turbine and $q = \dot{V}$ is the volume flow rate of water through the turbine (m^3/s) , i.e, the discharge (Singh and Singal, 2017). As equation (3.2) states, the power output is proportional to the discharge and the head. This relationship is inherently nonlinear: when the water is discharged through the plant, reservoir level decreases and the tail water increases. In other words, the head decreases, which decreases the power output. From now on, the dependency of the water levels is referred to as the *head effect*. Additionally, the turbine efficiency is actually also dependent on the discharge, i.e., $\eta = \eta(q)$. For instance, higher discharges may decrease the turbine efficiency, whereas too small discharges might not even be feasible since turbines can break from cavitation (Mäkiharju, 2012).

In addition to the actual hydropower plant, water can be also directed to a spillway that leads past the plant. This is called spilling the water, or spillage. It might be necessary when the turbines are under maintenance, or when the inflow is so high that the maximum discharge capacity of the power plant is not enough to prevent flooding in the reservoir above the plant. However, since spillage does not contribute to the electricity production, it represents a lost opportunity of energy generation, wherefore it should be avoided if possible (Kinnunen, 2013). One of the contributions of this thesis is to use inflow scenarios to help anticipate these situations, thereby providing risk management regarding spillage and flooding.

The principle described here is the basis for all kinds of hydropower plants (Bøckman et al., 2008). It is common that several power plants are cascaded one after the other, such that the energy of the water can be exploited multiple times (Statkraft, 2017). The plants are often characterized by their possibilities to regulate the production. Figure 3.1 is an example of reservoir hydropower, or conventional hydropower. In addition, there are Run-of-River hydropower and pumped storage hydropower plants. These three different types are introduced in the next sections.

3.2 Reservoir Hydropower

Reservoir hydropower plants have the ability to store the water in a reservoir by utilizing dams that prevent the water flowing through the turbines, and then releasing it based on the needs of the producer. This regulating possibility makes hydropower a very flexible power source, which is beneficial for both the power producer and the market.

The power producer typically aims to schedule the production such that the water is released during the most expensive hours when it is the most profitable. On the other hand, the production might be halted entirely during cheap hours, such as nights or weekends. Besides the electricity prices, the producer obviously needs to take other relevant factors into account as well, such as the environmental regulations (reservoir limits), and the uncertain inflow.

From the market point of view, hydropower is a significant balancing power resource due to its ability to quickly increase or decrease the production (IRENA, 2014). As the supply must meet the demand at all times, hydropower can provide stability to the grid via regulating power market and the frequency reserves.

Reservoirs can be categorized based on their size into short-term, seasonal, and over-seasonal reservoirs. Small short-term reservoirs can only store the water for short periods of time, such as over the night or weekend, and then discharging it during more expensive hours. Seasonal reservoirs are larger in size, therefore able to store noteworthy amounts of seasonal inflow. Consequently, they can be operated by considering a longer time period, from a couple of weeks to 18 months for instance. Seasonal reservoirs are also the focus in this thesis. Lastly, over-seasonal reservoirs can store water even for several years, thereby being the most flexible with the longest operating time horizon. (Mäkiharju, 2012; Kinnunen, 2013)

The size of the reservoir also has an effect on the modelling considerations. The bigger the reservoir size, the longer time horizon should be considered in the production scheduling. For seasonal and over-seasonal reservoirs, there are usually different models for long-term and short-term scheduling, which are linked together. This is addressed in more detail in Chapter 4.

3.3 Run-of-River Hydropower

Contrary to reservoir hydropower, Run-of-River (RoR) hydropower plant has little or no storage capability. Hence, the river flow goes directly through the turbines and the generated power is proportional to the local inflow (Jacobs et al., 1995; Singal et al., 2010). This causes a few notable differences compared to conventional hydropower. Firstly, RoR plants cannot regulate the power production similarly, which is why they are generally used as a base power for the power system. Electricity is always produced provided that there is some water flowing in the river. However, RoR plants are still able to spill the water, which might be necessary in cases such as excessive inflow situation, turbine breakdowns, or even when there is too much production in the grid.

3.4 Pumped Storage Hydropower

Pumped storage hydropower integrates two reservoirs, such that the water can be pumped from the lower reservoir back into the upper reservoir after the discharge, thereby enabling the usage of the same water over and over again. This is not strictly renewable energy, since pumping requires electricity. However, if the pumping and discharging are scheduled well, it is still profitable. Generally, the water is discharged during the daytime when the prices are high, and the pumping is performed during the night-time when the prices are low. Pumped storage hydropower is also specifically useful for balancing purposes and maintaining the grid stability. (IEA, 2012; IRENA, 2014)

3.5 Inflow in the Nordics

Inflow is a measure describing the incoming water into a reservoir, which mostly consists of precipitation and melting of snow (Kännö, 2013). Therefore, the amount of inflow affects the production capacity. The changes in the reservoir level between consecutive time periods can be depicted with a $hydro\ balance\ equation:$

$$x(t+1) = x(t) + v(t) - q(t) - w(t),$$
(3.3)

where x(t) is the reservoir content, v(t) is the inflow to the reservoir, and q(t) is the discharge from the reservoir at period t. The possible spillage from the reservoir is denoted by w(t). Thus, the difference between the inflow and discharge (plus spillage) at each period determine whether the reservoir level increases or decreases. However, inflow is a stochastic factor, which makes hydropower planning a stochastic problem as well. Lynch (2008) argues that good seasonal weather forecasts in the European region has not yet been achieved. Consequently, taking the uncertainty of future inflows into account becomes more relevant especially in longer term planning, in order to avoid flooding or draining. In this thesis, the inflow uncertainty is dealt with by using several inflow scenarios which are based on weather forecasts in the short run, and historical data in the longer run.

The amount of inflow in the Nordics has a typical seasonal profile. During the winter, the reservoirs might freeze and most precipitation comes as snow. As the snow melts during spring or early summer, the reservoirs receive large amount of inflow in relatively short time period. Therefore, the reservoir levels need to be decreased during the winter time in order to make room for the incoming spring flood. Despite of that, unexpected inflow amounts can sometimes surprise the hydropower operators due to its stochastic nature, which might lead to spilling the water. During the fall it is common to increase the water level, such that it could be used during the winter when consumption is higher and the freezing of the lakes limits the incoming inflow (Mäkiharju, 2012).

Since these aforementioned seasonal profiles occur on individual reservoirs, the same profiles can be seen from aggregated data for the whole countries or the whole Nordic area. Figure 3.2 shows the yearly inflows and the corresponding reservoir contents in Finland for 2017 and 2016, from January 1st till the end of the year. Furthermore, the variation intervals between minimum and maximum values are based on historical data from 1978 to 2014. The amount of inflow is presented as energy units (GWh), and the reservoir content is presented as the percentage of total reservoir capacity in Finland.



(b) Reservoir content percentage in Finland, where 100 % reservoir capacity equals 5530 GWh

Figure 3.2: Yearly profiles of inflow and reservoir contents with aggregated data for Finland. The region covered between the minimum and maximum values are based on historical data from 1978 to 2014. The data is available at SYKE (2017).

By comparing the years 2016 and 2017, it is clear that the timing of spring flood can vary by several weeks, and the volume of the flood can also have significant differences. Moreover, the history based variation interval is also quite large, not only during the peak but throughout the year. In conclusion, the inflow variations both within and between years might be voluminous, which greatly affects the hydropower capacity. As the Nordic market is hydro-dominant, the inflow variations impact the electricity prices as well (Bye et al., 2008).

3.6 Water Value

The valuation of the stored water in reservoirs can be obtained by calculating the so called marginal water value, which describes the opportunity cost of releasing the water at current period as opposed to storing it for future periods (Botterud et al., 2010). To get an intuitive idea behind its meaning, first consider a thermal power plant, where the production decisions are based on its short-term marginal cost (e.g. fuel costs) and the electricity price. When the electricity price exceeds the marginal cost, the production is profitable, and vice versa. However, since the marginal costs of hydropower are negligible, similar approach is not reasonable. Instead, the production decisions can be based on marginal water values. This is due to the scarcity of water: the decisions at current period affect to the production capacity in the future. Thus, the problem is to balance income in the short-run against the expectations about future income (Fosso et al., 1999).

The marginal water value is defined as the expected value of marginal change in the reservoir content, i.e, the value of storing an additional unit of water in the reservoir. Figure 3.3 illustrates the principle in case of one reservoir, by showing the expected future income as a function of initial reservoir content. The slope of this function at a given reservoir content then represents the marginal water value. Note that the expected future income is a concave function, because increased volume reduces the marginal water value due to the risk of spilling (Fosso and Belsnes, 2004). When the reservoir is full, the marginal water value is zero because delaying the production would lead to spilling. Theoretically, water should be discharged when the electricity price is higher than the current marginal water value, and delayed when the price is lower (Lehtonen, 2015).

The marginal water values can be calculated with e.g. stochastic dynamic programming, as in Fosso et al. (1999). Alternatively, they can be obtained as the dual values, i.e., the shadow prices, of the hydro balance equation (Botterud et al., 2010; Eusébio et al., 2011). In practice, accurate calculations of the marginal water values might not be easy, since they depend on future prices, inflows and the limits for reservoir contents and plant discharges. Moreover, Fosso et al. (1999) notes that when there are several cascaded reservoirs in the system, the marginal water value function of a reservoir depends on the water contents in the other reservoirs as well.



Figure 3.3: Illustrative visualization of the expected future income as a function of initial reservoir content. The derivative of this function represents the marginal water values. (Fosso and Belsnes, 2004; Kervinen, 2010)

Chapter 4

Review of Reservoir Optimization Methods

This chapter reviews literature on the application of optimization models to reservoir operation and hydropower planning, which has been under intensive research during the recent decades. While the point of view of this thesis is profit maximization in the Nordic environment, the following review is not restricted to similar cases only. Instead, the aim is to provide an overall view of different modelling approaches and how the uncertainties can be accounted.

Section 4.1 first presents the modelling aspects and purposes of hydropower optimization in different time horizons. Section 4.2 then briefly introduces the most common optimization methods that can be used in reservoir operation. Sections 4.3-4.4 describe ways to incorporate uncertainty to these methods. Finally, Section 4.5 very briefly addresses some heuristic approaches and concludes this chapter.

4.1 Planning Hierarchy

Before going into the actual modelling approaches, we present the big picture of the hydropower scheduling process, following mostly Fosso and Belsnes (2004). Generally speaking, hydropower optimization models usually attempt to maximize profits or minimize costs over some predefined time horizon, subject to the hydrobalance equation, minimum/maximum limits of the reservoir contents and the plant discharges, and possible other constraints. This is the basic setup that we have followed throughout this whole thesis. As stated in Section 3.2, the reservoir sizes and the scheduling time horizon affects the modelling choices and purposes. In systems with seasonal or over-seasonal reservoir storage capacity, shortterm production decisions are coupled with longer-term strategic decisions, which are often not feasible to have within the same model. Therefore, the production scheduling problem is decomposed into a planning hierarchy. Figure 4.1 illustrates the basic idea: the results from longer-term models are used as boundary conditions for models with shorter time horizon. Each planning horizon has its own characteristics in terms of time resolution, system description and the uncertainties. Both long and mid-term models usually consider the uncertainties in inflow and/or in spot price one way or another, thereby handling the risk management. On the other hand, short-term models can often be solved as deterministic problems.



