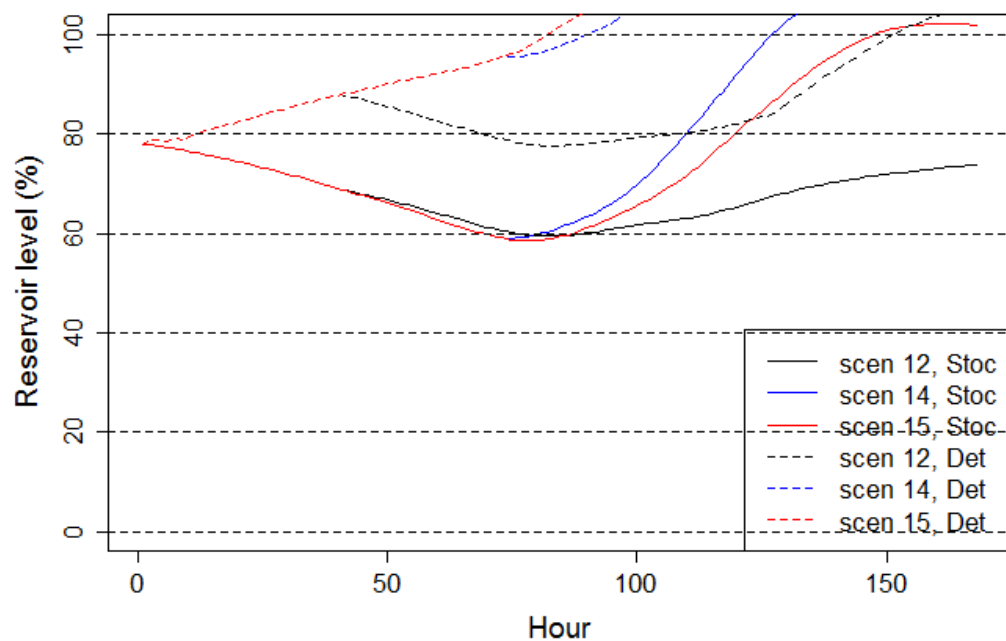


Report

Validating the SHARM model

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ABSTRACT

A prototype for stochastic short-term optimization of hydropower, called Short-term Hydro Application with Risk Modeling (SHARM), is tested together with participating hydropower companies. SHARM is a stochastic formulation of the successive linear programming method used in SHOP. The ability to take into account uncertainty means that the SHARM concept has a potential to provide improved decision support. The benefits of stochastic modelling are well grounded in theory, but how much additional value can be obtained by producers in practice? This report assesses the potential costs and benefits to producers by operationalizing the stochastic short-term model, and summarizes the work that has been done in the IPN-project 226237/E20 Validating the SHARM model. Our results cannot give any firm conclusion on the added value of stochastic modelling, but has led to increased insight into the short-term production scheduling problem for hydropower.

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Summary

This project has attempted to calculate the added benefit of applying stochastic programming to the short-term hydropower scheduling problem. Even in the short run, the important input parameters of electricity prices and inflow to the reservoirs are best modelled as stochastic processes. The results from deterministic models in use today require manual adaptation in order to compensate for the often too bold reservoir management strategy chosen by a decision support tool where uncertainty is not adequately modelled. These adjustments are based on expert knowledge of how the water courses should be operated under uncertain conditions, and require extra resources for the planning process in terms of time and skilled operators.

The uncertain parameters could be considered in the optimization model by using stochastic programming, and such tools therefore have the ability to yield added value for producers in the sense of more robust production schedules that balance profit and risk. A stochastic model for short-term optimization for hydropower, the SHARM model, has been developed by SINTEF Energy Research. The gains obtainable to producers from using this model instead of the currently used deterministic model has been tested together with a group of Norwegian hydropower producers.

The added benefit of stochastic modelling was assessed through different test procedures and case studies. Our results show no consistent indication of improved profits from using the stochastic model over the deterministic method for all water course topologies. For some topologies we get substantial gains from SHARM, while we for other systems observe losses from using the stochastic model. Our test procedures are designed to always evaluate the stochastic solution as equal to or better than the deterministic approach, so a loss is a clear indication of inconsistencies in our results. Due to this noise in the calculations we are unable to quantify the improvement, and we must thus conclude that the improvement from stochastic modelling is rather small for the current market situation and weather conditions. However, we see that the reservoir management strategy is slightly improved when using the stochastic model.

The project has resulted in increased knowledge about stochastic optimization for hydropower scheduling and given valuable input for future research projects.

Table of contents

| | | |
|----------|--|-----------|
| 1 | Introduction | 6 |
| 2 | Short-term scheduling under uncertainty | 9 |
| 2.1 | Challenges due to uncertainty | 9 |
| 2.2 | Markets and bidding | 11 |
| 3 | Test Procedures..... | 12 |
| 3.1 | Testing at the hydropower companies | 12 |
| 3.2 | The value of stochastic modelling..... | 12 |
| 3.3 | The mean trees test | 14 |
| 3.4 | The production schedule test | 17 |
| 3.5 | Scripts for automating the test procedures..... | 19 |
| 4 | Test Results..... | 20 |
| 4.1 | Mørre reservoir..... | 20 |
| 4.1.1 | Results from the mean trees test | 20 |
| 4.1.2 | Results from the production schedule test | 22 |
| 4.2 | Langvatn reservoir | 22 |
| 4.2.1 | Results from mean trees test | 23 |
| 4.2.2 | Results from production schedule test..... | 23 |
| 4.3 | Hemsil reservoir system..... | 24 |
| 4.3.1 | Results from mean trees test | 26 |
| 4.3.2 | Results from production schedule test..... | 27 |
| 4.4 | RSK East river system | 28 |
| 4.4.1 | Results from the mean trees test | 28 |
| 4.4.2 | Results from the production schedule test | 30 |
| 4.5 | Mandal river system | 30 |
| 4.5.1 | Results from the mean trees test | 32 |
| 4.5.2 | Results from the production schedule test | 33 |
| 5 | Lessons learned..... | 35 |
| 5.1 | Iteration logic and margins of error | 35 |
| 5.2 | Quality scenario tree input | 36 |
| 5.3 | The effect of using common decision period | 37 |
| 5.4 | Sensitivity for tree reduction | 42 |
| 5.5 | Simulation, not optimization | 45 |
| 5.6 | Penalty costs should reflect the cost of the real-world alternative..... | 46 |
| 5.7 | Full potential by implementing multiple markets | 47 |

| | | |
|----------|--|-----------|
| 6 | Operationalization of SHARM | 50 |
| 6.1 | Challenges of operationalization | 50 |
| 6.1.1 | Generation of valid input..... | 50 |
| 6.1.2 | Easy access..... | 50 |
| 6.1.3 | Computation time..... | 50 |
| 6.2 | Process and costs for using SHARM..... | 51 |
| 6.3 | Industrial impact of the SHARM model | 52 |
| 7 | Discussion | 55 |
| 8 | References | 58 |

APPENDICES

[List appendices here]

1 Introduction

Short-term hydropower scheduling refers to the daily physical operation of hydropower with an hourly or even finer time resolution. The aim of short-term hydropower scheduling is to maximize the income from hydropower production, balancing the short-term profit and the value of stored water at the end of the scheduling horizon. It could be one hydro power plant, several cascaded hydropower plants in a water course, or a set of plants or water courses operating together to cover a joint load. In the Nordic region, all large hydropower producers solve the short-term scheduling by deterministic optimization with the SHOP software (Fosso and Belsnes, 2004). Using deterministic optimization and linear modelling makes it possible to account for the connections in time and topology that are important when operating hydropower systems. Handling all relevant technical constraints is important to get solutions that can be applied to the physical system with minimum modification.

Short-term scheduling is the tool for implementing the strategy for long-term utilization of the hydropower resources as illustrated in Fig.1-1 which describes a hierarchy of optimization models for hydropower scheduling (Flatabø, Haugstad, Mo and Fosso, 1998) implemented by SINTEF Energy Research. The optimization horizon for short-term scheduling may be as long as one to two weeks ahead in time depending on when it is possible to get boundary conditions from the long-term strategy, but it is only the results for the next 12-36 hours that are used in an operative setting.

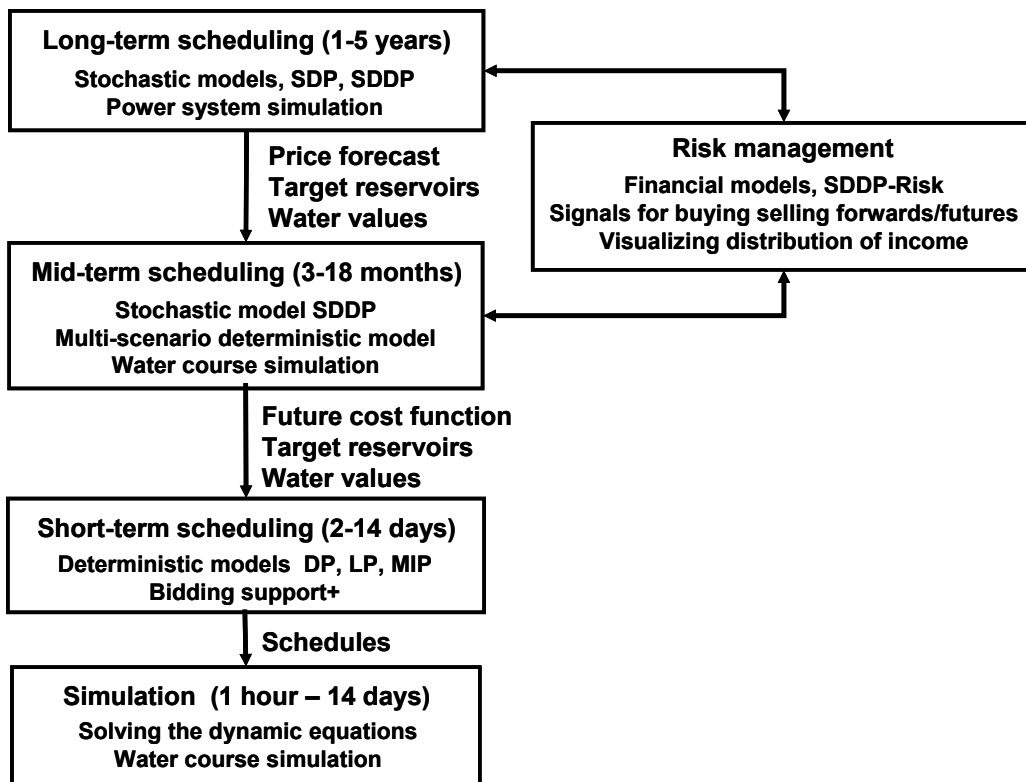


Figure 1-1: The hierarchy for optimal scheduling of hydropower resources as implemented by SINTEF Energy and used by most large Nordic hydro producers.