Figure 4.1: Planning hierarchy of hydropower scheduling (Fosso and Belsnes, 2004; Fosso et al., 1999).

This planning hierarchy is necessary, because all models cannot support the same level of detail. Zambelli et al. (2012) argue that stochastic long-term models in multireservoir systems usually require some kind of simplifications to the system description, such as aggregated reservoirs, because the computational requirements might get quite intense. Thus, long-term models are unable to provide boundary conditions to the short-term models with sufficient accuracy. Mid-term models have typically the same time resolution as the long term model, e.g., one week or one month, but should have approximately similar system description as the short-term model. Hence, it can be seen as a link between the long and short term models that transforms the results from the long-term scheduling into suitable inputs for the short-term model (Fosso and Belsnes, 2004). However, if the reservoir capacities are not large enough for over-seasonal scheduling, as is the case in this thesis, the long-term model is not needed and the mid-term model itself provides the relevant longer term decisions. The short-term models are then used in real time operation with a time resolution of one hour, whereby they need to be the most accurate and detailed regarding the system description.

The coupling between mid-term and short-term models can be done either with target reservoir levels or with the marginal water values. If target levels are used, the mid-term model provides reservoir endpoints for the short-term model. On the other hand, the mid-term model can be used to calculate the marginal water values, in which case the short-term model does not optimize towards predefined endpoints. Instead, the production can be priced based on these water values, i.e., balancing the income in the short-run against the expected future income (Fosso et al., 1999). Kervinen (2010) introduces this approach in more detail. According to Fosso et al. (1999), coupling through the marginal water values is a better approach, because it gives enhanced flexibility to adapt the production scheduling to the inflow situation. However, the mid-term model implemented in this thesis provides target level coupling, since accurate calculations of the marginal water values might be difficult to achieve in practice. Moreover, Røtting and Gjelsvik (1992) argue that short-term scheduling results can be sensitive to errors in the provided water values.

4.2 Basic Optimization Techniques

This section briefly presents the basic classification of optimization techniques that are used in reservoir operation, consisting of Linear Programming (LP), Nonlinear Programming (NLP) and Dynamic Programming (DP). Each of these techniques can be applied in both deterministic and stochastic context (Simonovic, 1992).

4.2.1 Linear Programming

Linear Programming (LP) has been considered as one of the most important scientific advances in recent history, which can be used to solve problems in many disciplines (Simonovic, 1992). It was first proposed by George Dantzig in 1947, who also developed a popular Simplex algorithm for solving linear programs (Dantzig, 1963). In LP, the objective function and constraints must be in a linear form. Real life situations often include nonlinearities, in which case linear models are approximations. However, LP has several significant advantages, such as the ability to efficiently solve large-scale problems, convergence to global optimum and well developed duality theory for sensitivity analysis (Labadie, 2004). Moreover, the models are usually somewhat simple to implement and can be solved with available LP solvers which do not require initial solutions from the user. Nowadays the commercially available LP solvers also contain other algorithms in addition to Simplex, such as Interior-Point (IP) method, and all kinds of sophisticated setups that enable fast computation (see e.g. Gurobi Optimization, Inc. (2017)).

Linear Programming is also widely used in hydropower optimization, even though the power generation function is nonlinear. In many cases, it is accurate enough to assume a linear or piecewise linear dependency between discharge and power generation, especially in mid- and long-term models (Kervinen, 2010). Moreover, the head effect is often ignored, particularly if the head variations are small compared to reservoir level. Whether or not the system can be sufficiently modelled as a linear program depends very much on the model purpose and the desired accuracy. The implemented model in this thesis is essentially a deterministic linear program, which is presented in Chapter 5.2.

Introducing integer or binary variables extends LP into Mixed Integer Linear Programming (MILP). Binary variables may be necessary for representing some nonlinear or nonconvex terms in the model. For instance, discharges below some certain level might not be feasible since the turbines can break from cavitation. In such cases, the discharge variable can either be zero, or above that certain level. This kind of discontinuities can be handled with binary variables. However, integer variables increase the computational effort significantly. Solving the problem then necessitates additional methods, such as Branch and Bound algorithm.

Stochastic extensions of LP include Multi-Stage Stochastic Programming and Chance-Constrained Programming (CCP). These will be explained in more detail in Sections 4.3.1 and 4.3.3.

4.2.2 Nonlinear Programming

Nonlinear Programming (NLP) offers more general mathematical formulation than LP, in which the objective and constraints are not restricted to be linear. NLP is reasonable in such reservoir systems where the nonlinear power generation function cannot be linearized with sufficient accuracy, which might be the case in short-term models that often require the most accurate descriptions of the system. The downside of NLP is that convergence to global optimum is generally not guaranteed unless the problem is convex, which might not be the case in power generation function, especially if the power plant contains multiple turbines. Moreover, NLP algorithms might be slow and require an initial solution. According to Labadie (2004), the most powerful and robust NLP algorithms include Sequential Linear Programming (SLP), Sequential Quadratic Programming (SQP), augmented Lagrangian method and the generalized reduced gradient method.

The applications and algorithms of NLP are not given much focus in this thesis, but few references are given. Catalão et al. (2006) use quadratic programming in short-term hydro scheduling problem to consider the nonlinear power generation function as a function of discharge and the head. They argue that the proposed NLP method provides a higher profit compared to LP based methods that ignore the head dependency and nonlinearity of the objective function, without much extra computational effort. Barros et al. (2003) use NLP in a multipurpose large-scale system in Brazil, that consists of even 75 hydropower plants. Additionally, they linearized the NLP model and solved it by LP and SLP as well. In their analysis, they conclude that both LP and SLP models were sufficient for planning purposes, but the NLP model is the most accurate and therefore suitable for real-time operation.

4.2.3 Dynamic Programming

Dynamic Programming (DP) deals with sequential decision problems, and was first introduced in its general form by Bellman (1957). It has been the most popular technique in reservoir operation problems in addition to LP. It is not restricted to any particular problem structure, thus being able to handle nonlinear functions as well (Simonovic, 1992).

We next describe the principle of DP, following Labadie (2004). It is commonly applied in its discrete form, meaning that the state variable, e.g., the water content x(t), and the control variable, e.g., the discharge q(t), can take only a finite number of discrete values. The original problem is then decomposed into simpler subproblems that are solved sequentially over each time period. This idea involves calculating a *profit-to-go* (or cost-to-go in minimization problems) function $J_t(x(t))$, which represents the accumulated maximum return from the current period t to the final period T, conditioned on the state variable x(t). This profit-to-go function is optimized for all discrete combinations of x(t) over each time period, usually with a backward recursion for t = T, T - 1, ..., 1 as follows:

$$J_t(x(t)) = \max[L(q(t)) + J_{t+1}(x(t+1))], \qquad (4.1)$$

where the term L(q(t)) denotes the profits in period t (which depend on the discharges q(t)) and J_{t+1} is the future income after period t. This is based on Bellman's principle of optimality, which implies that there is an optimal policy from period t to T, regardless of the initial state. Note that the optimization in (4.1) is obviously subject to the hydrobalance and the limit constraints, and that the final term $J_{T+1}(x(T+1))$ must be defined to start the recursion.

Dynamic Programming solves globally optimal discharges (in a discrete sense), given that the optimization is performed by enumerating over all discrete combinations of discharges q(t). As this optimization must be done over all possible discrete combinations of the reservoir contents x(t), one might imagine that the computational effort increases significantly with the number of discretization levels, especially in multireservoir systems. For instance, if there are n reservoirs with an average of m discretization levels each, the computational effort is proportional to m^n . This is commonly known as the *curse of dimensionality*, which limits the usage of DP in river systems with multiple reservoirs, wherefore it is commonly used in long-term models where the reservoirs are aggregated, as in Fosso et al. (1999).

In the deterministic form presented in (4.1), the current state x(t) and the decision q(t) fully determine the next state. Section 4.3.2 presents applications of Stochastic Dynamic Programming (SDP), which has the same principle as described here, but the uncertainties also have an impact on the next state.

4.3 Explicit Stochastic Optimization

Explicit Stochastic Optimization (ESO) incorporates the uncertainties directly to the model formulation, e.g., inflow is considered as a random variable with probabilistic description. Thereby, the optimization is performed without perfect foreknowledge of the future, unlike in deterministic models. The result from ESO is not necessarily only one production plan, but an optimal policy regarding the possible realizations of uncertainty.

4.3.1 Multi-Stage Stochastic Programs

This section describes the basic idea of multi-stage stochastic programs, following closely Abgottspon (2015). Multi-stage stochastic program refers to a problem formulation where only the initial decisions are actually implemented, but future decisions depend on the realizations of uncertain variables. In hydropower planning, the term stage is equivalent to time period t. For simplicity, assume that discharge q(t) is the only decision to be made at each period t = 1, ..., T. After each decision, previously unknown inflow v(t) is revealed. When this is repeated through all periods, the course of T-stage stochastic program is as follows:

$$q(1), v(1), q(2), v(2), ..., q(T-1), v(T-1), q(T).$$
 (4.2)

We denote $v_{[1,t]} = v(1), ..., v(t)$ as the available information up to period t. Multi-stage stochastic programs are often represented with a scenario tree, which basically tries to represent the probability model of the random variable such that it can only have finite number of realizations in each period. Figure 4.2 shows an example of a simple scenario tree with three periods and four scenarios. Each node corresponds to a state where decision has to be made, whereas each link between nodes corresponds to one possible realization of inflow v(t) between time periods. A path from the root node at t = 1 to a leaf at t = 3 represents one scenario, e.g., a possible sequence of $v_{[1,T]}^s$, $s \in \{s_1, s_2, s_3, s_4\}$, each having a certain probability of occurrence. An



Figure 4.2: A simple scenario tree with T = 3 periods and $S = \{s_1, s_2, s_3, s_4\}$ scenarios.

important aspect in stochastic multi-stage programs is that the decisions are

non-anticipative, meaning that they may only depend on the information up to period t, but not on the future observations. On the contrary, deterministic models can make anticipative decisions due to the assumption of perfect knowledge of future inflow. One way to implement the non-anticipative decisions is by adding equality constraints that forces the decisions to be equal for identical histories. To illustrate this, consider the decision variables as scenario specific, i.e., $q^s(t)$ denotes the discharge at time $t \in \{1, 2, 3\}$ for scenario $s \in \{s_1, s_2, s_3, s_4\}$. The non-anticipativity constraints are then expressed as $q^s(t) = q^{s'}(t) \forall s, s'$, for which $v_{[1,t]}^s = v_{[1,t]}^{s'}$. Intuitively this means that if two scenarios s and s' are identical up to period t, then their decision variables must also be identical up to period t (Escudero et al., 1996).

Multi-stage stochastic programs can be solved by formulating the socalled *deterministic equivalent*, which is commonly a linear program, i.e., Stochastic Linear Programming (SLP) model. In hydropower application, the objective function would then be to maximize the expected profit from all future decisions corresponding to different realizations of inflow, weighted by their conditional probabilities. Abgottspon (2009) shows in more detail how the deterministic equivalent can be formulated. He solves a mixedinteger linear problem on monthly resolution, with inflows and spot prices as uncertain variables. Commonly, multi-stage programs are applied in longer term planning with time resolution of one week or a month. However, Fleten and Kristoffersen (2008) use mixed-integer linear stochastic programming for short-term planning as well.

The downside of this approach is that the scenario tree grows exponentially with the number of periods and branches, wherefore large number of scenarios and time periods results in extremely large-scale linear program. Attempts can be made by applying e.g. Benders decomposition to reduce the computational effort, as in Jacobs et al. (1995). Growe-Kuska et al. (2003) describe algorithms for scenario reduction and scenario tree construction, but these are topics by themselves and are not further covered here.

In addition to the scenario tree formulation, Linear Decision Rules (LDR) provide a robust approach for solving multi-stage stochastic problems. Decision rule maps the realizations of uncertainty into decisions, such that the decision variables are functions of the uncertainty. However, the problem of searching the functions that would produce the best performance under the uncertainty is computationally intractable for realistic sizes. Restricting the decision rules to be affine functions of the uncertainty provides a tractable approximation. (Braaten et al., 2015)

Braaten et al. (2016) uses LDR to generate weekly policies with profit maximization objective, where both inflow and spot price are uncertain. The discharge and other decisions at each time period are formulated as
affine reactions to the realizations of the uncertain variables, consisting of a fixed intercept and a linear reaction to the uncertainty. The intercept represents a scheduled value, whereas the linear reaction represents a real time adjustment, e.g., a *recourse* decision. These adjustments can depend on the realizations of the uncertain variables on all or some of the previous time periods, but not on the future periods. Based on this idea, they show how deterministic optimization model can be reformulated to a robust optimization problem with LDR. The aforementioned intercepts and the slopes of the linear reactions are solved as decision variables in a purely linear model, thus identifying the optimal affine reactions.

According to Grønvik et al. (2014), LDR approximation is a promising addition to other multistage stochastic hydropower models, as it is effective at reducing computational complexity. Moreover, it gives the advantage of not requiring any assumptions regarding the distributions of the random variables (Egging et al., 2017). However, Risberg (2015) argues that restricting the decision rules to be linear reduces flexibility, which may result in losing a lot of optimality. Braaten et al. (2016) also points out that quantifying the approximation error will be important to test the applicability of LDR in hydropower scheduling.

4.3.2 Stochastic Dynamic Programming

Stochastic Dynamic Programming (SDP) has a similar formulation as the deterministic form described earlier, the difference being that the current decision and state do not completely determine the outcome for the next stage, i.e., uncertainty has an impact too. Due to its sequential decision structure, SDP essentially deals with same types of problems as multi-stage stochastic programs, e.g., probability distributions are used for deriving optimal policies without the presumption of knowing the future inflows.

As the uncertainty is directly incorporated to the model formulation, the Bellman equation in SDP can be expressed as follows:

$$J_t(x(t)) = \max \mathbb{E}[L(q(t)) + J_{t+1}(x(t+1))].$$
(4.3)

Contrary to the deterministic version, the problem is maximized for the expected future profit-to-go, wherefore the optimal policy maximizes the objective on average. Similarly to the scenario tree representation, the random variables are often sampled such that they have a finite number of possible realizations at each stage, in which case the expectation operator in (4.3) can be replaced by simply averaging. The problem can then be solved by going through all combinations of states, decisions and sampled random variables, such that the value of a certain decision is defined by the expected value over all possible random data realizations. (Abgottspon, 2015)

Fosso et al. (1999) uses SDP in long-term scheduling at weekly resolution such that both inflow and spot price are dealt as stochastic variables. Hence, the state variables in their model are the water content (determined by the decision and the realization of inflow), and the spot price. They use this model to calculate marginal water values at each period for given reservoir level and market price. Generally, SDP formulation assumes stage-wise independence. Indeed, Fosso et al. (1999) treats inflow as independent from one week to the next, but they point out that it is slightly incorrect, as there exists some temporal correlation. However, it would also be possible to formulate the problem such that the sampled inflows at t are conditioned on the samples at t - 1.

According to Abgottspon (2015), the main advantage of Dynamic Programming algorithms compared to a general multistage stochastic program is that the complexity scales linearly with the number of time periods. However, similarly to deterministic version, SDP also suffers from the curse of dimensionality, i.e., the number of subproblems to solve increases exponentially with the number of discretizations of the state and decision variables, as well as with the number of possible outcomes of the stochastic variables. Stochastic Dual Dynamic Programming (SDDP) is a method that mitigates the curse of dimensionality by approximating the expected profit-to-go functions by piecewise linear functions, so that the state discretization is not needed (Pereira, 1989; Pereira and Pinto, 1991). More detailed descriptions of SDDP and its applications to Nordic countries can be found in Røtting and Gjelsvik (1992) and Gjelsvik et al. (2010). Mujumdar and Nirmala (2007) propose another interesting application, in which they incorporate a Bayesian approach within classical SDP with monthly resolution to model uncertainties in inflow and in its forecasts. They manage to use the resulting Bayesian Stochastic Dynamic Programming (BSDP) model in multi-reservoir system by taking aggregate inflow as a state variable, instead of reservoir specific inflows.

4.3.3 Chance-Constrained Programming

Since the inflows v(t) are considered as random variables in ESO, the water contents x(t) are consequently also random. Chance-Constrained Programming (CCP) attempts to find operating policies that ensure the satisfaction of certain constraints with a specified probability. For instance, the limits for reservoir content can be expressed probabilistically as follows:

$$\Pr[x(t) \ge \underline{x}(t)] \ge (1 - \alpha) \tag{4.4}$$

$$\Pr[x(t) \le \overline{x}(t)] \ge (1 - \beta), \ t = 1, ..., T,$$
(4.5)

where $\underline{x}(t), \overline{x}(t)$ are the minimum and maximum water levels, respectively, and $\alpha, \beta \in [0, 1]$ are predetermined risk levels of violating these constraints, which may also vary by season. (Labadie, 2004)

Assuming that the cumulative probability distribution of inflow at each time period is known, the constraints (4.4), (4.5) can be expressed in deterministically equivalent form that is suitable for optimization. Ouarda and Labadie (2001) show how this can be done, by combining the hydrobalance equation and the cumulative probability distributions.

When the desired risk levels α, β get smaller, the required probabilities of satisfying the constraints increase, which leads to more conservative production plans. Loucks and Dorfman (1975) according to Labadie (2004) argued that chance constrained models are overly conservative, and that α, β do not represent the true risk for violating the constraints. Hence, they can only be regarded as parameters having an influence on the desired risk levels. Moreover, Simonovic and Srinivasan (1993) point out that CCP models do not provide a recourse action to correct the realized constraint violations, or explicitly penalize these violations. The risk levels must be also a priori selected, which might be difficult in practice due to economic considerations. One way to cope with this limitation is Reliability Programming (RP), in which the risk levels are included as additional decision variables in the model, thus enabling better quantification of risks and losses. Simonovic and Srinivasan (1993) present this kind of reliability model for multipurpose reservoir for hydropower generation and flood control. Nevertheless, despite the aforementioned drawbacks of CCP, the uncertainty of inflow can be incorporated in a linear program, which may be considered as an advantage. Sreenivasan and Vedula (1996) use chance-constrained linear programming formulation for multipurpose reservoir for hydropower and irrigation in South India.

The selected approach in this thesis for the risk control is somewhat close to CCP, but it does not use any actual probability distributions. Instead, the model calculates simultaneously water contents based on several inflow scenarios and then penalizes possible violations, thus having an influence on reducing the risk. The proportion of scenarios that are penalized are predetermined. The concept is explained in more detail in Chapter 5.3.

4.4 Implicit Stochastic Optimization

Contrary to ESO, Implicit Stochastic Optimization (ISO) does not incorporate the stochastic variables directly to the model formulation. Instead, a deterministic optimization model is used to find optimal discharges, spillages and water contents under several different inflow scenarios which can either be synthetically generated or based on historical inflow time series. Hence, ISO can also be referred to as Monte Carlo optimization (Celeste et al., 2009). While it is clear that the obtained solutions from deterministic optimization are unique to their corresponding inflow scenario, the stochastic aspects can still be implicitly handled by analysing the ensemble of these deterministic solutions (Zambelli et al., 2012). General operating rules can be developed by applying e.g. multiple regression analysis to the deterministic solutions. Figure 4.3 demonstrates the whole process: deterministic model is solved for N different inflow scenarios, which yields solutions specific to each of them. Then, optimal operating rules, i.e., *rule curves*, can be developed by exploiting these solutions.



Figure 4.3: Implicit stochastic optimization (Celeste et al., 2009).

For instance, the optimal operating rules for discharge could be obtained by conditioning it on the water content at the beginning of the current time period x(t), and the previous period inflows and/or forecasted inflow v(t), as follows:

$$q(t) = \alpha_t x(t) + \beta_t v(t) + \gamma_t, \qquad (4.6)$$

where parameters $\alpha_t, \beta_t, \gamma_t$ are obtained from multiple regression analysis performed on the ensemble of deterministic solutions. To clarify, one rule curve is determined for each time period, wherefore the parameters in equation (4.6) are only used for period t. In principle, these regression equations could be used to obtain the discharge q(t) at any time based on the current state of the system. Celeste and Billib (2009) show fine visualizations of the fitted rule curves into the data $(x_n(t), q_n(t), v_n(t), n = 1, ..., N)$.

Celeste et al. (2009) notes that the regression equations need not necessarily be linear. Many predefined forms of policies and inference methods, such as linear and nonlinear polynomials, Artificial Neural Networks (ANN) and fuzzy rules can be used to derive the rule curves. They use multiple nonlinear regression and two-dimensional interpolation to derive monthly operating rules to a water supply system in a semiarid region of Brazil, given initial water level and inflow. These rule curves were then applied to operate under new inflow sequences, and compared to deterministic model results taking the same new inflows as perfect forecasts. Both ISO-based operating rules were capable of allocating water similarly to deterministic optimization. Simoes de Farias et al. (2011) utilizes ANN to derive daily operating rules in the same system.