Deterministic optimization will give the optimal trajectory for one future scenario within the horizon of 2-14 days, but this approach is not always adequate for robust decision support for daily operation in cascaded rivers. It is not always enough to be able to balance the marginal efficiency of the generation units with the market price. The uncertainty of important parameters such as market prices, inflow, and degree of market access should also be included in the calculation. Explicit consideration of these uncertainties calls for

stochastic models that can balance profit and risk, and thus give more robust operating schedules than the currently used deterministic models. In the near future, price volatility is expected to increase due to stronger connections to the European continent and increased shares of renewables. Inflow variability is also expected to increase due to climate change, making the potential gain from stochastic modeling even larger.

In the KMB project 190999/S60 Optimal Short-term Scheduling of Wind and Hydro Resources a prototype for stochastic short-term optimization of hydropower was developed, called Short-term Hydro Application with Risk Modeling, SHARM. SHARM is a stochastic formulation of the successive linear programming method used in SHOP. SHARM is able to manage details in the physical reservoir system as well as uncertainty in future inflow and price. The ability to take into account uncertainty means that the SHARM concept has a potential to provide improved decision support, in particular facing a future market with more volatile prices due to an increased share of wind and other intermittent energy sources. But how much additional value is actually obtainable for producers when switching to a stochastic model? Can this value be measured in a fair way, and how does it compare to the costs of developing and integrating the new software in the hydropower companies?

Operators at the hydropower companies have expert knowledge about their systems and experience about the possible impact of uncertainty, and take measures to adapt the solution from the deterministic optimization model in order to avoid too risky production schedules. The optimization model offers decision support, but is only an element of a complicated process for generating a final production schedule. This process is illustrated in Fig. 1-2. This figure will be used throughout the report in order to illustrate how changing the optimization model from a deterministic to a stochastic model might influence the other elements of the production scheduling process.

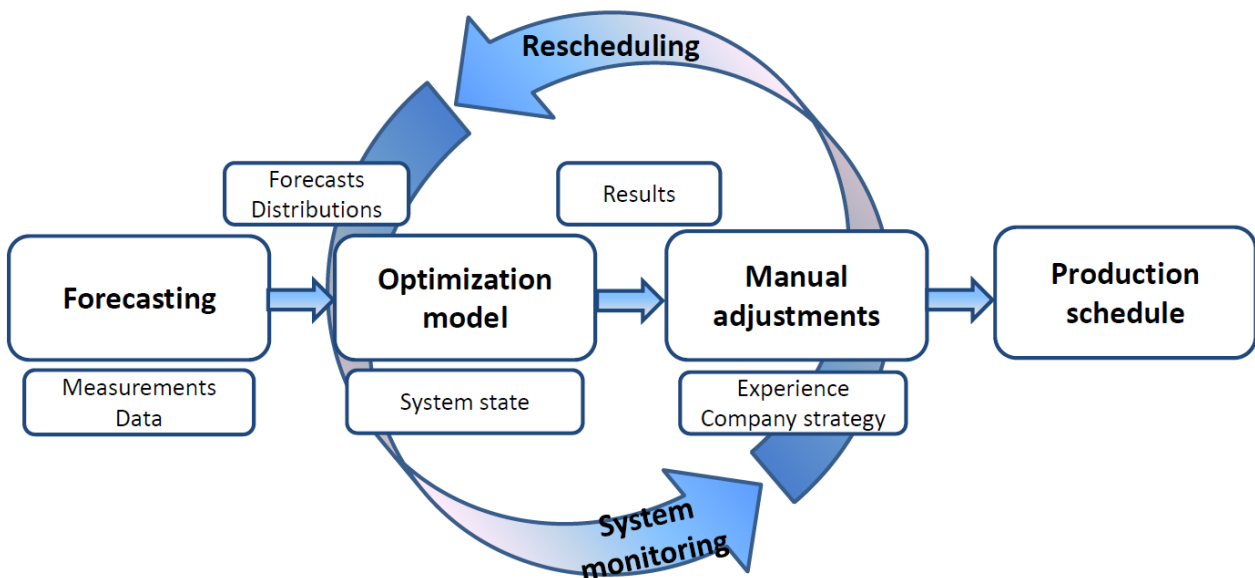


Figure 1-2: Illustration of the process for determining an optimal production schedule. Forecasts for prices and inflow are generated daily and are input to the optimization model. The results from the optimization model are subject to manual adjustments before the production schedule is determined.

The production scheduling process starts with generation of forecasts for price and inflow for the coming days or week. Forecasting may be done by in-house analysis departments for hydrology or markets, or they may be obtained from commercial analysis companies. Forecasted values for price and inflow are inputs into an optimization model together with the current system state. The optimization model gives results in the

form of schedules for the next day's operation. Operators at the hydropower companies evaluate and adjust the schedules from the optimization model based on experience and company strategies. Not all information or constraints can be modelled in an optimization model and hence some manual adjustments may be necessary before a final production schedule is obtained. New information about the current system state or new forecasts might induce rescheduling or re-optimization. The process of forecasting, monitoring the system, optimization, evaluating and adjusting plans is performed in a continuous manner throughout the week.

Under current practice, uncertainty in variables such as inflow and market prices are handled by the frequent reapplication of models with updated input parameters or by adding safety constraints that limit the characteristics of deterministic optimization models to produce too smart (too bold) schedules for the hydropower system. The cost of such uncertainty imposed constraints is calculated from sensitivity analyses or based on specific and practical system experience. This works fine as long as some flexibility is available in the hydropower system or in the different markets for power.

The behavior of the markets is expected to become more volatile due to the transition towards more renewable power production in the energy systems. The European Union Renewable Energy Directive 2009/28/EC that was implemented in 2010 define binding targets for 20% renewable contribution to total energy demand by 2020. From January 2012 a joint certificate system was implemented in the Nordic market to ensure development of 26.4 TWh of new renewable energy towards 2020. To reach European and Nordic targets, intermittent production such as wind- and solar power will play a major role. As a consequence of the increased variability of inter-Nordic balancing and regulating power and new cables that are planned from the Nordic system to the rest of Europe, Nordic power prices may also become more volatile in the future. Hydropower producers might then have to use more of the capacity towards the intra-day market or the balancing markets. To optimize production in the future, hydropower companies must therefore schedule the watercourses in such a way that obligations in several different markets can be honored. The challenge is to maintain flexibility for fast changes in generation levels without increased spillage or loss of efficiency, and to decide what part of the capacity to use in what market. This task calls for an explicit representation of the uncertainty of price and inflow. Continued operation with multiple re-runs or manual rules for maintaining system flexibility is difficult when the boundary conditions are constantly changing, in which case the safety limits should become an integrated part of the operational decisions. The SHARM model will accommodate this, and a stochastic representation of prices will be the foundation for building models for optimal allocation of capacity in a multi-market setting.

The benefits of stochastic modelling are well grounded in theory, but how much additional gain can be obtained by producers in practice? Stochastic models both require and generate more data than deterministic models, and interpreting results might be difficult in an operating setting. The main objective for short-term scheduling is to generate results that with little or no changes can be used as the physical production schedule. The results should be transparent, so that relationships between input and output are easy to identify, and quick, that is, the computational time for the models cannot be excessive. Transparency is an important factor when it comes to control and trust for the operator of the model. This may be a challenge when moving from single forecasts to working with distributions of the uncertain variables. Solving SHARM on large scenario trees will require long calculation times, and it is crucial that the response time of the optimization model adheres to the routines established at the hydropower companies due to the rules and time constraints of the electricity market. The benefits in terms of possibly better strategies from using a stochastic model must be compared to any additional costs from working with a more complicated model. The combined benefits and costs of SHARM must then be compared to the costs and results of the manual analysis and multiple re-runs of a deterministic model.

The aim of this project is to obtain sufficient knowledge to decide whether to proceed with implementation of the SHARM prototype for short-term optimization in the industry or to use the concept as a research prototype. Secondary objectives are:

- 1) Calculate added economic value from using SHARM based on extensive testing in the individual utilities and at SINTEF Energy Research.
- 2) Identify and mitigate the challenges of implementation of the stochastic model for operative decisions in the utilities.
- 3) Generate an overview of the process required for operationalizing the model on partner level and in general.
- 4) Estimate the intra utility cost of implementing SHARM.

The current project builds the bridge between the research prototype SHARM and future operationalization of a stochastic short-term model in the hydropower companies. Economic feasibility is one of the questions addressed but mitigation of the obstacles for getting the SHARM concept operational is also included. A key activity during the project period has been the industry tests performed by and in the partner companies. The tests have been carried out in close cooperation with SINTEF. The most important challenge has been the design and development of a test framework that substitutes testing over many years of climate data. In addition, the large amount of input and output data is a new challenge, in particular how to interpret and use the results from the stochastic model.

The rest of this report is organized as follows: In Chapter 2 we summarize some characteristics of the short-term hydropower scheduling problem as seen from the view of a price-taking producer, with specific focus on uncertainty and how this complicates the problem. Chapter 3 discusses and develops the test procedures that have been used by SINTEF and the participating hydropower companies. In Chapter 4, results from testing together with the industry are reported. The results reported here are examples of the tests from Chapter 3 applied to real reservoir systems and data, and are representative of what has been found by industry participants in their testing of SHARM. Chapter 5 summarizes some of the lessons learned during testing, and explains some of the inconsistencies in our results. Chapter 6 discusses the process for operationalizing SHARM in the hydropower industry. In Chapter 7, weaknesses in our methods and challenges for further research are elaborated, before final conclusions from SINTEF and from all participating companies are given in Chapter 8.

2 Short-term scheduling under uncertainty

2.1 Challenges due to uncertainty

The challenge of short-term scheduling is to handle non-linear and non-convex elements together with state-dependencies. Nonlinearities are present almost everywhere in hydropower modelling, in efficiency curves, reservoir curves, losses and so on. Examples of non-convex elements are minimum generation and spill descriptions. State-dependency also occur several places; in water flow through gates and hydraulic connections, but regarding overall hydropower efficiency the state-dependency in turbine curves are the most important. Efficiency of hydro turbines depends on head and head depends on reservoir levels which again depend on discharge and discharge dependent losses above and sometimes below the turbine. The head, or pressure height, the coming hours depends on the decision that the operator is making this particular hour. This makes it impossible to build an exact efficiency curve for the turbines for all hours and in a two-week perspective errors might be large. Different techniques are in use for handling this issue. One method is to apply successive linear programming, which is the method implemented in SHOP. A large effort has been put into the development of this general hydro scheduling model so that it includes many details important for Scandinavian watercourses.

Challenges regarding modelling of the physical reservoir and production system are interesting, but for the purposes of this report the question of stochasticity is the main objective. SHOP assumes that only *one* future scenario is possible for inflow and price, whereas this is far from the case in reality; prices are volatile and expected to become even more so in the near future, inflow may be highly uncertain due to local weather conditions and terrain surrounding the reservoirs. In the future, hydropower utilities must schedule the watercourses in such a way that flexibility for fast changes in generation levels is obtained without loss of water or efficiency. In other words, it is a need for an explicit representation of the uncertainty of price and resource availability. This is accomplished by applying a stochastic version of successive linear programming, stochastic successive linear programming, to the short-term scheduling problem. This is the mathematical foundation of the SHARM model. Details about the formulation of the SHARM model can be found in TR A7223 Aspects of stochastic models for short-term scheduling and in Belsnes, Wolfgang, Follestad and Aasgård (2015).