The advantage of ISO is that since the optimization is performed with deterministic models, more detailed system descriptions can be used (Zambelli et al., 2012). However, Labadie (2004) comments that there is no guarantee that regression analysis would result in good correlations, wherefore the general applicability of the operating rules might not be that good. ISO models can also be large-scale due to several inflow scenarios, so it still might be reasonable to apply only the most efficient deterministic optimization methods, such as LP. Furthermore, Liu et al. (2014) argue that identifying the actual optimal operating rules using ISO is difficult since they depend on the used inflow scenarios. Consequently, there always exists uncertainty in the derived operating rule parameters (e.g. in $\alpha_t, \beta_t, \gamma_t$). For this reason, they perform parameter uncertainty analysis using statistical methods. More detailed descriptions of their analyses are omitted in this thesis, but the core idea is as follows: instead of only deriving the optimal operating rule parameters, it is assumed that they are random variables, thereby providing a set of decisions and their confidence intervals. Liu et al. (2014) conclude that for real operations, parameter uncertainty analysis can provide more information than a single decision by indicating a range of alternative solutions for which the operating decisions remain near-optimal, and the corresponding sensitivity of the objective function to the variations in the decisions.

4.5 Heuristic Methods

Contrary to the well-defined and convergent optimization procedures described in previous sections, heuristic methods can be based on rules-ofthumb, experience or even qualitative information, and they generally do not guarantee the convergence even to local optimal solutions. However, they can be useful for finding quickly good enough approximate solutions, in situations where the traditional optimization algorithms are too slow, or when they fail to converge. (Labadie, 2004)

Such heuristic methods include e.g. Genetic Algorithms (GA), artificial neural networks, fuzzy rule-based modelling, and Particle Swarm Optimization (PSO). More detailed descriptions of heuristic methods are not addressed in this thesis. For fuzzy rule-based application, we refer to Russel and Campbell (1996). Reis et al. (2005) propose an alternative stochastic approach for multi-reservoir planning by using a hybrid of GA and LP (GA-LP), and Celeste and Billib (2009) evaluates different PSO-based models. In addition, Ahmad et al. (2014) reviews other techniques such as evolutionary computation, combination of simulation-optimization, Artificial Bee Colony (ABC) and Gravitational Search Algorithm (GSA). Nazari-Heris et al. (2017) present a comprehensive review of heuristic algorithms applied in short-term scheduling of hydropower.

Heuristic methods can also be of use by the side of traditional optimization algorithms. Labadie (2004) concludes that applying heuristic techniques to ESO may solve some computational challenges. Moreover, fuzzy rulebased systems and neural networks may help to overcome the difficulties in inferring applicable operating rules from ISO. However, Li et al. (2010) reviews ISO methods using GAs, neural networks, decision trees and PSO, and concludes that these methods have their drawbacks as well.

To conclude this whole chapter, we presented an overall view of the hydropower planning hierarchy from longer term models to short-term models, introduced the common optimization methods for solving hydropower scheduling problems, and especially approaches for accounting the uncertainties. However, as the literature on reservoir operation is rich, there are also many things and details not covered here. For a general review paper, see Singh and Singal (2017).

Chapter 5

Decision Support System

Despite the vast array of developed hydropower optimization models, Simonovic (1992) and Labadie (2004) argue that a gap still exists between research studies and practical applications. Possible reasons for this might include:

- Planners are not directly involved in the model development, and they might be skeptical to let models replace their own judgement
- Complex optimization models might be difficult to understand
- Most optimization models do not consider risk and uncertainty
- The wide range of optimization methods causes confusion in selecting the appropriate choice for a particular application
- Published research often considers overly simplified reservoir systems

It is difficult to assess whether or not this gap still exists today, or how large it may be. Nevertheless, it stands to reason that the applied optimization method should take into account the relevant aspects of the reservoir system in terms of the model purpose, with a sufficient accuracy to be actually useful in practice. Due to the possible deficiencies in the applied optimization models, they are often embedded in Decision Support Systems (DSS), which are information systems that help businesses to make decisions in a setting that is not fully automated.

This chapter presents a *Model-driven* DSS for mid-term hydropower planning in a certain river system. By definition, one or more quantitative models provide the primary functionality in a model-driven DSS, such that the user can for example manipulate model parameters or conduct some ad hoc "what if"- analysis (Power and Sharda, 2007). Our DSS is basically a web-based diagnostics tool, consisting of input data processing, optimization model, variety of visualizations, and some user defined choices. Hence, the focus is on providing decision support for the planner, or the Decision Maker (DM), who is ultimately in charge for deciding the final production plan. This DSS is to be used on a weekly basis in order to follow the hydrological situation in the river system and to update the production plans accordingly. Section 5.1 characterizes the case river system, and Section 5.2 describes the optimization model in detail. Section 5.3 presents the overall mid-term planning process in the DSS and how the inflow risk is accounted. However, the actual user interface is not presented. The results and visualizations are presented in Chapter 6.

5.1 The River System

Figure 5.1 shows the river system considered in this thesis, consisting of two reservoirs $I = \{R1, R2\}$ and four power plants $J = \{P1, P2, P3, P4\}$. At this point, we also define indicator matrices G and C that are later on needed in the hydrobalance equations. The $I \times J$ matrix G defines the topology of the river system, such that the element $G_{i,j} = -1$ if reservoir i is directly above plant j, $G_{i,j} = 1$ if reservoir i is directly below plant j, and zero otherwise. The $J \times J$ matrix C is only needed for RoR-plants j, such that $C_{j,j} = -1$, $C_{j,(j-1)} = 1$, and zero otherwise. These non-zero elements of C are thus defined only for such pairs of power plants that have no reservoir between them. Essentially C indicates that if plant j has no reservoir upstream, it discharges the same amount of water that the previous plant j - 1 has discharged (provided that there are no local inflows between j - 1 and j). The topology matrices G and C in our case are

$$\mathbf{G} = \begin{pmatrix} -1 & 0 & 0 & 0\\ 0 & 1 & -1 & -1 \end{pmatrix}, \ \mathbf{C} = \begin{pmatrix} 0 & 0 & 0 & 0\\ 1 & -1 & 0 & 0\\ 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 \end{pmatrix}.$$
 (5.1)

5.2 Optimization Model

This section presents the implemented mid-term optimization model used in the DSS, with a time horizon of one year. Abgottspon (2015) argues that the modelling of uncertainties is more important than having more



Figure 5.1: Schematic description of the river system.

accurate system representation, wherefore mid-term models should be formulated stochastically if possible. However, in practice this might not be the case. Stochastic models need realistic probability distributions of the uncertain variables to be useful in real life, and the results may be more difficult to structure and utilize in practice (Fjelldal and Nafstad, 2014). Moreover, our case requires relatively detailed system description in terms of the decision variables and the time resolution, such that the model can provide guidance to the short-term operation with a sufficient accuracy. For the aforementioned reasons, the chosen approach is to use deterministic Linear Programming. The inflow uncertainty is then accounted in the DSS by utilizing several scenarios and visualizations in an interactive way, instead of attempting to formulate a stochastic model that would produce general operating rules.

The model description in this section considers only one inflow scenario and its corresponding water contents, and the next section describes the inflow risk management. The model is built based on the currently used model by the case company, similar to those presented in Mäkiharju (2012) and Kinnunen (2013). Nonetheless, it contains some updates and improvements, which is why it is implemented from scratch using Python-programming language. Solving the model is done with a commercially available Gurobi-solver (Gurobi Optimization, Inc., 2017).

5.2.1 Notation and Units

The actual decision variables consists of the discharges and spillages, whereas the water contents are sort of state variables which depend on the decision variables and the inflows. These are modelled using day units (DU), which is the amount of water when discharge equals $1m^3/s$ for 24 hours, i.e., $1DU = 1m^3/s \cdot 24h \cdot 3600s/h = 86400m^3$.

Contrary to common mid-term models with a time resolution of one week or one month, our model has a time resolution of one day. Since the reservoirs are relatively small, the situation might change quite rapidly, which is why e.g. monthly time resolution would not be nearly accurate enough. The notation for time step is denoted by $t \in \mathcal{T} = \{1, ..., T\}$. Furthermore, the discharges, and consequently the produced energies too, are divided into daytime and night-time variables. As most production is always allocated to daytime, this yields more accurate insight on whether the night-time production is needed. This also enables the inclusion of frequency containment reserves in a relatively realistic way. General guideline to facilitate reading is that day/night differentiation is denoted as d or n in a superscript. The reservoirs and plants indices i and j are placed in a subscript, and the time dependency is denoted with parentheses. Other variables and parameters are explained as we describe the model.

5.2.2 Objective Function

The objective is to maximize total revenue TR throughout the time horizon, minus the total penalties PEN_{TOT} :

$$\max TR - PEN_{TOT}.$$
 (5.2)

The total revenues are calculated by summing the sales to the spot market (Elspot), and sales to the FCR-markets:

$$TR = \sum_{t \in \mathcal{T}} (R(t) + R_f(t) + R_h(t)), \qquad (5.3)$$

where R(t) represents the total revenue from spot market at day t, and $R_f(t), R_h(t)$ are the revenues from FCR-N and FCR-D markets at day t, respectively. The total penalty term PEN_{TOT} mainly consists of reservoir limit violations.

5.2.3 Plant Constraints

The general limit constraints for the discharge variables are presented as

$$\underline{q}_{j}(t) \le q_{j}^{d}(t) \le \overline{q}_{j}(t), \ j \in J, t \in \mathcal{T}$$

$$(5.4)$$

$$\underline{q}_{i}(t) \leq q_{j}^{n}(t) \leq \overline{q}_{j}(t), \ j \in J, t \in \mathcal{T},$$

$$(5.5)$$

where $\underline{q}_j(t), \overline{q}_j(t)$ are the minimum and maximum discharges of plant j at day t, respectively. These limits are usually constant, but the plant maintenances may cause some changes from time to time, hence the time dependency. The decision variables $q_j^d(t)$ and $q_j^n(t)$ denote the daytime and night-time discharges such that the average discharge during day t is a weighted sum of these two:

$$q_j(t) = \frac{h_d}{h} q_j^d(t) + \frac{h_n}{h} q_j^{\mathrm{n}}(t), \ j \in J, t \in \mathcal{T},$$
(5.6)

where $h_d = 15$ is the amount of day hours, $h_n = 9$ is the amount of night hours, and h = 24 is the amount of hours on the whole day.

The energy generation function is assumed to be piecewise-linear with respect to discharge. The generated day and night time energies for plant j are denoted as $E_j^d(t)$ and $E_j^n(t)$, and can be modelled with several inequality constraints as follows:

$$E_j^d(t) \le \alpha_{jk} q_j^d(t) + \beta_{jk}, \ j \in J, k \in K_j, t \in \mathcal{T}$$

$$(5.7)$$

$$E_j^n(t) \le \alpha_{jk} q_j^n(t) + \beta_{jk}, \ j \in J, k \in K_j, t \in \mathcal{T},$$
(5.8)

where K_j is the set of energy equation multiplier indices for plant j. Figure 5.2 shows an example of what the energy generation function might look like. Each dashed line corresponds to one set of multipliers α_{jk} , β_{jk} , where $k \in K_j = \{1, 2, 3, 4\}$ in this particular case. Since the generated energy is restricted to be smaller than equal as each of these linear functions, the shaded region represents the feasible region for $E_j^d(t)$ and $E_j^n(t)$. As the objective is to maximize revenue, these energy variables always end up taking the maximal value for a given discharge, i.e., they are on the black line. The multipliers α_{jk} , β_{jk} are such that they convert daily discharge (DU) into daily energy (MWh), rather than momentary discharge (m^3/s) into power (MW). Since the day and night energies are calculated separately, the total daily energy is calculated as

$$E_j(t) = \frac{h_d}{h} E_j^d(t) + \frac{h_n}{h} E_j^n(t), \ j \in J, t \in \mathcal{T}.$$
(5.9)



Figure 5.2: Example of a piecewise linear energy generation function.

In addition to the energies that are sold to the spot market, the plants can offer adjustable production capacity to frequency reserves subject to the activation conditions explained in Section 2.3.3. As a new contribution compared to the currently used mid-term models, we implement the possibility to sell capacity to the yearly market with fixed prices. Since the offered capacities must be at an hourly level, this model obviously cannot calculate these capacities in an entirely realistic and accurate way. The division into day and night time variables still enables somewhat reasonable approximation. We denote $E_{f,j}^d(t), E_{f,j}^n(t)$ as the variables for offered power capacity (multiplied by 24 hours to get coherent units) to FCR-N from plant j at day t in correspondence to the day and night time energy variables, respectively. Similarly, $E_{h,j}^d(t), E_{h,j}^n(t)$ denote the variables for offered capacities to FCR-D. These variables are subject to the activation conditions:

$$E_{f,j}^d(t) \le E_{f,j}, \ E_{h,j}^d(t) \le E_{h,j}, \ j \in J, \ t \in \mathcal{T}$$

$$E_{f,j}^n(t) \le \overline{E}_{f,j}, \ E_{h,j}^n(t) \le \overline{E}_{h,j}, \ j \in J, \ t \in \mathcal{T},$$
(5.10)

where $\overline{E}_{f,j}$, $\overline{E}_{h,j}$ are the maximum capacities that plant j can offer to FCR-N and FCR-D, respectively. Furthermore, capacities can be offered only if the plant is not producing at its full power:

$$E_j^d(t) + E_{f,j}^d(t) + E_{h,j}^d(t) \le \overline{E}_j, \ j \in J, \ t \in \mathcal{T}$$

$$E_j^n(t) + E_{f,j}^n(t) + E_{h,j}^n(t) \le \overline{E}_j, \ j \in J, \ t \in \mathcal{T},$$

(5.11)

where \overline{E}_{j} is the maximum energy of plant j which corresponds to full power.

Additionally, we define the following equations

which ensure that the frequency reserves do no yield revenue if the plant is out of use, i.e., if $E_j^d(t)$ or $E_j^n(t)$ are zero. This is because automatic activation cannot happen if the plant is not in use. The equations (5.10)-(5.12) are based on the principle in Figure 2.4.

There is one more thing to consider, that is, discharges below some certain level might be infeasible. In the testing phase, we found out that the equations (5.12) tend to lead to production plans where the discharge is sometimes too small, e.g., $E_j^d(t)$ would be smaller than the amount of energy that corresponds to the minimum feasible discharge, which we denote as \underline{E}_j for plant j. This is because the maximum capacities $\overline{E}_{f,j}, \overline{E}_{h,j}$ are generally smaller than \underline{E}_j , which could lead to production plans where the discharge is at such level that we get the full compensations $\overline{E}_{f,j}, \overline{E}_{h,j}$ from the reserves, but $E_j^d(t) < \underline{E}_j$. Such situations would not be feasible in real life. To be exact, this should be handled with binary variables which ensure that the discharges do not take values on the forbidden area. However, we prefer to avoid MILP-formulation in order to maintain quick computation time, which is why we use the following approximation:

$$E_{f,j}^{d}(t) \leq \frac{E_{j}^{d}(t) \cdot \overline{E}_{f,j}}{\underline{E}_{j}}, E_{f,j}^{n}(t) \leq \frac{E_{j}^{n}(t) \cdot \overline{E}_{f,j}}{\underline{E}_{j}}, \ j \in J, \ t \in \mathcal{T}$$

$$E_{h,j}^{d}(t) \leq \frac{E_{j}^{d}(t) \cdot \overline{E}_{h,j}}{\underline{E}_{j}}, E_{h,j}^{n}(t) \leq \frac{E_{j}^{n}(t) \cdot \overline{E}_{h,j}}{\underline{E}_{j}}, \ j \in J, \ t \in \mathcal{T}.$$
(5.13)

Equations (5.13) do not strictly forbid the produced energies $E_j^d(t)$, $E_j^n(t)$ for being smaller than \underline{E}_j , but they limit the amount of compensation that we get from the reserves when $E_j^d(t)$, $E_j^n(t)$ are smaller than \underline{E}_j . This causes the optimization to not want to produce at such levels, thus avoiding too small discharges for the most part. When $E_j^d(t)$, $E_j^n(t)$ exceed \underline{E}_j , equations (5.13) are not bounding anymore, since the constraints (5.10) must always hold. We also formulated the model with binary variables, and compared the production plans to those obtained with this pure LP model. The results were very similar, indicating that the approximation (5.13) works well in our particular case, and that our LP-relaxation is sufficient and more useful in practical usage due to faster computation times.

Now we are finally ready to write out the revenue components in equation

(5.3):

$$R(t) = \sum_{j \in J} P_{spot}(t) \cdot \left(\frac{h_d}{h} c_d E_j^d(t) + \frac{h_n}{h} c_n E_j^n(t)\right), \ t \in \mathcal{T}$$
(5.14)

$$R_f(t) = \sum_{j \in J} p_f \cdot \left(\frac{h_d}{h} E^d_{f,j}(t) + \frac{h_n}{h} E^n_{f,j}(t)\right), \ t \in \mathcal{T}$$
(5.15)

$$R_h(t) = \sum_{j \in J} p_h \cdot \left(\frac{h_d}{h} E^d_{h,j}(t) + \frac{h_n}{h} E^n_{h,j}(t)\right), \ t \in \mathcal{T},$$
(5.16)

where $P_{spot}(t)$ is the forecast for average spot price for day t. The differentiation in day/night-time prices is currently made with constant coefficients $c_d > 1$ and $c_n < 1$. The fixed yearly prices for FCR-N and FCR-D are denoted by p_f and p_h , respectively.

5.2.4 Reservoir Constraints

Constraints for reservoirs generally consists of the content limits and the hydrobalance equation. The water content at beginning of the scheduling horizon must be set for all reservoirs in the system as

$$x_i(1) = x_{i,1}, i \in I, \tag{5.17}$$

where $x_{i,1}$ are inputs to the model. There are two types of upper and lower limits for the reservoirs; the "hard" limits which should always be maintained, and the planning limits, which are not as important, but are still desirable to maintain in case of unexpected precipitation or due to other practical reasons. The model should still be usable in situations where violations have occurred, wherefore both of these limits are implemented as soft constraints as follows:

$$\underline{x}_{i}(t) - x_{i}^{\text{down}}(t) \le x_{i}(t) \le x_{i}^{\text{up}}(t) + \overline{x}_{i}(t), \ i \in I, t \in \mathcal{T}$$

$$(5.18)$$

$$\underline{x}_{i}^{\text{plan}}(t) - x_{i}^{\text{plan down}}(t) \le x_{i}(t) \le x_{i}^{\text{plan up}}(t) + \overline{x}_{i}^{\text{plan}}(t), \ i \in I, t \in \mathcal{T}, \quad (5.19)$$

where $\overline{x}_i(t), \underline{x}_i(t)$ are the upper and lower "hard limits", and $\overline{x}_i^{\text{plan}}(t), \underline{x}_i^{\text{plan}}(t)$ are the upper and lower planning limits for reservoir *i*. These are all time dependent, since the water contents must be decreased during the winter time in order to survive the spring flood. Variables $x_i^{\text{down}}(t), x_i^{\text{up}}(t), x_i^{\text{plan up}}(t), x_i^{\text{plan up}}(t), x_i^{\text{plan down}}(t)$ represent the possible violations regarding their respective limit. These variables are penalized, which is why they are all equal to zero if the water content is inside the allowed range. The hydrobalance equation for the reservoirs describes how the water content evolves between time steps, i.e., how it depends on the discharges $q_j(t)$, spillages $w_j(t)$ and inflows $v_i(t)$:

$$x_i(t+1) = x_i(t) + v_i(t) + \sum_{j \in J} G_{i,j} \cdot (q_j(t) + w_j(t)), \ i \in I, t \in \mathcal{T} \setminus \{T\}.$$
(5.20)

For such power plants that have no reservoir upstream, i.e., RoR-plants located directly below another power plant, the hydrobalance equation can be presented as

$$\sum_{j' \in J} C_{j,j'} \cdot (q_{j'}(t) + w_{j'}(t)) + v_j(t) = 0, \ j \in J, \ t \in \mathcal{T},$$
(5.21)

where $v_j(t)$ is a possible local inflow to plant j (which are not needed in the case study of this thesis). The topology matrices G and C are used to make the model more general, i.e., there is no need to define the hydrobalances separately for each reservoir and plant when these matrices are given as inputs.

The final constraint is the reservoir target level at end of the scheduling period T, which is also defined as a soft constraint:

$$x_{i,T} - x_i^{\text{targ down}}(T) \le x_i(T) \le x_i^{\text{targ up}}(T) + x_{i,T},$$
(5.22)

where $x_i^{\text{targ down}}(T)$, $x_i^{\text{targ up}}(T)$ are penalized deviations from the end reservoir level $x_{i,T}$, which is an input parameter to the model. As the time horizon is one year, usually $x_{i,T}$ is set equal to the starting reservoir level $x_{i,1}$. Additionally, the model includes possibilities to set reservoir target levels for arbitrary time instances and penalty terms for not meeting them, as well as penalizing too large day-to-day deviations in the water contents, but these constraints are not commonly used. Setting some target levels for other time instances than the end period might be sometimes necessary due to practical reasons. However, this might draw the attention away from the actual objective, i.e., the revenue maximization, wherefore it is reasonable to avoid them if possible.

Now, we can finally write out the total penalty term in the objective function (5.2) as follows:

$$PEN_{TOT} = \sum_{t \in \mathcal{T}} \sum_{i \in I} PEN \cdot (x_i^{down}(t) + x_i^{up}(t))$$

+
$$\sum_{t \in \mathcal{T}} \sum_{i \in I} PEN_{plan} \cdot (x_i^{plan down}(t) + x_i^{plan up}(t))$$

+
$$\sum_{i \in I} PEN_{end} \cdot (x_i^{targ up}(T) + x_i^{targ down}(T)),$$
(5.23)

where PEN, PEN_{plan} , PEN_{end} are constants, such that PEN is the biggest because violating the "hard" limits is the least desirable thing to happen.

5.2.5 Head Effect

The energy equations (5.7), (5.8) do not take the head effect into account, as the generated energy is assumed to be independent on the water level. In terms of mid-term model purpose, this is usually a sufficient approximation. Nevertheless, we describe a way to model the dependency on the water content in an entirely linear way. This was presented already in Kinnunen (2013), and we call this approach a λ -technique.