There are several important uncertain factors in hydropower scheduling. The uncertain variables can be divided into three classes:

- Climatic variables
- Market prices
- Other factors

The most important climatic variable is inflow to the reservoirs, while wind-power and temperature are other variables within this class. Other factors include the allowance to produce for the balancing market at the defined price, unpredicted troubles for the plants or fundamental changes that affect the value of stored water at the end of the short-term planning period. In the current implementation of the SHARM model, only the spot-market price and inflow to the reservoirs can be considered as stochastic variables.

Inflow to reservoirs is possibly the most important stochastic variable for hydropower scheduling and closely connected to optimal use of hydropower reservoirs. Many of the economic optimization methods and models that have been developed for hydropower scheduling address this uncertainty, e.g. the water value method. One important motive for reservoir management is to move generation to periods where the expected price is higher than the present price. A high reservoir volume will also give a high head of water, and this increases turbine efficiency. On the other hand, more inflow than predicted in advance and full reservoirs will lead to losses due to spillage. In such situations a deterministic approach will fail to establish the correct balance between the advantage of head over the turbine and the risk of spillage. The optimization will therefore benefit from taking into account the inherent stochastic nature of the natural inflows to the reservoirs.

The spot market price is also stochastic on a short-term basis. Electricity prices usually follow a daily pattern with higher prices during daytime than during night time. Peaks usually occur in the morning and afternoon, but it may be difficult to forecast the exact time of a peak as well as the magnitude. Electricity prices in general depend on the season, the current and expected state of reservoir storage in the total system, the current price and expected future price of fossil fuels, wind, network constraints etc. As already stated, integration of intermittent renewable energy both in the Nordic countries and on the European continent are expected to increase the volatility of electricity prices. As an example of when a deterministic strategy fails, consider a case with some probability for increasing market prices throughout the optimization period. Here, a deterministic model will tend to shift as much generation as possible towards the horizon to exploit the high prices. A robust plan, accounting for uncertainty in price, would be a mixture of generation today still saving water for the expected high prices but now balanced with the chance of the future prices to end up lower.

The plan that maximizes the expected profit is not necessarily the preferred plan since a risk adverse player is willing to pay a premium to reduce uncertainty. This can affect the operation of reservoirs. One example is

cases where on the one hand there is a danger for reservoir spillage if the uncertain inflow becomes large, while on the other hand the price is expected to increase. A risk adverse player prefers to generate more at a relatively low price to avoid spillage, while a risk neutral or risk loving player saves more water to utilize expected higher prices in the future, accepting a higher risk for spillage.

Our claim is that a stochastic model to a larger extent will weigh different strategies against each other and generate a more robust production schedule. If the production plan must be valid for several different future states - which in the extreme case could include high inflow, low inflow, high prices, low prices, decreasing prices, increasing prices etc., then a much less bold strategy would be chosen than if the production schedule only has to be valid for a single future state, of, say, low inflow. This is the fundamental difference between a stochastic and deterministic model, and even if the deterministic model is run several times for different input values and the results are somehow combined, the results would not be the same as the strategy from a stochastic model. Each of the deterministic optimizations will be optimally adapted to its particular input and therefore do not take any safety measures, as such considerations are not necessary if it is known exactly what will happen. There is no value of a flexible and robust schedule if it is known with certainty that this flexibility is never needed, and so the deterministic model makes decisions that exploit the extreme values of all constraints. Manually adding safety measures such as tactical boundaries on the reservoir storage level will limit the range of possible strategies taken by the deterministic model, but it will not change the nature of deterministic optimization with regards to exploiting extreme values. The stochastic model, on the other hand, sees a value of flexible plans and will generate schedules that hold back from extreme values in order to give satisfactory results for a range of different futures. If these theoretic results are as prominent in practice as in theory, we expect that stochastic modelling will offer substantial gains over the current deterministic method, and that the implementation of the SHARM model for operational use is well worth while.

2.2 Markets and bidding

The market for power actually consists of several different markets. The most important market is the day-ahead spot market, where expected generation and consumption from 12 to 36 hours ahead in time is traded. The intra-day market (i.e. the Elbas market at Nord Pool) makes it possible for consumers and suppliers to trade themselves into balance according to their obligation in the spot market. The reserve capacity market (RKOM) and the real-time balancing market (RK) provide a mechanism for handling the unbalance between consumption and generation during actual system operation. The first will give the system operator a security for available assets for balancing power within the week while the second will settle the action for balancing power whenever upwards or downwards regulation are required.

The day-ahead spot market is the main market for electrical energy in the Nordic area. A market equilibrium for each hour of the following day is calculated by Nord Pool once a day, such that there will be 168 different prices within a week. The market is cleared within 12-14 PM for delivery from 12 AM the next day. During the SHARM project, focus has been on the day-ahead market, and the other markets are not described in detail in this report or modelled in the software.

Determination of the optimal market bids for hydropower is a problem in its own right, and short-term scheduling may be divided into two sequential tasks: the bidding problem which finds the optimal bids to the power market for the next day, and then the problem of optimal allocation of generation resources after commitments are known from the market clearing. These two problems may also be referred to as price-dependent and price-independent production scheduling, respectively, as the bidding problem produce price-dependent bids to submit to the market, whereas the production allocation problem finds a production schedule that maximizes the efficiency of all units in the system independent of the market price (i.e. for a given deterministic market price). The SHOP model is used for both tasks today, but has to be combined with heuristic methods for price-dependent bidding since a formal optimization of the bids require a

stochastic representation of the market prices for the next day. At the time of bidding, the prices for tomorrow are not yet known and thus the bidding process must somehow accommodate decision-making under uncertainty of tomorrow's prices.

A feasibility study has been carried out within this project to estimate the effort needed to add explicit bidding optimization in SHARM. Bid determination seems to be an area where a stochastic model would yield larger benefits, as there is no formal optimization of bids today. In the current project, the focus has been on testing the core bidding concepts in the SHARM model for production allocation as this is the area where SHARM and SHOP are direct competitors. Testing for price-independent scheduling will result in a more conservative estimate of the gains obtainable from stochastic modelling. Some test procedures and discussion of results can be found in Aasgård, Skjelbred and Solbakk, 2015. Implementation details for the bidding functionality can be found in project memo Prospective Bidding Functionality in SHARM.

3 Test Procedures

3.1 Testing at the hydropower companies

As noted in the Introduction section, a key activity during the project has been testing by and in the participating hydropower companies. User participation in the testing of SHARM has served several purposes:

1. Familiarizing users with the new model and the process surrounding it. This involves getting experience with the increased amount of input/output data and interpretation of results. Working with the model during the project period have revealed and mitigated problems that might have become barriers for implementation later on. This includes new formats for output data, the option of generating one schedule for a prescribed period, plots of the results etc. These issues will be further discussed in Chapter 6.

2. Developing test procedures and measure gains from SHARM. The practical gains of stochastic modelling may vary from watercourse to watercourse due to the inherent flexibility of the different systems. How the results from the optimization model are used in operational scheduling also vary across companies, and we wanted test procedures that gave the individual producers the results they needed to draw a confident conclusion regarding the gains from SHARM. The original idea was that test procedures could be tailor-made for each producer. During the project period, discussions led to the two test procedures presented in the rest of Chapter 3.

3. Validation of and feedback for new versions of the software. Continuous improvements have been made to the SHARM software throughout the project period. Operators at the utilities have expert knowledge of their systems and the current use of the deterministic SHOP model, and have been valuable assets for testing and improving the modelling of the SHARM software and the accompanying scripts for scenario generation and test procedures.

This Chapter will deal with item 2 on the above list, and Chapter 4 will show results of the test procedures when applied to real reservoir systems and data.

3.2 The value of stochastic modelling

In theory, the added value of stochastic modelling seems quite obvious. The discussion in Chapter 2 makes it clear why a stochastic model gives a different and more robust production schedule than a deterministic model. But what is the value of a more robust schedule? How can we measure if the decision support from the stochastic model is *truly* better, and then *how much* better? Developing a method for assessing the value of stochastic modelling used in real operations is one of the main objectives of this project.

Different measures for the value of stochastic modelling are reported in the literature (Birge 1982, Maggioni and Wallace 2010) and many of them have also been applied to hydropower scheduling (Fleten and Wallace, 2003). A few of these methods have been investigated in project memo Validation methods for SHARM, for the purpose of comparing the results from SHARM to the deterministic method. The problem with most of these methods is that they do not consider how the deterministic model is actually used in the hydropower companies. Operators have the opportunity of rescheduling within the week and often even within the day if new information is obtained. The system is not locked to the deterministic decisions for an entire week at a time. If scheduling is made on Monday, one has the chance of updating the strategy on Tuesday, Wednesday and so on if new information or updated forecasts indicate that something must be changed. The decisions already taken cannot be reversed, and if bad decisions are taken on Monday there might not be possible to make up for this later in the week.

The process of continuously monitoring and rescheduling the release of water require resources in terms of people and knowledge at the hydropower companies, and the combined effort make up what in this report will be called *the deterministic method*, *the deterministic strategy* or *current industry practice*. We choose these terms over "the deterministic model" to emphasize that the process of hydropower production scheduling involve much more than just running an optimization model. The model gives results that should be close to physical schedules, but modifications made by the operators are an integral part of the final scheduling strategy. Information and knowledge that cannot be represented in the mathematical model such as the level of risk aversion or other company strategies is left to the judgement of the individual operator. The optimization model only offers decision *support*, and in many cases not the final decision.

Our aim in hence to compare the results from the stochastic model with the current practice, and quantify any gains. For this purpose, some of the methods reported in the literature are too simple, or at least need some adaptations to fit our purposes. Two test procedures have been developed in the project, called the mean trees test and the production schedule test. These are explained in Sections 3.2 and 3.3. However, even these methods have their drawbacks. As stated in the previous paragraph, we want to compare the final scheduling strategies from the stochastic and deterministic model. Both strategies actually include several integrated processes such as forecasting, obtaining results from the optimization model, evaluating and adapting results, monitoring the state of the system, rescheduling etc. in a continuous loop, see Fig. 3-1. By switching to a stochastic model, the optimization procedure is changed, and this will affect the other processes and the final scheduling strategy. However, the overall process might not change that much, i.e. there will still be opportunities for rescheduling, updating information and other modifications when using the stochastic model. Thus, we really want to measure the gain of using the stochastic strategy compared to using the deterministic strategy, where we in both cases use the term *strategy* to include not just the results from the optimization models, but the overall effort to generate a production schedule for the system. Evaluating this would require running the models in parallel over an extended time period or testing on several years of historic data. This would require too much resources and data that may not exist or are subject to confidentiality, and would also diminish the resources for further developing the software.