For power plants with a reservoir directly upstream, such as the pair R1, P1 which we use here as an example, we can tie together the water contents, daytime energies and discharges as follows:

$$x_{1}(t) = \sum_{m=1}^{M} \lambda_{1m}^{d}(t) \cdot x_{1m}, \ t \in \mathcal{T}$$
(5.24)

$$q_1^d(t) = \sum_{m=1}^M \lambda_{1m}^d(t) \cdot q_{1m}, \ t \in \mathcal{T}$$
 (5.25)

$$E_1^d(t) = \sum_{m=1}^M \lambda_{1m}^d(t) \cdot E_{1m}, \ t \in \mathcal{T}$$
 (5.26)

$$\sum_{m=1}^{M} \lambda_{1m}^d(t) = 1, \ \lambda_{1m}^d \ge 0 \ \forall m, \ t \in \mathcal{T}$$

$$(5.27)$$

where x_{1m} , q_{1m} , E_{1m} are predefined data points of water level-discharge-energy combinations for R1, P1, and $\lambda_{1m}^d(t)$ are the weight variables with respect to daytime variables. Similar equations can then be formulated for night variables too, meaning that both day and night time variables would be tied to the current water content $x_1(t)$. Alternatively, one can choose to only tie the daytime energies together with the water content.

Figure 5.3 illustrates the idea more clearly. Each of the blue dots represents one combination of (x_{1m}, q_{1m}, E_{1m}) -triplet, such that the lower energies at each discharge correspond to minimum water content $\underline{x}_1(t)$, and the higher energies correspond to maximum water content $\overline{x}_1(t)$, since higher water level (=higher head) leads to increased amount of generated energy. As the weights $\lambda_{1m}^d(t)$ are taken as decision variables, the optimization can then select the values for discharge and energy variables as a convex combination of these predefined M points, based on what the current water level is. The optimization always ends up selecting the best possible combination.



Figure 5.3: Predetermined points and their enclosed area for plant 1.

The weights $\lambda_{1m}^d(t)$ increase the number of variables in the model quite much, as there are M variables per each day, for each reservoir-plant pair to which this λ -technique is used. However, in our particular case, only the pair R1, P1 is feasible for this technique due to practical reasons and the available data. As such, the water content is of course not the same thing as the head, but if the tail water after P1 is assumed be somewhat constant, it is accurate enough to use directly the water level of R1 in equation (5.24). It is also worth noting that using this technique restricts the water content to be strictly inside $[\underline{x}_1(t), \overline{x}_1(t)]$, so the model gets infeasible in such situations where the limit violations are inevitable.

5.3 Planning Process and Inflow Scenarios

The described mid-term optimization model is used for a couple of different purposes. One is to estimate yearly production volumes for the case company. In the DSS, user can select the inflow scenario that is used in the optimization, and thus conduct "what if"-analysis regarding how the production plans would differ in different inflow scenarios. Rough intervals for the estimated yearly production volumes can therefore be somewhat easily obtained by running the deterministic optimization model with wet and dry inflow scenarios.

The most important purpose of the mid-term model is to provide a mandate for the short-term planning, which specifies end-of-week reservoir target levels and estimates of the usable weekly energies and daily discharges. When it comes to managing the inflow risk, i.e., the risk of violating the water content limits, the emphasis is generally only on the next four weeks. The reservoirs are quite small, wherefore it is not that relevant to consider the inflow risk for e.g. 6 months ahead in our case.

The idea in the DSS is to first choose one base scenario, on the basis of which the optimization is carried out through the whole year. Therefore, the inflows $v_i(t)$ and water contents $x_i(t)$, and the corresponding constraints presented in the previous section are all related to the chosen base scenario, which is usually a median scenario. The inflow risk is then accounted by simultaneously calculating water contents with respect to several other inflow scenarios, and then penalizing their possible violations in a shorter time horizon, if needed. We denote scenario by s, its probability by Pr(s), and the set of all scenarios by S. The number of time periods during which the scenario contents are calculated and penalized is denoted by T_S , which is usually 28 days, but can be altered by the user.

We indicate the inflows and variables corresponding to different scenarios by using s in the superscript. The optimization model then gets the following additional scenario specific equations:

$$x_{i}^{s}(1) = x_{i,1}, i \in I, s \in S$$

$$\underline{x}_{i}^{s,\text{down}}(t) \leq x_{i}^{s}(t) \leq x_{i}^{s,\text{up}}(t) + \overline{x}_{i}(t), i \in I, s \in S, t \in \{1, ..., T_{S}\}$$
(5.29)

$$x_{i}^{s}(t+1) = x_{i}^{s}(t) + v_{i}^{s}(t) + \sum_{j \in J} \left(G_{i,j} \cdot \left(q_{j}(t) + w_{j}(t) \right) \right), \ i \in I, s \in S, t \in \{1, ..., T_{S} - 1\}.$$
(5.30)

The total penalty (5.23) thus gets an additional penalty term from the scenario specific violations, and is rewritten as

$$PEN_{TOT} = \sum_{t \in \mathcal{T}} \sum_{i \in I} PEN \cdot (x_i^{down}(t) + x_i^{up}(t)) + \sum_{t \in \mathcal{T}} \sum_{i \in I} PEN_{plan} \cdot (x_i^{plan down}(t) + x_i^{plan up}(t)) + \sum_{i \in I} PEN_{end} \cdot (x_i^{targ up}(T) + x_i^{targ down}(T)) + \sum_{s \in S} \sum_{t=1}^{T_S} \sum_{i \in I} Pr(s) \cdot P_{spot}(t) \cdot \gamma_i \cdot (x_i^{s,down}(t) + x_i^{s,up}(t)), \quad (5.31)$$

where γ_i is a reservoir specific constant that approximately maps one DU into MWh. These violations are further multiplied with spot forecast $P_{spot}(t)$

in order to transform them into monetary value, such that the trade-off between profits and scenario specific violations are in the same units. This transformation is not, however, very accurate, since these violations and their corresponding "lost" amount of money would not accumulate again for each day, and in practice the reservoir operator would react to these violations. Nevertheless, adding this kind of penalty term from scenario specific violations enables to optimize such production plans that attempt to take the inflow risk into account in the first T_S days.

The proportion of scenarios that are included in the penalty term (5.31)is determined by the user via the probabilities Pr(s). For this purpose, we define a scenario coverage measure $c \in [0, 1]$. The user first chooses T_S , after which the inflow scenarios are sorted based on their cumulative sum during the first T_S days. If c = 1, all scenarios are accounted. In that case we set $\Pr(s) = \frac{1}{N} \ \forall s \in S$, where N is the number of scenarios, since we have no reason to believe that some scenarios would be more likely than others. If c =0.95, the probabilities of the wettest 2.5% and driest 2.5% of the scenarios are set to zero, and the probabilities of the other scenarios remain at $\Pr\{s\} = \frac{1}{N}$. In practice, case c = 0.95 means that the optimization is performed assuming that the short-run "extreme" scenarios will not occur. Same principle applies for smaller c, meaning that c = 0 corresponds to a situation where the optimization is performed as a fully deterministic problem with respect to the base scenario only, i.e., the probabilities of all other scenarios are set to zero. The user can thus obtain alternative production plans and visualizations by performing the optimization with several different T_S and c, and see for herself whether or not the situation looks too risky in the short run.

In summary, optimization performed with larger c attempts to maintain a larger proportion of scenario specific water contents inside the limits during the first T_S days. However, if c = 1 for instance, it is worth noting that it is not by any means guaranteed that violations would not occur in any scenario; it merely means that all scenarios are accounted in the penalty term (5.31). As it includes the probability Pr(s), the effect of one scenario is relatively small. Therefore the optimization model might very well see that a few violations here and there does not hurt much, but violations in several accounted scenarios would already result in quite a significant penalty.

The entire planning process in the DSS is presented in the steps 1-6 below, and Figure 5.4 illustrates a visual representation of it.

- 1. Input data, e.g., spot forecast, inflow scenarios and initial water contents are fetched, and some preprocessing is made.
- 2. Decision maker chooses the base scenario, short term horizon T_S and the scenario coverages c. Scenarios are sorted based on their cumulative

sum during the first T_S days.

- 3. The optimization is performed for all chosen c.
- 4. The results of the optimization, e.g., the water contents, energies and discharges, are visualized.
- 5. If DM is not satisfied with any of the results, she can go back to step 2, or manually define target water levels, and perform the optimization again.
- 6. DM chooses the final production plan.



Figure 5.4: Illustration of the planning process.

Chapter 6

Results and Discussion

This chapter presents the results of the optimization model that is applied to the case river system. Section 6.1 shows examples of yearly production profiles with a couple of different inflow scenarios. Section 6.2 illustrates how the inclusion of FCR-markets affects the production plans, and Section 6.3 discusses energy generation and its accuracy in the model. Finally, Section 6.4 demonstrates how the inflow risk is accounted on the upcoming month, and the corresponding visualizations for the DSS. All of these aspects are important information to the decision maker in terms of increased awareness of uncertainties and for the planning process as a whole. The inflow scenarios are provided by Finnish Environment Institute (SYKE, 2018). The upcoming days of the scenarios are based on weather forecasts (so they start from the same value), after which they follow statistical weather data from years 1961 to 2012. Additionally, the optimization and final production plan is often decided using a separate inflow forecast that is not based on any particular year, but usually corresponds to median. This forecast is often chosen as the so-called base scenario. For the most part, we use realized Finnish area spot price data from 2017, because the case company's own spot forecast that is actually used in the production planning is confidential. Moreover, the values for generated energies or powers are not shown for the same reason. In order to follow the visualizations in this chapter, recall the topology of the river system presented in Figure 5.1.

6.1 Yearly Production Profile

We start by running the deterministic optimization model with two very different inflow scenarios based on years 1990 and 2004, and comparing their results in terms of production allocation and reservoir contents. The starting date of optimization is chosen to be January 1st, and the ending date as one year later. In this example, λ -technique is not used, only the piecewise-linear equations between discharges and generated energies. Figure 6.1 shows the optimized reservoir contents and the inflow scenarios for reservoir 1, as well as aggregated daily energies from plants 1 and 2 along with the daily average spot price. Figure 6.2 is similar, but for reservoir 2 and plants 3 and 4.





(b) Produced energy $E_1 + E_2$ from plants 1 and 2

Figure 6.1: Results for reservoir 1 and plants 1 and 2, based on inflow scenarios 1990 and 2004.







Figure 6.2: Results for reservoir 2 and plants 3 and 4, based on inflow scenarios 1990 and 2004.