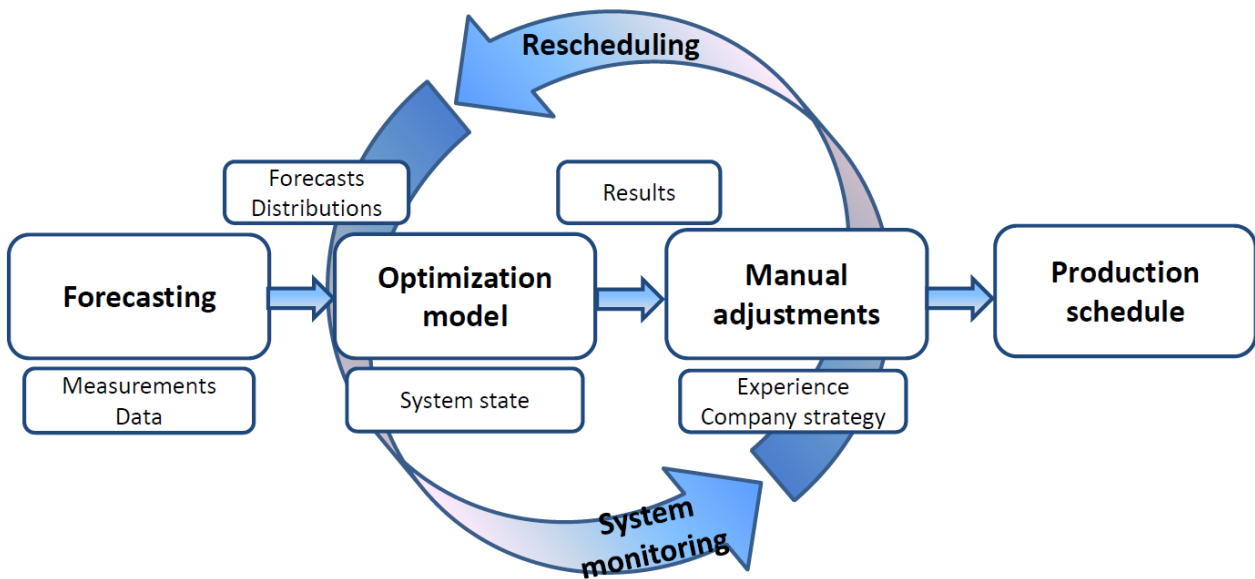


Figure 3-1: Illustration of the process for determining an optimal production schedule. We want to assess the costs and benefits by changing the optimization model from a deterministic model (SHOP) to a stochastic model (SHARM).

The test procedures to be presented in Sections 3.2 and 3.3 are a compromise between the objective stated above and what has been possible within the project period, with regards to resources at the partner companies and available data. The tests have been developed in cooperation with the industry and deemed valid as they extend some of the measures reported in the stochastic programming literature to our purposes. Examples of the test procedures applied to real cases from the hydropower industry are reported in Chapter 4.

3.3 The mean trees test

To quantify any gains of using a stochastic model over a deterministic model for developing the scheduling strategy, the expected profit from operating the system according to the decisions from each of the two models should be compared. The usual planning horizon for short-term scheduling is 7-14 days, but it is only the decisions for the first 24-36 hours that are used. The longer time period is kept for consistent coupling to longer-term models. The short-term model is run daily with updated information on future prices and inflows for the coming week. In practice, decisions may be rescheduled several times during the day based on the most recent information on prices and inflows. The method for comparison must take into consideration this rolling horizon-approach of using the models, and try to simulate the rescheduling process as close as possible. It is therefore too simple to compare the results from the stochastic and deterministic model directly for the full week, as this would not reflect the opportunity for rescheduling during the week or day.

In real operations, it is always possible to change future decisions based on newly acquired information, and this is why a deterministic model in many cases performs sufficiently. However, for the assessment of added value of stochastic modelling, it is necessary to develop a simulation strategy that reflects how the deterministic model is used with updated information throughout the week. The results from using this updated deterministic strategy will then be compared to using the decisions from the stochastic model. Our chosen approach for comparing the two models is that the profit from the deterministic decisions is evaluated with respect to the scenario tree used for the stochastic model, using a step-by-step approach as described below. By taking this approach we try to quantify how well a deterministic approach will perform compared

to the stochastic, if we assume that the scenario tree is the true distribution of uncertainty throughout the week. Our selected approach implies that the expected profit from the stochastic model will always be evaluated to be equal to or higher than that from the deterministic model, as illustrated in Fig. 3-2.

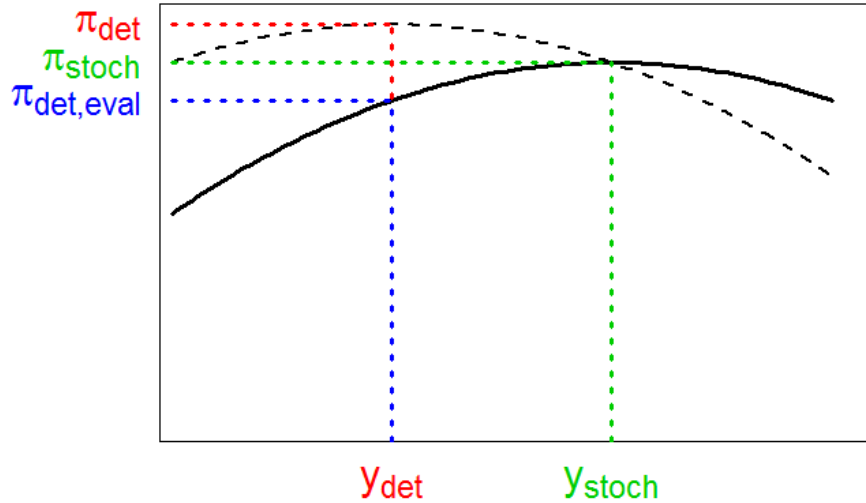


Figure 3-2: Expected profit π from the stochastic model (full line) and the deterministic model (dashed line) for a one-dimensional decision variable y . The values π_{stoch} and π_{det} are the expected profits for the optimal decisions y_{stoch} and y_{det} , and $\pi_{det,eval}$ is the expected profit for decision y_{det} evaluated with respect to the scenario tree.

The expected profit from operating the system according to the optimal decisions from the deterministic model is evaluated by a step-by-step procedure similar to that presented by Follestad, Wolfgang and Belsnes, 2011. Optimal first-stage decisions are computed for a set of deterministic sub-problems at each branching point of the scenario tree. A branching point is a point in time when at least one branching occurs in the scenario tree. The decision variables include scheduled production on each generator or pump and discharge in each gate and bypass gate. The approach is illustrated in Fig. 3-3.

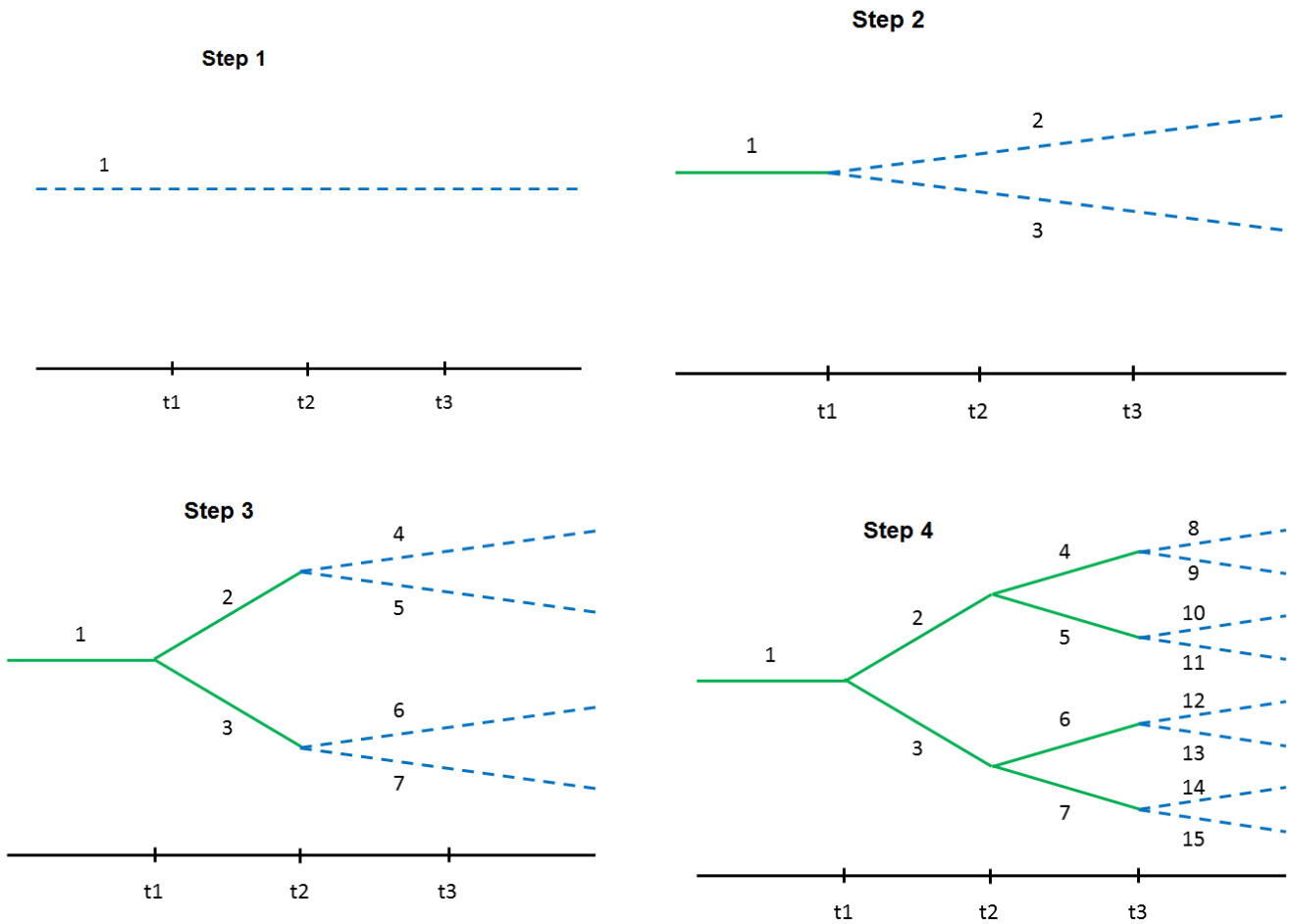


Figure 3-3: Subtrees used in the consecutive runs for developing the deterministic strategy in the mean trees test.

Referring to Fig. 3-3, in Step 1 the optimal solution to the deterministic problem for the whole planning period is found. The deterministic forecast is computed as the point-wise probability weighted mean, thereof the name *mean trees test*. The three remaining steps correspond to the branching points at t_1 , t_2 , and t_3 . At each branching point one deterministic sub-problem is specified for each successor branch, using the mean values of the future scenarios seen from the branching point as input for stochastic parameters. All sub-problems at each branching point are solved simultaneously by a single run of SHARM, keeping decision variables for time points prior to the branching point fixed to optimal values from previous steps. In Step 2 there are two successor branches at t_1 , leading to two deterministic sub-problems. For example, branch 2 in Step 2 equals branch 2 in the full tree between t_1 and t_2 , the weighted mean of branches 4 and 5 between t_2 and t_3 , and the weighted mean of branches 8-11 from t_3 and onwards. The sub-problems for branches 2 and 3 are solved simultaneously by running SHARM using the scenario tree consisting of the three branches 1, 2, and 3 in Step 2, keeping the decision variables for branch 1 fixed to the optimal values from Step 1. Since no path from time t_1 and onwards share the same branches, the results should be similar to the ones obtained by solving each of the two deterministic sub-problems one at a time. At Step 3 there are four deterministic sub-problems. In the single SHARM run at this step, decision variables at branch 1 are kept fixed to the solution from Step 1, and at branches 2 and 3 the values are fixed to the solutions from Step 2.