The optimization manages to keep the reservoir contents inside the planning limits in both scenarios. By looking at these figures, it is clear that differences in inflow scenarios result in very different reservoir trajectories and production allocations. Scenario 2004 is much wetter than 1990 in total, and their temporal aspects also differ significantly. In 2004, the winter is dry, spring flood is late but voluminous, and the rest of the year is wet. In comparison, 1990 has a wetter winter, earlier spring flood, and the rest of the year is dry. The production profiles in Figures 6.1(b), 6.2(b) follow these differences quite intuitively. The production of 1990 is larger until May because the water contents need to be decreased earlier. From May onwards, the production of 2004 is much larger since the inflow is larger too. In reservoir 1, the spring floods of the scenarios are so voluminous that the production is set to maximum in order to maintain the limits. Even spillage was required, although not shown in the figures.

These deterministic examples indicate that the model works as it should. The production volumes follow the price profile as well as possible in order to maximize revenue, such that the environmental constraints are still maintained subject to the inflow volumes. Nevertheless, it is clear that since the inflow scenarios might be significantly different in terms of their cumulative volumes and temporal distribution, it is not possible to obtain only one yearly production plan that would be satisfying in all scenarios. The production plans in this example look quite messy because we used realized spot price data. In practice, the mid-term spot forecast is much flatter than realized data, in which case the intra-week production plans will also be more regular.

In the DSS, solving the optimization model separately with different inflow scenarios allows the decision maker to analyze how much the production plans would ideally change in different scenarios or whether the water levels should be increased or decreased. However, one must understand that in practice the yearly reservoir operation is always more conservative compared to what any fully deterministic optimization suggests.

6.2 FCR-Markets

This section illustrates how the inclusion of FCR-markets affects the production plans as opposed to the situation when they are not included. We perform deterministic optimization for both cases over one scenario, such that λ -technique is not used, and the starting date is again at the beginning of the year. In this example, we do not focus on the reservoir contents, only the production plans. Moreover, we specifically focus on the generated powers with respect to the day and night discharges, which are obtained from the energy equations by simply dividing them with 24 hours (MWh/h = MW).

For the sake of brevity and clarity, we only visualize the results for the first 28 days, but acknowledge that similar effects can be seen on the remainder of the time horizon as well. Figure 6.3 shows the optimized power production plans of plant 4 for both cases. Generally, we see that most production is naturally allocated to daytime, whereas the night-time production is usually much smaller or even zero. Additionally, the weekend production is decreased or entirely halted, e.g., on days 6 and 7 or 20 and 21.



(a) Daytime power production of plant 4



(b) Night-time power production of plant 4



By comparing these plans with and without FCR markets, we see that there are seemingly small, yet important, differences. Recalling the conditions of calculating the available reserve capacities from Section 2.3.3, we remind that adjustable capacity can be sold to FCR markets only if the power production is not too close to its minimum or maximum value. If the FCR-markets are not included, we see that the daytime power production is always at its maximum during the weekdays. On the contrary, when FCR is included, the production is rarely at full power. In addition, the weekend and night-time productions are not halted nearly as often. Similar observations can be seen for plants 1 and 2, but not equally clearly as for plant 4. Plant 3 does not have the ability to participate in the FCR-markets in the first place. Figure 6.4 shows the total power production from the river system for both cases. There are a couple of relevant observations in general. When the optimization is performed without FCR-markets, the production profile follows the spot price a bit more aggressively, especially during high price peaks. This is because in that case the spot market is the only source of revenue. In comparison, when the FCR-markets are included in the optimization, the overall production profile is little bit flatter as the extra revenue from FCRmarkets is based on the available power capacity. Since these production plans are different in the first place, there is clearly a minor additional value in leaving some amount of capacity to be sold to the FCR-markets.



Figure 6.4: Comparison of total power production from the river system with and without FCR markets.

The FCR-N variables behave such that they take the biggest possible value with respect to the activation constraints that depend on the current power production level. The maximum FCR-N capacities of the plants are somewhat small compared to power production levels, which is why their maximum value can be almost always achieved unless the plant is halted or producing at full power. On the other hand, the remaining FCR-D capacity should be calculated only after FCR-N has taken its maximum value. Optimization ensures this simply because FCR-N yields a higher price. Nonetheless, FCR-D variables are still often able take their maximum value as well, but sometimes there might not be enough "room" for that because FCR-N comes first. The revenues from these markets are then calculated accordingly, with fixed yearly prices. Figure 6.5 shows the cumulative revenues from the whole river system for both cases. We see that the revenues from spot market are approximately equal, but the revenue from FCR-markets increases the total revenue. From the first 28 days, the revenue from spot market is $\approx 0.2\%$ worse when FCR-markets are included, but the total revenue is $\approx 4.0\%$ higher. The total yearly revenue also increases $\approx 2.8\%$ in this deterministic case. These results suggest that it indeed would be beneficial to make such production plans that would enable more frequent participation in the FCR-markets, i.e., not producing at full power during the daytime, and also allocating some production to night-time and weekends more frequently.



Figure 6.5: Cumulative revenues for the first 28 days.

In practice, the offered FCR capacities must be provided at an hourly level, which is why these results are not directly applicable as such. Despite of that, one must understand that the purpose of mid-term models is usually not to be entirely accurate in terms of real life, but instead to provide more general guidelines to the short-term operation and the decision maker. As our model has separate daytime and night-time variables, the results are good enough approximations, whereas the short-term model then essentially produces more accurate hourly plans. In fact, Kinnunen (2013) found qualitatively similar results in his short-term model.

6.3 Energy Generation

In mid-term models, it is often sufficient to ignore the head dependency and assume linear or piecewise-linear relationship between discharge and energy. In practice, this might also lead to significant errors between the realized energy and that given by the optimization. This section evaluates the accuracy of the energies obtained with the piecewise-linear equations (5.7),(5.8) and with the λ -technique (5.24)-(5.27). This evaluation can be done by comparing the optimized energies to simulated energies, which are calculated with a nonlinear formula that takes the optimized water level and discharge as inputs. Due to its nonlinearity, the accuracy of simulated energy is assumed to be better than those obtained from the optimization, allowing us to approximately calculate how much energy would have really been generated compared to the optimized energies.

We only focus on reservoir 1 and plant 1, since that is the only pair where the λ -technique can be applied to. We also choose to perform the evaluation with respect to daytime energies E_1^d only. Most production is generated during the daytime, which allows more interpretable visualizations on weekto-week basis. The optimization is performed over one scenario, such that the starting date is again at the beginning of the year. Our particular interest lies on the relationship between the water level and the generated energy. For this reason, we visualize the results from January to July, because that time scope captures the low water levels before the spring flood, as well as high water levels at the beginning of the year and after the spring flood.

Figure 6.6 shows the water level and the daytime energies obtained with piecewise-linear equations and simulation. We clearly see significant errors in the energy given by the piecewise-linear equations. The production profile is somewhat flat and obviously independent of the water level. Only around March-April the optimized energy coincides quite well to the simulated energy, which indicates that the parameters of the piecewise-linear equations are calibrated with respect to relatively low water level. The simulated energy, on the other hand, follows intuitively the water level such that higher water level clearly yields higher energy output due to the increased head.

Figure 6.7 shows similar comparison between the energies obtained with λ -technique and the corresponding simulated energies. It is evident that the λ -technique gives much more realistic results, as the optimized energy is very close to the simulated energy with only minor errors. Table 6.1 shows commonly used metrics, i.e., Mean Absolute Error (MEA), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and coefficient of determination (R^2) to compare the errors between the energies given by



Figure 6.6: Water level of reservoir 1 and daytime energies of plant 1, using simulated energies and the energies obtained with piecewise-linear equations.

the optimization and their respective simulated energies. These metrics are calculated from the same time horizon as in the figures. The energy obtained with λ -technique outperforms piecewise-linear equations on every metric. For instance, the difference to the simulated energy is on average only 3.01 MWh, whereas that of piecewise-linear equations is even 15.24 MWh.

Table 6.1: Metrics for calculating the errors between energies obtained from optimization and their corresponding simulated energies.

	MAE	MAPE	MSE	\mathbb{R}^2
Piecewise-linear eqs	15.24	12.61	369.46	0.72
λ -technique	3.01	3.76	16.79	0.97

The λ -technique allows more accurate energy calculations than piecewiselinear equations, since it models the dependency between the water level and energy output almost as well as the simulation. It is of course desirable that the optimization would calculate the generated energy accurately in the first place, because it might have a significant effect on the results of the optimization. For instance, if the price forecast suggests high prices in two weeks, λ -technique sees more value in increasing the water level before those high prices since it would lead to increased energy output as well. Therefore, the discharge plans given by λ -technique are also usually a bit different to those obtained with piecewise-linear equations. This is also the reason why



Figure 6.7: Water content for reservoir 1 and daytime energies for plant 1, using simulated energies and the energies obtained with λ -technique.

the production profiles "in general" are not entirely similar in Figures 6.6 and 6.7; their underlying discharge plan is a bit different.

It is worth noting that by the time of writing, not all model parameters are calibrated perfectly. Furthermore, the errors in the piecewise-linear equations are not equally significant when looking at the total daily energies; this example considered only daytime energies because it illustrates the phenomenon more clearly. Nonetheless, the most important purpose of this example was to demonstrate that ignoring the impact of the water level might sometimes lead to significant errors in some reservoirs (but not in all). For this reason, the simulated energy is often calculated afterwards as an additional decision support.

6.4 Inflow Risk

While the previous sections illustrated different aspects of the model and verified that it works as it should, this section finally shows how the inflow risk is accounted in the DSS on the upcoming T_S days. We take an example from fall, starting date being 11th of September 2017. This date was chosen because it was in fact one week before unexpected precipitation increased the water contents above the upper limits, and spillage was required. We aim to replicate this situation to see how risky the situation would have seemed at a time. Thus, we use scenario forecasts and spot forecast (with hidden values

due to confidentiality) that were available at the time. For simplicity, we do not use λ -technique in this example.

The optimization is performed over the median base scenario, using three different scenario coverages, c = 0, c = 0.8 and c = 1, such that $T_S = 28$ days. We focus on reservoir 1 and production of plants 1 and 2, but the situation in reservoir 2 also contributes to the results in a similar manner. Figure 6.8 shows the optimized water contents with respect to the base scenario for the next 3 months. We note that the case c = 0, i.e., fully deterministic optimization considering only the base scenario, would like to increase the water content during the fall close to the upper limit. In contrast, the case c = 1 which penalizes all the other scenarios as well, increases the water content a bit later in order to avoid being too close to the upper limit. The case c = 0.8, which penalizes 80% of the other scenarios, is naturally between these two cases.



Figure 6.8: Base scenario contents of reservoir 1 for different c

Figure 6.9 shows the corresponding energy production plans, which are intuitively in accordance with the water contents: as the content for c = 1 increases the latest, the produced energy is highest during the first 4 weeks, whereas it is the lowest on the next 4 weeks. The produced energy for c = 0.8 is again between those of c = 0 and c = 1. After mid-November, the contents and productions coincide for all c, because the effect of the short term scenario violation penalties "wears off".



Figure 6.9: Energy production plans $E_1 + E_2$ for different c. Dashed horizontal line indicates the maximum energy.