The final step (Step 4) corresponds to solving the stochastic problem for the full scenario tree, but fixing all decisions prior to branching point t_3 to values obtained from previous steps. This step is equivalent to evaluating the objective function for the deterministic decisions, but using the forecast distribution defined by the full scenario tree. The optimal objective for the final step is therefore the sought for value for the

expected profit for the updated deterministic strategy. In the rest of this report we refer to the strategy obtained from this process as the updated deterministic strategy or the deterministic solution, and the test procedure of comparing this strategy to the stochastic solution is referred to as the *mean trees test*.

A drawback of the mean trees test described above is that the branching factor for the sub-problems is reduced as the tree is traversed. In addition, the length of the remaining planning period decreases as we move from one branching point to the next. The future will become less and less uncertain as the tree is traversed, favouring the deterministic model. Thus, the approximation to the stochastic model for the remaining part of the planning period will become less accurate as the tree is traversed, and the value of the stochastic model is expected to be decreased. In addition, we do not allow the stochastic decisions to be updated with new information throughout the week. This means that no rescheduling of the stochastic decisions is done, and that the scenario tree generated on the first day of the week accurately describes the uncertain parameters for the whole week. The same scenarios are used for optimization and performance evaluation of the stochastic model, potentially favouring the stochastic model. What we do is to quantify the reduction in solution quality by using a deterministic model, if we assume that the stochastic tree represents the "truth". The rolling horizon approach presented in Fleten, Høyland and Wallace (2002), where new sub-trees and corresponding deterministic forecasts are generated for each branching node of the tree is an alternative that accounts for these shortcomings of the proposed approach.

3.4 The production schedule test

The fact that the stochastic solution is not updated during the week in the mean trees test make the test somewhat unrealistic as this is not the way the stochastic model would be used in real operations. The stochastic model will be used in the same manner as the deterministic model is used today, that is, daily runs of the model will generate a solution for the full week, but only the first 24-36 hours are used before the model is run again with new information the next day. Hence, it is only the decisions for the first 24 hours that should be subject to comparison between the stochastic and deterministic model, as this is the production plan that is actually carried out in real operations. This led to the development of another method for comparing the stochastic and deterministic model, from here on referred to as the *production schedule test*.

In the production schedule test, two competing production schedules for the next day are generated – one from the stochastic model and one from the deterministic model. The deterministic production schedule can be generated based on mean values for the stochastic parameters or a user-selected scenario representing the "operational" or most likely scenario based on information about the current state of the energy system and weather conditions. The stochastic production schedule is generated based on a scenario tree description of the uncertain parameters, where the scenario tree can be a fan tree or a tree with branching throughout the optimization period.

A few subtleties exist, however, when generating a production plan from the stochastic model. When the underlying tree has more than one scenario for the scheduling time steps, the stochastic model gives out optimal decisions for all scenarios. These plans cannot be implemented as there is no way of knowing a priori which scenario will actually occur, and thus which plan to use. Had this been the case one would be better off using a deterministic model. It is only possible to get an implementable production plan from the stochastic model in time steps where the underlying tree has only one scenario, as shown in Fig. 3-4, where one can use the plan marked with red for the first 24 hours. This plan considers uncertainty after the scheduling time steps, but does not consider uncertainty within the operating day.

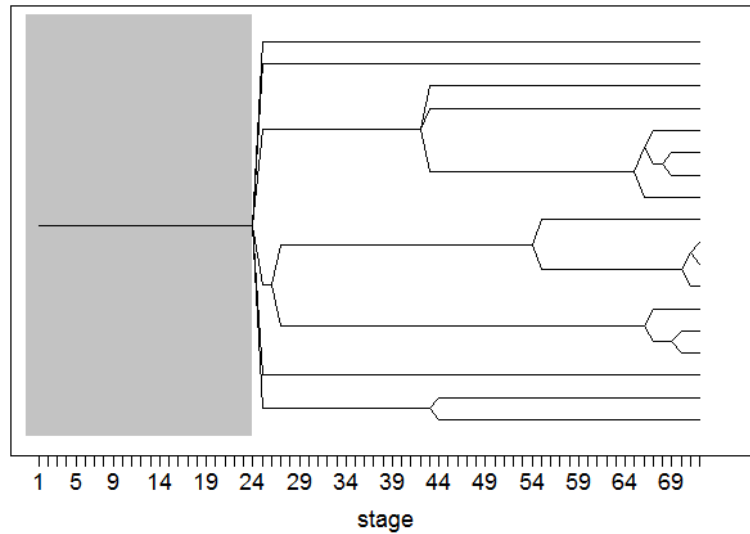


Figure 3-4: Scenario tree with 24-hour deterministic period in the start of the optimization horizon. The grey square indicate the hours where a single production plan should be obtained, and these hours are therefore modelled as deterministic

It is also possible to obtain an implementable production plan for the hours where the underlying scenario tree is not deterministic by using common decision variables as explained in project memo Introducing common decision variables in SHARM. This option will add constraints to the problem stating that the decisions on generator production, pump consumption and flow in main and bypass gates must be equal for all scenarios covering the current time step. The result is an implementable (physically feasible) production schedule from the stochastic model that is feasible for all scenarios in the tree, as shown in Fig. 3-5, where the decisions for the scheduling time steps 1-24 covered by the red lines are the same for each branch.

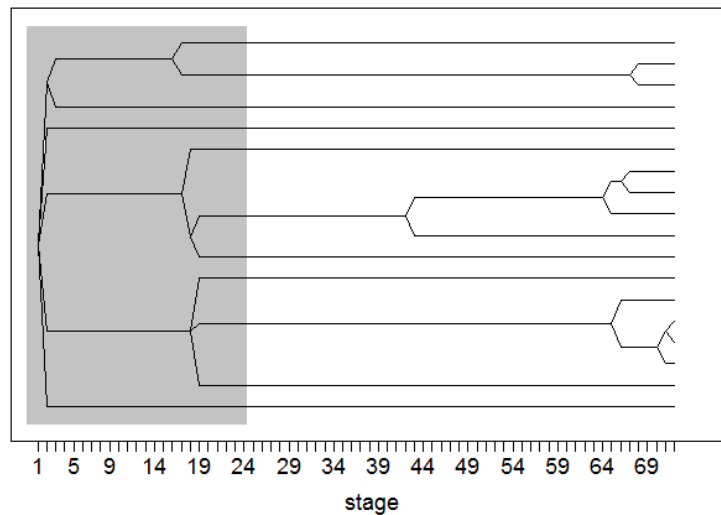


Figure 3-5: Scenario tree with stochastic structure for all hours after hour 1. The common decision period is marked with a grey square and a single production plan is obtained for all hours in this period.

Regardless of the method for generating the stochastic plan, the two competing production schedules (the schedule from the deterministic model and the schedule from the stochastic model) are evaluated based on how they perform for the full scenario tree. The full scenario tree may be a fan tree or a tree with branching, and it may be the same as the tree used to generate the stochastic plan or another tree representing the "true" distribution, i.e. we can test both in- and out-of-sample. The production schedule test is accomplished by four runs of the SHARM model; one deterministic run to generate the deterministic plan, one stochastic run to generate the stochastic plan and then two runs with the full scenario tree to evaluate the plans for all scenarios in the tree. This is shown in Fig. 3-6.

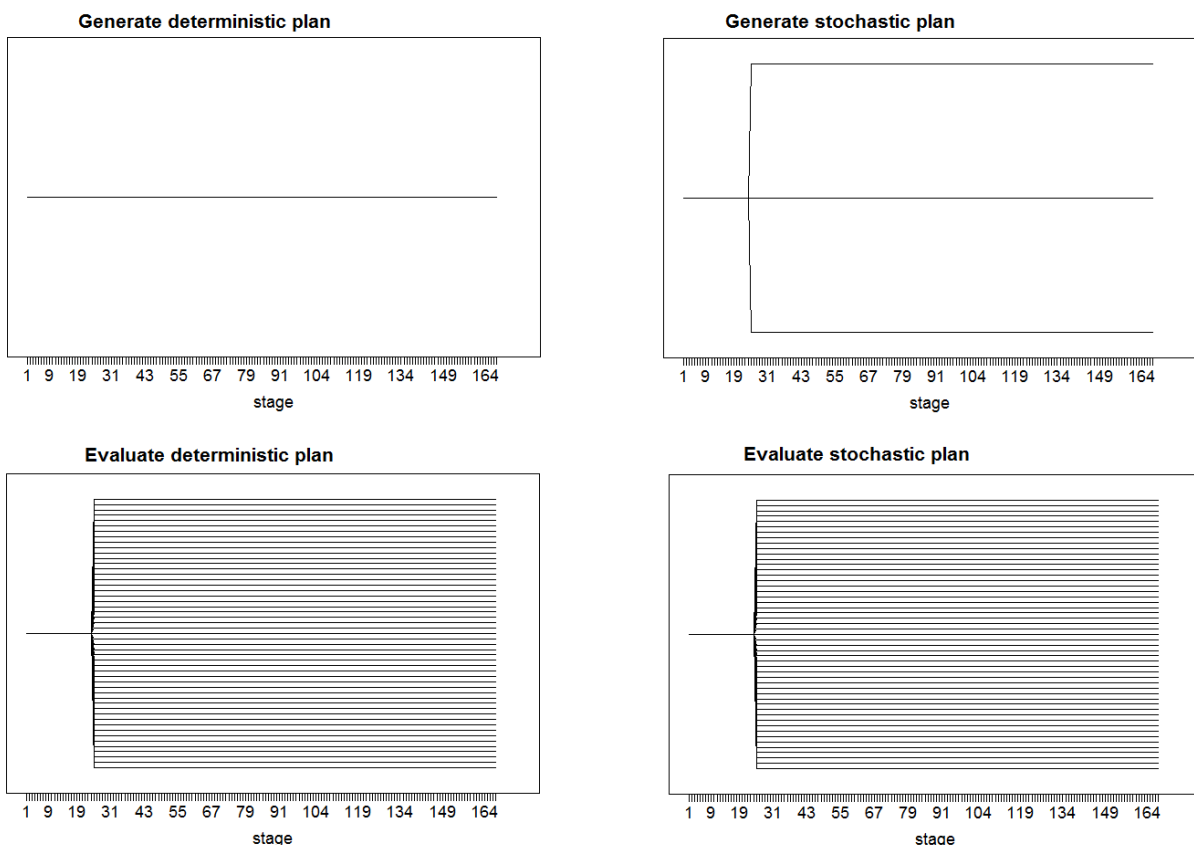


Figure 3-6: Illustration of the four SHARM runs in the production schedule test.

A drawback of this method of comparison is that it only gives a point-estimate of potential gains of stochastic modelling, as the results are only valid for one day. The test would have to be repeated for consecutive days in order to give results that are valid over time. The mean trees test aims at simulating the effect of using a stochastic or deterministic model over the course of a week, and is hence a step closer to evaluating the potential gains over time, but has the drawback the stochastic solution is not updated with new information. The production schedule test is an accurate description of how the stochastic model will be used in real operations for one day.

3.5 Scripts for automating the test procedures

In order to accommodate easier testing by and in the participating companies, a collection of scripts and programs are available with the SHARM software, called SHARM Toolbox. The scripts are mostly implemented in R while some of the larger programs are written in C++. Particularly important is a method for scenario tree generation and reduction based on the work reported in Heitsch and Römisich, (2003), Gröwe-Kuska, Heitsch and Römisich, (2003) and Dupačová, Gröwe-Kuska and Römisich, (2003) which has

been included in the toolbox as described in project memo AN 09.12.74 Scenario generation and scenario reduction for short-term hydropower scheduling models.

The toolbox programs can be called from an Excel macro-enabled spreadsheet to run both the mean trees test and the production schedule test. The details of how to use this test framework is given in project memo User Manual for SHARM Toolbox and are not reported here. We include this small description in the report since some of the statements from the participating hydropower companies may mention the SHARM Toolbox and the reader should be familiar with the name. For most partner companies, the Excel spreadsheet has functioned as a very simple "user interface" for SHARM during the project period, and important tasks such as specifying input, generating scenario trees, running the optimization model, running tests and comparing results has been controlled from here.

4 Test Results

This chapter will present results from testing the SHARM model in the hydropower companies. The results presented here are examples of what has been reported by the industry, or results from SINTEF based on data supplied by the industry partners. Results from all participating companies are presented to show the watercourse topologies that have been tested and illustrate some of our findings. There are some inconsistencies in the results which will be further addressed in Chapter 5. Since only a few cases are presented here, general conclusions cannot be drawn based on these results alone. Confidential reports that summarize the testing done by each partner company are available for internal use at each participating company. The statements given from all participating companies in Chapter 8 summarize the results of the total effort each producer has put into the testing of SHARM.

4.1 Mørre reservoir

The Mørre system consists of one power plant and one reservoir and is owned and operated by TrønderEnergi Kraft AS. The installed capacity of the plant is 14 MW and the annual production is about 50 GWh. The reservoir is mostly surrounded by mountains which make it hard to predict when actual inflow peaks will occur. This system has been tested for inflow uncertainty for a 168 hour period for different times of the year. The contact person at TrønderEnergi has been Dan Soknes.

4.1.1 Results from the mean trees test

The mean trees test has been run for the Mørre system using SHARM Toolbox. Finding test cases has been time consuming due to limited availability of data, but a few cases for different times of year and operating conditions has been analysed during the project period.

For a week in March 2015, the following scenario tree was generated based on ensemble scenarios from the HBV model. The tree was obtained using prescribed branching points every 24 hours for the first 5 days, after which all uncertainty is assumed resolved. The tree structure and the inflow values can be seen in Fig. 4-1. The initial reservoir level is very high.

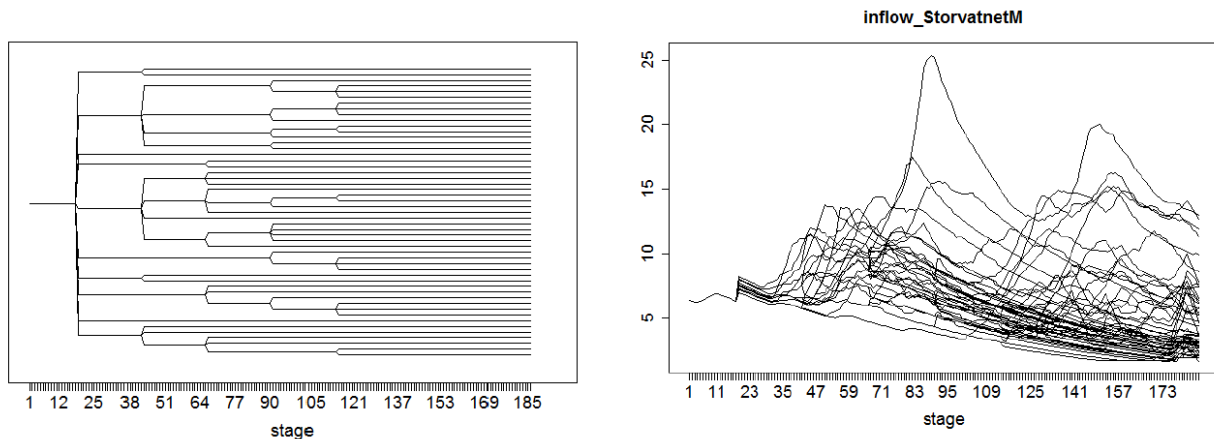


Figure 4-1: The scenario tree structure and the inflow time series values for Storevatn.

The results from the mean trees test are very similar for the deterministic and stochastic strategy, and no significant gain can be measured. The reason for this might be that regardless of the high initial reservoir level, inflows are not predicted to be very high so the risk of spill is actually quite low. The maximum discharge at the plant is large enough to handle even the highest inflow scenarios. The strategy for both the deterministic and stochastic solutions is to produce at a steady level near maximum production and thereby reduce the reservoir level throughout the horizon. This can be seen from the plot of the mean reservoir level for the stochastic and deterministic solution in Fig. 4-2.

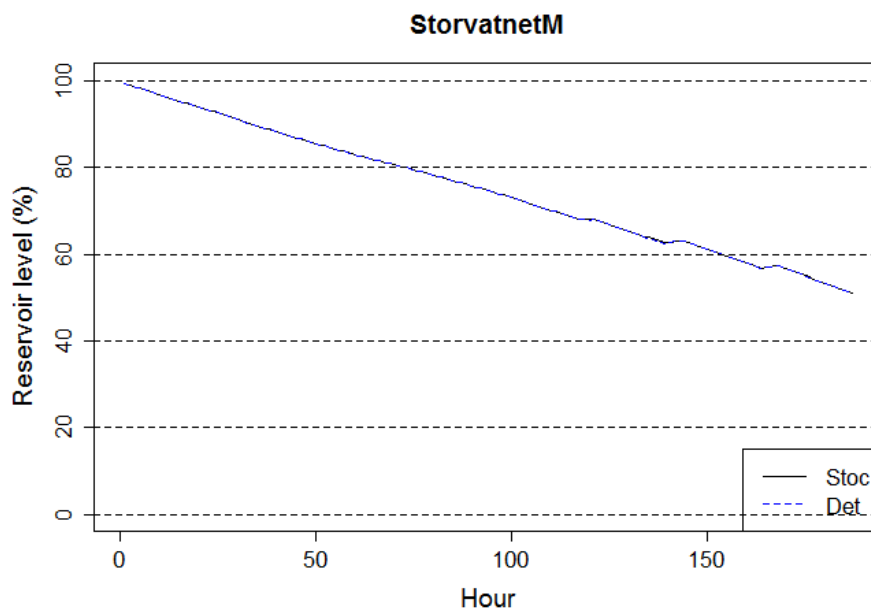


Figure 4-2: The mean reservoir level for the stochastic and deterministic strategy in the mean trees test.

The difference in objective function value between the stochastic and deterministic strategy is about 20 NOK for the 168 hour period. This is not a significant value and only make up about 0.02 % of the total objective function. Results from the mean trees test for a few different dates are shown in Table 4-1. For all days except Day 6 and Day 4 the stochastic and deterministic strategies show no significant differences. For Day 6, the total difference is about 1700 NOK. For Day 4, the difference is 290 NOK in favour of the

deterministic strategy. Negative gains (losses) should not be possible in this test framework. Similar inconsistencies occur when testing for other reservoir systems and are addressed in Chapter 5.

Table 4-1: Results from the mean trees test for Mørre.

| Day | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|----------------------|------|-------|------|------|------|------|------|------|------|
| Difference (NOK) | 20 | -118 | 12 | -290 | 50 | 1694 | 15 | 50 | 4 |
| Difference (Percent) | 0.02 | -0.01 | 0.00 | -0.6 | 0.04 | 3.48 | 0.02 | 0.04 | 0.00 |

4.1.2 Results from the production schedule test

The production schedule test is run for the same data set from March 2015. The results showed no significant difference between the plan generated from the stochastic and deterministic model. The test was performed with a 24 hour deterministic period at the start of the tree and then common decision period in the planning period in hours 25-48. The obtained plans were exactly the same, resulting in a difference in objective function values of less than 1 NOK. Results from the production schedule test for two different days can be seen in Table 4-2. The result for Day 1 is not significant, but at least illustrate that SHARM is able to reproduce the solution from the deterministic model.

Table 4-2: Results from the production schedule test for Mørre.

| Day | 1 | 2 |
|----------------------|-------|------|
| Difference (NOK) | -0.14 | 145 |
| Difference (Percent) | 0.00 | 0.12 |

The Mørre system has a simple topology of only one reservoir with a downstream plant, which should be manageable as long as the inflow level and uncertainty is not too large compared to the capacity at the plant and there is some flexibility in the reservoir. It is easy to set up cases for Mørre where the benefit from stochastic modelling is large, for instance by starting at a high initial reservoir level and giving inflow distributions that show increasing inflows which may become larger than the capacity of the plant. This situation of limited flexibility has shown over 10% improvement from stochastic modelling which would be a substantial result if it occurred in practice. It seems, however, that these situations occur due to inconsistencies in the relationship between the initial state of the system and the water value. Given the situation explained above, the water value should be low indicating that water should be released to prevent spill. If the water value is adjusted accordingly, the difference between the stochastic and the deterministic strategies diminishes. This implies that a consistent coupling to or improvements in the long-term models may be just as valuable as stochastic modelling of short-term hydropower scheduling.

4.2 Langvatn reservoir

SHARM has been tested for another one-reservoir system, Langvatn which is owned and operated by Statkraft Energi AS. The installed capacity is 90 MW and the annual production is about 242 GWh. The reservoir has a large catchment area and the flexibility is low due to the relative small volume of the reservoir. Any gain of stochastic modelling for this system is thought to be due to decreased spillage. The contact persons at Statkraft has been Tellef Juell Larsen and Fredd Kristiansen.

4.2.1 Results from mean trees test

SHARM has been tested using the mean trees test for a chosen date in January 2015. Inflow to the reservoir is stochastic, while price is kept deterministic. The scenario tree structure is shown in Fig. 4-3.