The reason why these production plans behave as they do can be explained by visualizing how the water contents would evolve in all other scenarios during the first T_S days. Figures 6.10 and 6.11 shows these visualizations for c = 0 and c = 1, respectively. The colors of the base scenario correspond to those in Figure 6.8, and all the other lines correspond to different inflow scenarios. The contents based on minimum and maximum scenarios, i.e., the scenarios having the smallest and biggest cumulative inflow sum during the first T_S days, are represented with brown and purple. Figure 6.10 shows that the c = 0 case results in limit violations in ≈ 7 scenarios, indicating that the inflow risk is not significant but still noteworthy. On the contrary, from the case c = 1 in Figure 6.11, we see that all but three scenario contents are maintained within the limits, which indicates that the inflow risk corresponding to plan c = 1 is smaller. The limit violations in Figure 6.11 are also not as extensive as in Figure 6.10. Additionally, although not shown here, the inflow risk in this particular example was much larger in reservoir 2, wherefore the risk reduction from plans c = 0 to c = 1 is even more influential in reservoir 2. As we have more than 50 scenarios, it is assumed that they cover the whole range of possible realizations.



Figure 6.10: Scenario specific contents for c = 0. Red line is the upper limit.



Figure 6.11: Scenario specific contents for c = 1. Red line is the upper limit.

This is a simple, yet informative way, to get some insight on whether the hydrological situation is risky in the short run or not. It is of course reasonable that penalizing several scenario specific limit violations does not come for free. In this particular example, case c = 1 produces energy quite aggressively during the first month in order to reduce the risk. This might decrease the short run achieved price, which is the average selling price of production. Figure 6.12 shows the achieved prices during the first T_S days for each c. Due to confidentiality, we only show the differences to some predefined price level p.



Figure 6.12: Achieved prices during the first T_S days. The values are shown as a difference to some reference price p.

Even though the achieved price is not specifically the objective to be maximized, it is worth noting that playing it safe with plan c = 1 would lead to a selling price that might be on average almost $0.30 \in /MWh$ worse than that of plan c = 0. Nevertheless, the decision makers probably tend to prefer less risky plans, because limit violations would require spillage which has a "selling price" of $0 \in /MWh$. The yearly revenue from optimization also decreases with larger c, but since the price and inflow forecasts are updated frequently, it is difficult to assess if that would happen in practice.

In addition to providing visualizations on how the water contents would evolve in different scenarios given a fixed production plan, the DSS also provides visualizations from other way around, that is, how much weekly energy would be approximately needed in different scenarios in order to maintain the water content as it is in the base scenario. Figure 6.13 illustrates an example for case c = 0. These weekly energies are obtained from the hydrobalance equation by first calculating how much discharge would be needed in each scenario, and then multiplying that discharge by the coefficient γ_i that approximately converts one DU to MWh for reservoir *i*. These values are then aggregated to weekly level. Note that this method does not take into account whether or not such discharges/energies would be actually feasible. Figure 6.13 shows that if some of the wettest scenarios would realize, it would not be possible to keep the water content exactly as in the base scenario, at least without spilling the water. Nonetheless, the important indication here is that if the operator follows the optimized base scenario content, the required energies might differ quite significantly from what the deterministic optimization suggests, due to inflow uncertainty.



Figure 6.13: Approximate scenario specific weekly energies for case c = 0, given that the water content of the base scenario is fixed. Each dot corresponds to one scenario, whereas the base scenario energies as well as the energies required for minimum and maximum scenarios are represented with similar colors as in Figure 6.10. The dashed black line indicates approximate maximum weekly energy level that can be produced from reservoir 1.

The visualizations in Figures 6.8-6.13 form the basis for the interactive risk control in the DSS, and providing a mandate for the short-term operation. We have two, sort of opposite, approaches:

- 1. Given a fixed discharge/energy production plan, visualize how the water contents may evolve.
- 2. Given a fixed water content (corresponding to base scenario), visualize the interval of the weekly energies needed to meet this fixed content.

In practice, the reservoir operation might be somewhere between these two approaches. The decision maker essentially decides the final production plan, such that the results corresponding to different c produces alternatives. The inflow risk control of this whole concept is, as of yet, partly a qualitative nature. We do not have an actual probability model for the inflow, so the scenarios (other than the base scenario) are treated equally. Thus, the visualizations do provide more information about future uncertainty, but proper quantification of the risk levels is not achieved here. It is also worth noting that if the water content is not nowhere near the minimum or maximum limits and therefore the risk of violations is small, then the results corresponding to different c might be exactly equal.

After all, this DSS is basically a diagnostics tool developed for a pragmatic need of increased awareness about inflow uncertainty. The primary functionality is still provided by deterministic optimization. The discharge and spillage variables in the model fundamentally still correspond to the chosen base scenario, which is why we penalize explicitly on the scenario specific limit violations, as a sort of additional penalty term in the model. The spillage itself is not penalized, as the optimization usually avoids it anyway because it yields no revenue. If this approach will help to avoid the limit violations and spillage even on rare occasions, the concept is useful. The realized limit violations at the time might have been able to avoid if the chosen plan at the time would have corresponded to c = 1, and being aware of the possible need to increase the production according to Figure 6.13 early enough. Even though spillage directly represents a lost opportunity of energy generation, it is not the only reason why maintaining the limits is important. Violations may cause unhappiness amongst the local people, discussions with the environmental officials and actual penalty fines (Mäkiharju, 2012).

In some cases, it might be reasonable to consider the inflow uncertainty in shorter or longer horizon than just $T_S = 28$ days. For instance, prior and during spring flood, the uncertainty might be greater, in which case the scenarios could be more spread even from the beginning. In such situations, it might not simply be possible to obtain a fixed production plan where the
limits would not break in several scenarios, even with c = 1. The usefulness of this concept might be limited in such situations, but the visualizations still give more insight about possible outcomes and energies. Prior to spring flood, the planner might want to ensure that the water level starts to increase early enough. In such cases, one can choose to perform the optimization with a dry scenario. This would yield a production plan that ensures that the water content will most likely increase more than that of the chosen scenario. On the other hand, during the spring flood, when the water content has already increased, the planner may want to ensure that flooding does not occur afterwards. In that case, one may choose to perform the optimization with a wet scenario. However, during spring flood it is also often necessary to just use the maximum discharges as the inflows can be very voluminous. Be that as it may, since the mid-term production plans and the forecasts are updated every week, the violations and spillage are somewhat rare in practice. Thus, this example only showed a "snapshot" about some of the considerations in a weekly planning process.

Chapter 7

Conclusions

This thesis presented a Decision Support System for mid-term hydropower planning, where the primary functionality is provided by a deterministic linear optimization model. It was developed for a specific river system operated by a case company that participates in the Nordic electricity market. The optimization model maximizes revenue by allocating the production against the electricity price forecast, subject to the environmental constraints and inflow forecasts. The entire planning horizon is one year with daily resolution, but one of the key objectives was to provide more information and enhanced decision support to the planning process by taking the inflow uncertainty better into account especially during the upcoming month. This was achieved by utilizing several inflow scenarios and visualizations in a web-based diagnostics tool, such that the planner can perform quick "what-if" -scenario analysis by optimizing the model under different scenarios. The most common base case is to perform the optimization with a certain median inflow forecast, and analyzing the possible outcomes by visualizing the development directions of the water levels in other scenarios as well, given the optimized production plan. If it seems that too many scenarios would result in violating the reservoir limits in the near future, the tool includes a possibility to obtain alternative production plans by adding penalty terms from these scenario specific violations to the optimization model, which reduces the inflow risk. Conversely, the tool provides visualizations of the approximate weekly energies that would be needed in different scenarios, if the planner desires to follow a fixed water level instead. All of the aforementioned aspects are important information to the decision maker, who is ultimately in charge for the final production plan. This concept as a whole provides increased awareness of the inflow uncertainty to the planning process in an interactive way.

Another objective was to improve the previously used model by the case

company. A new, more detailed optimization model was implemented from scratch based on the old one. The most important update is that the new model adds the possibility to participate in the Frequency Containment Reserve -markets, which yield revenue based on available power capacity rather than production itself. This update changes the optimized plans into a bit steadier direction, indicating that it is beneficial to make such production plans that enables more frequent participation in the FCR markets. In practice this means to not always produce at full power during the daytime, and also allocating some production to night-time and weekends every once in a while. Future will show if the power plants in the case river system increase their involvement in these markets due to the new mid-term model. After all, it is the short-term model and the planner that decide the more accurate hourly production plans.

Illustrative examples of the aforementioned contributions were presented to examine the behaviour of the model and its different aspects. As the results were logical, the model works reasonably and as expected. The next step is to take the developed decision support system into use on a weekly basis. The planning process will not change significantly compared to the old approach, but providing more information and control of the inflow uncertainty was somewhat successfully achieved. If the new DSS helps to avoid flooding and spilling the water even on rare occasions, the concept can be considered useful.

There still exists several avenues for future developments. Despite the extensive literature on stochastic optimization of hydropower, the chosen approach in this thesis was somewhat pragmatic, interactive and partly qualitative. The reason is that the inclusion of inflow uncertainties needed to be compatible with the current way of production planning used by the case company. One area of improvement would be in better quantification of the risks and estimated profits of alternative production plans, which would further enhance the decision support. However, as the deterministic optimization model does not produce any recourse actions with respect to the possible realizations of uncertainty, this was not a straightforward thing to do. Some attempts were made by using heuristic calculations to obtain estimates for expected profits and expected spillage losses, but these were not realistic nor accurate, and thereby excluded from this thesis.

In the future, a viable direction of development in the big picture would be indeed to change the planning process into a more strategy based, rather than using more or less fixed production plans. This could be achieved by following some of the concepts presented in the literature review, e.g., by setting up the problem with a scenario tree, for example for the upcoming month with weekly resolution. This would produce more general planning guidelines that are dependent on how the uncertainty unfolds. In real life, the planners obviously react to unexpected situations, wherefore an actual stochastic optimization model which provides recourse decisions would be more realistic in that sense too. However, accurate probabilistic descriptions of the inflow uncertainties might not be that easy to achieve in practice, and using a stochastic model might limit the level of detail in the system description due to increasing computational requirements. In this thesis, detailed system description and fast computation times were considered as important attributes. Implicit stochastic optimization was also attempted, but the derived general operating rules were not sufficient to be useful in practice.

Another interesting aspect is the coupling between mid-term and shortterm models, which is currently done such that the mid-term model provides target water levels for the short-term model as boundary conditions. It would be interesting to see if the water allocation would improve if this coupling principle would be based on the marginal water values instead, as it would enable enhanced balancing between short-term and long-term profits, and flexibility with respect to the inflow conditions. This would require sufficient estimates for the water values from the mid-term model, which is challenging to achieve due to small reservoir sizes, environmental limits, inflow and price uncertainties, and the inter-reservoir dependency.

In addition to the possible future directions and developments in terms of the modelling approaches, one essential future need is to include the price uncertainty to the planning process as well, which was not yet considered.

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