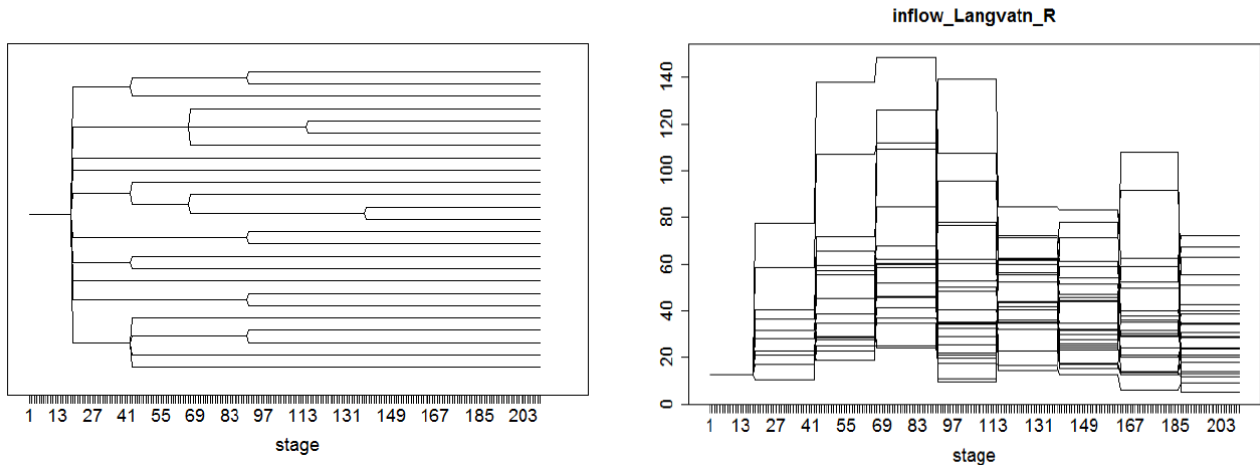


Figure 4-3: The scenario tree structure and the inflow time series values for Langvatn.

The deterministic strategy has some spill which the stochastic strategy is able to avoid by producing slightly higher volumes in some hours early in the period. The initial reservoir level is high, but even the highest inflow scenario is only slightly higher than the discharge capacity of the plant below, and hence the risk of spill is actually quite low. The deterministic model fails because the solution dictated by the mean scenarios release too little water prior to the inflow peaks and result in spillage in some of the highest scenarios. The difference in objective function value is about 0.3 % of the total objective function value. This value is influenced by the penalty cost for spillage set by the user or default values in the software, and may be overestimated.

4.2.2 Results from production schedule test

The production schedule test is run for a dataset from July 2013 with an 18 hour deterministic period followed by the planning period in hours 19-42 where the common decision constraint is applied. Here, inflow is deterministic and price is stochastic and represented by 27 scenarios in a fan tree. The production plans from the stochastic and deterministic models are similar and the unit commitment decisions are the same except that the production varies a few MW for hours 3-7 where the price has a small dip, see Fig. 4-4.

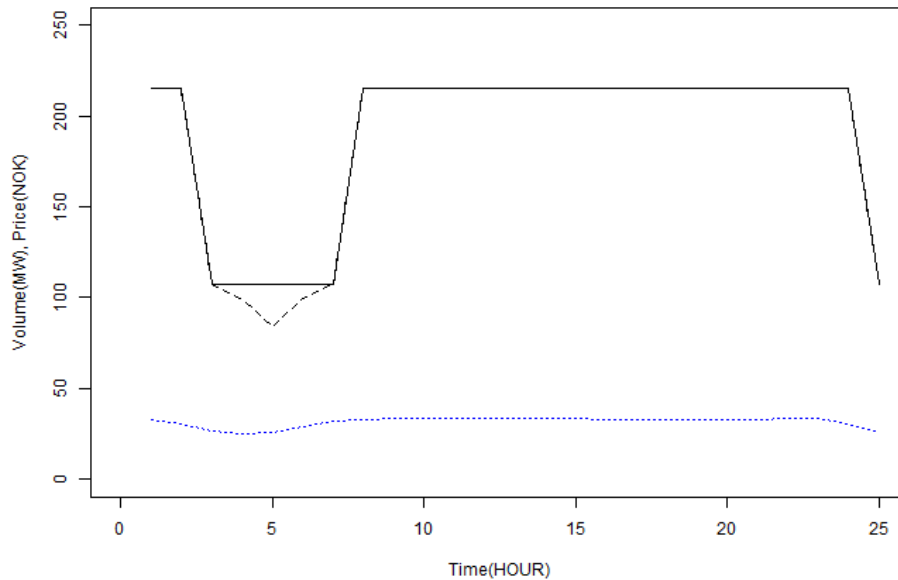


Figure 4-4: The production schedule from the stochastic (straight line) and deterministic (dotted black line) strategy in the production schedule price. The dotted blue line is the average price for all scenarios.

The objective function values show a *loss* of 0.06 % of the total objective function value by using the stochastic strategy for the full tree. By design, it should not be possible for the production schedule test to yield a negative result, even if the value is very small as in this case. The flat best-point production in hours 3-7 from the deterministic model seems like a better decision than the more varying production of the stochastic model. The decision to produce less in the stochastic plan may be due to the common decision constraint, and the effect of this restriction is assessed in Chapter 5.

4.3 Hemsil reservoir system

The Hemsil reservoir system consists of four reservoirs and four plants, as illustrated in Fig. 4-5. The system is owned and operated by E-CO Energi AS and contact persons have been Rita Berthelsen Johnsen and Tor Halvor Bolkesjø.

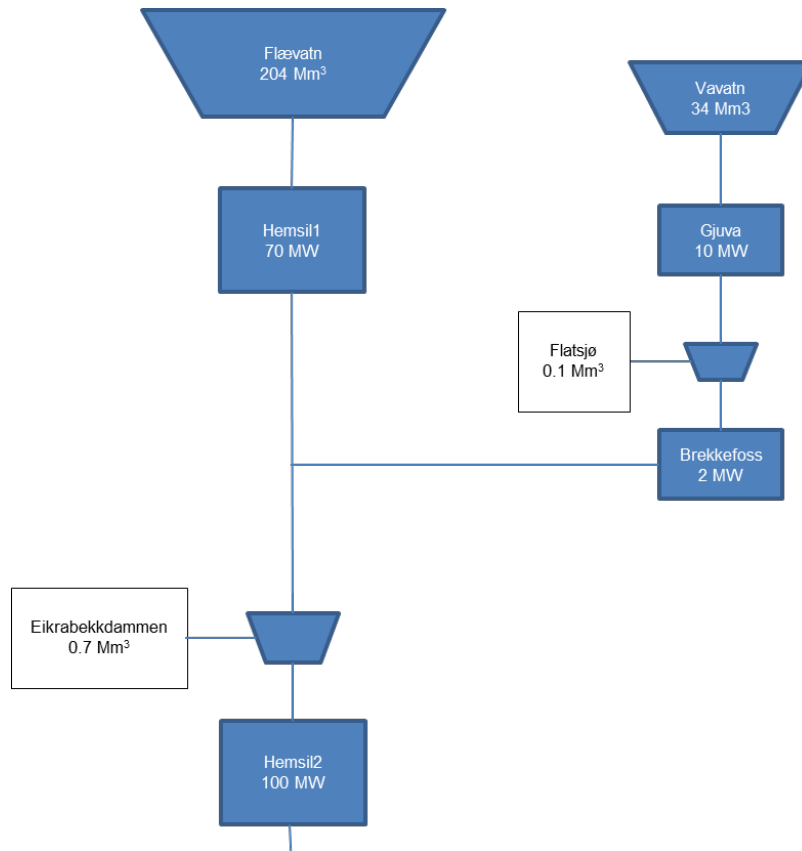


Figure 4-5: Illustration of the Hemsil reservoir system.

Some characteristics of the system are given in Table 4-3. The small Eikrabekkdammen reservoir has to handle all the discharge from the upstream reservoirs and its own uncertain inflow. When using the deterministic SHOP model in real operations, safety limits on the reservoir storage level is applied to Eikrabekkdammen in order to limit the optimization model from utilizing the reservoir too boldly.

Table 4-3: Specifications for the Hemsil reservoir system.

| Power plant | Reservoir | Reservoir size (Mm3) | Annual discharge (Mm3) | Capacity at plant (m3/s) | Capacity at plant (MW) | Comment |
|-------------|-----------------|----------------------|------------------------|--------------------------|------------------------|------------------|
| Gjuva | Vavatn | 34 | 34.7 | 3 | 10 | |
| Brekkefoss | Flatsjø | 0.1 | | 4.5 | 1.5 | "creek intake" |
| Hemsil 1 | Flævatn | 205 | 217 | 16 | 70 | |
| Hemsil 2 | Eikrabekkdammen | 0.7 | 459 | 31 | 98 | Daily regulation |

When testing SHARM, inflow to Eikrabekkdammen is considered uncertain while the other reservoirs have deterministic inflow. The optimization period is 168 hours, and scenarios for inflow are obtained from the HBV ensemble scenarios.

4.3.1 Results from mean trees test

The mean trees test is set up for a dataset corresponding to the information available and system state for a day in August 2014. The scenario tree for inflow is generated with a 24-hour branching period, and can be seen in Fig. 4-6.

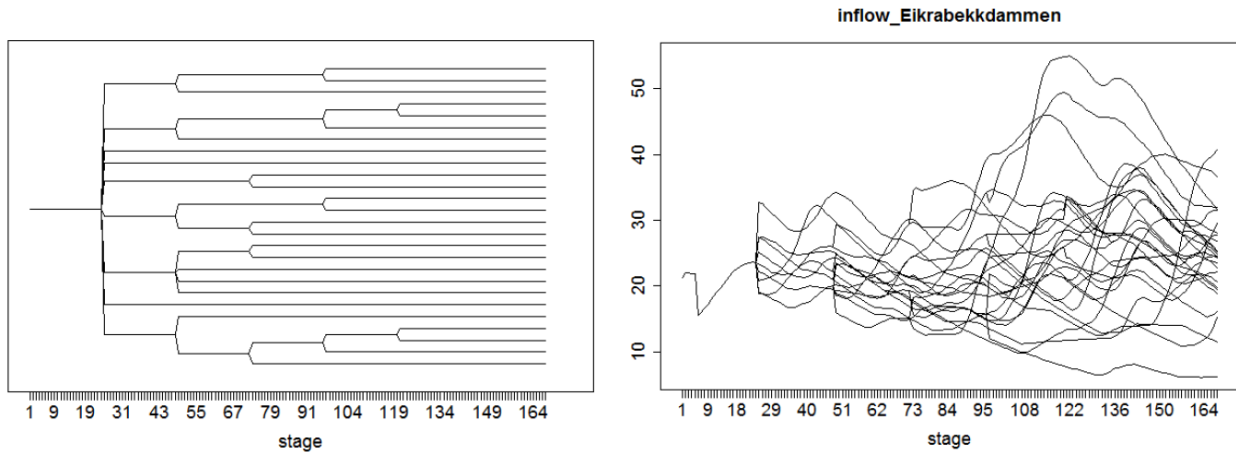


Figure 4-6: The scenario tree structure and the inflow time series values for Eikrabbekdammen.

As seen from Fig. 4-6, higher inflows than the capacity at the downstream plant Hemsil2 may occur in this period. Initial reservoir levels are around half the total reservoir volume.

The results show an improvement for the stochastic strategy due to less spillage from Eikrabbekdammen. The difference in objective function value over the one week horizon is over 3 MNOK which make up 2.8 % of the total objective function value. This is a very large gain if it is obtainable on an average basis, and is mainly due to avoided spill penalty costs in the stochastic strategy. This can be seen from Fig. 4-7 which shows the reservoir level at Eikrabbekdammen for the three scenarios with most spillage. The stochastic strategy clearly handles the reservoir better, and avoids spill in all scenarios.

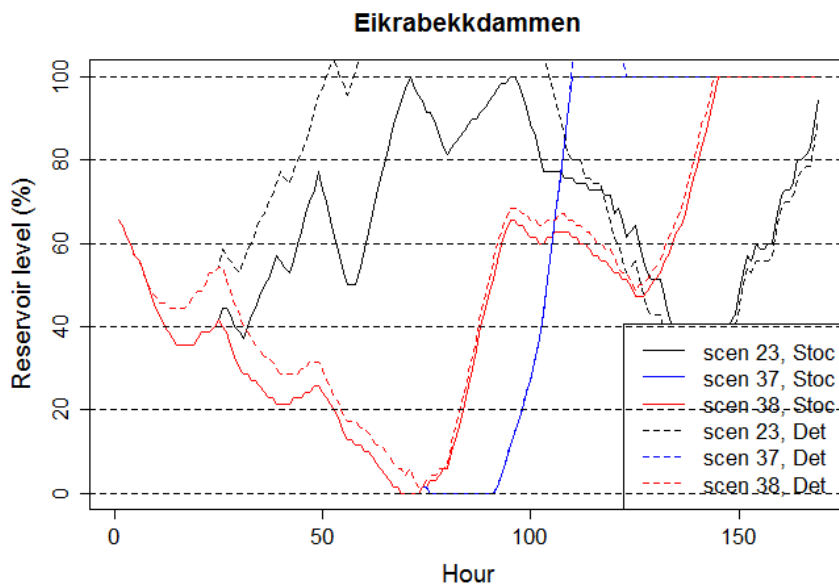


Figure 4-7: The reservoir level at Eikrabbekdammen for the three scenarios with highest spill.

However, the monetary gain of 3 MNOK for this case is overestimated by the penalty cost values used in the test framework. These costs are often set unreasonably high in order to avoid certain production patterns, but here the same values are used for valuation of the stochastic model. For a realistic estimate of the value of stochastic modelling, all penalty costs should represent the real-world cost of breaking a constraint. An alternative is to disregard any decreases in the objective function due to incurred penalties, but this would underestimate the added value from SHARM. If penalties are disregarded in this case, the difference in objective function is about 20.000 NOK, which is 0.2 % of the total objective function.

Results from the mean trees test for two different dates can be found in Table 4-4. The results without penalties underestimate the value of SHARM while the results with penalties overestimate the value, and so the answer must lie somewhere in between. Unfortunately, the bounds obtained from the two results are not close and no firm conclusions can be made.

Table 4-4: Results from the mean trees test for the Hemsil system.

| Day | 1 | 2 |
|--|-----------|-----------|
| Difference without penalties (NOK) | -1 060 | 22 376 |
| Difference without penalties (Percent) | -0.00 | 0.21 |
| Difference with penalties (NOK) | 1 190 902 | 3 023 253 |
| Difference with penalties (Percent) | 1.74 | 2.79 |

4.3.2 Results from production schedule test

For the same day in August 2014, the production schedule test was also run. The test was performed with a 24 hour deterministic period at the start of the tree and then common decision period in the planning period in hours 25-48.

The difference in objective function value is 80.000 NOK which is 0.07 % of the total objective function. Penalty values are small here, and the difference is roughly the same when penalties are disregarded. The deterministic plan discharges more water from the upstream plants Hemsil1 and Brekkefoss than the stochastic model, filling up Eikrabekkdammen as it does not recognize that inflows might become large towards the end of the period. This leads to breaking of safety boundaries and in some cases spill.

Results from other runs of the production schedule test can be seen in Table 4-5. The percentage differences are here given in terms of the objective function value less the value of the initial reservoir storage level in order to compare differences incurred within the one-week optimization horizon.

Table 4-5: Results from the production schedule test for the Hemsil system.

| Day | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|----------------------|--------|-------|-------|--------|-------|-------|--------|--------|--------|
| Difference (NOK) | 80 274 | 6 325 | -810 | 19 886 | 2 616 | 1 662 | -5 336 | 41 775 | 64 067 |
| Difference (Percent) | 1.29 | 0.21 | -0.01 | 0.47 | 0.06 | 0.04 | -0.13 | 1.08 | 1.40 |

There are some inconsistencies in the results: The deterministic schedule should never perform better than the stochastic schedule when evaluated for the full tree and hence the difference in objective function should never be negative. Here it is negative for Days 3 and 7. The result for Day 3 may not be significant, but the negative result obtained on Day 7 has a large enough value for concern.

4.4 RSK East river system

The RSK East river system is owned by Hydro Energi AS and consists of four reservoirs and two plants. Reservoirs Isvatn, Holmevatn and Sandvatn are connected to the Kvanndal power station, and the Kvanndalsfoss reservoir is connected to the Suldal2 power station. Installed capacity is 200 MW and the annual production is about 820 GWh. Kvanndalsfoss is by far the smallest reservoir in the system, and is in that regard considered to be a bottleneck production-wise. This means that there is less flexibility than for the other reservoirs, and the occurrence of overflow is more likely.

When testing SHARM, each reservoir has been defined as an independent inflow group. In this way it is possible to maintain the properties of the physical system, and to let each reservoir have its own set of inflow forecasts. The inflow forecasts for each reservoir consist of a base case and four other cases ranging from -50% to +50% of the base.

Three unique forecasts are used for the market price; a base case, a minimum and a maximum price. For some of runs of the mean trees test, scale factors are applied to the three price series to yield up to 13 scenarios for price.

SHARM is tested for a one-week horizon in both the mean trees test and the production schedule test.

Contact persons at Hydro have been Hans Ole Riddervold, Knut-Harald Bakke and Ole Elvetun.

4.4.1 Results from the mean trees test

The mean trees test is run for a week in June 2014 for the tree structure shown in Fig. 4-8. The situation is dominated by high inflow risk and a downside risk related to price. The stochastic solution produces a more flexible plan, and manages the reservoirs better. Particularly, the stochastic solution prevents the Sandvatn reservoir from flooding, which the deterministic solution does not. The stochastic solution produces less than the deterministic solution, and it holds back more of the water in the largest upper reservoir, Holmevatn, which results in better management of Sandvatn reservoir, as seen from Fig. 4-9. We can also see that the stochastic solution is able to better cope with the downside risk of the nightly prices by holding back with more production in these periods.

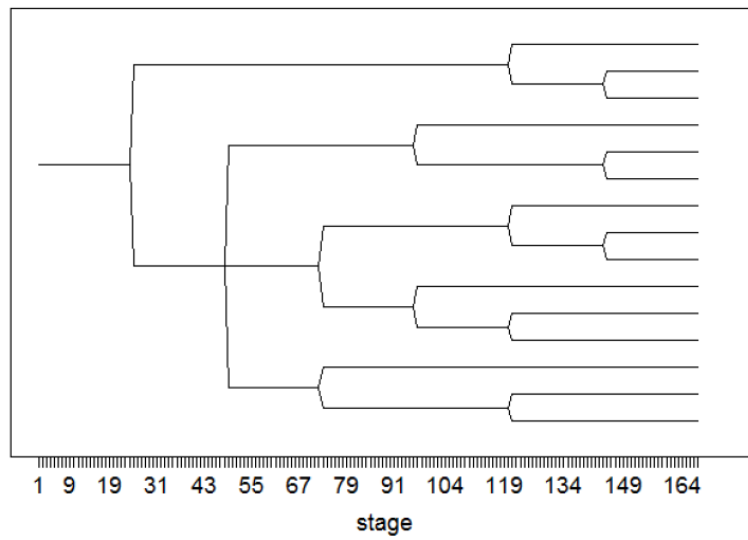


Figure 4-8: The scenario tree structure used in the mean trees test.

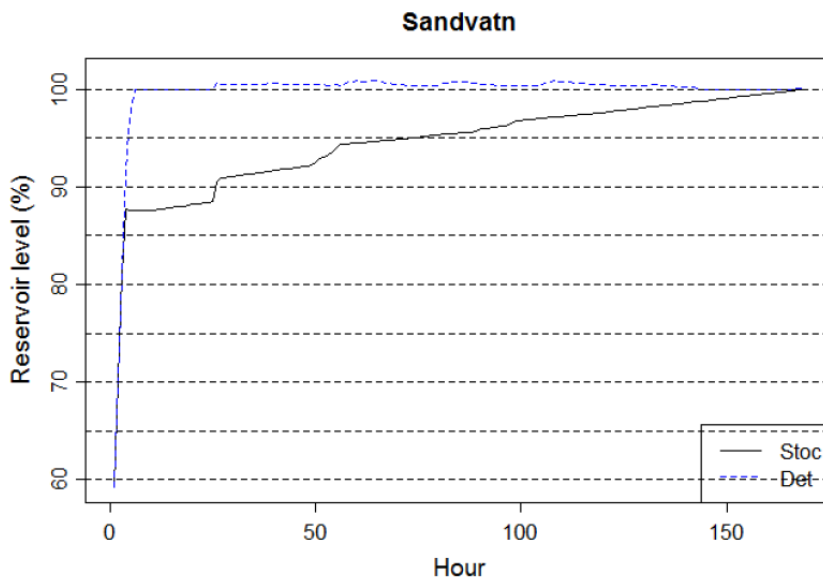


Figure 4-9: The mean reservoir level for Sandvatn in the stochastic and deterministic strategy.

Results from the mean trees test for different dates are shown in Table 4-6. For Day 4, the percentage value is calculated based on the total objective function less the value of the initial reservoir storage.

Table 4-6: Results from the mean trees test for RSK East.

| Day | 1 | 2 | 3 | 4 |
|----------------------|-----|-----|------|--------|
| Difference (NOK) | - | - | - | 40 933 |
| Difference (Percent) | 3.7 | 2.4 | 0.38 | 2.22 |

For all dates, penalty costs are incurred due to for instance spill. Penalty costs are included in both SHOP and SHARM to tell the user that the system is pushed to its limits, and to maintain the opportunity to get a valid solution in a broad range of cases. Some of the penalty costs are incurred due to the use of slack variables which are necessary in order to get feasible solutions. The idea is to first get a solution and then tell the user that boundaries have been exceeded with subsequent costs. SHARM contains no penalties in excess of the ones implemented in SHOP, and none of them are constructed to favor the stochastic over the deterministic alternative. Still, the opportunity of using different slack and penalty variables to get feasible solutions makes it hard to evaluate the value of stochastic modelling by the mean trees framework. The optimizations in successive branching points of the tree sometimes utilize different penalties in order to make up for bad decisions taken at an earlier time step. These decisions would in reality be irreversible, and in the cases where they are not the cost of using penalty variables should reflect the true cost of breaking the constraint and not some imaginary (and often too high) value. An example of a reversible decision taken at an earlier time step is the production volume, which can be changed closer to real-time by trading in the intra-day market. The penalty cost of breaking the production schedule should hence be the intra-day market price. The water released through different gates to move water is irreversible decisions that cannot be changed at later time step. Challenges regarding this behavior of the mean trees test are addressed in Chapter 5.

4.4.2 Results from the production schedule test

The production schedule test is also run for the RSK East system. An 18 hour deterministic period is used before the planning period from hour 19-42 begins. Common decision period is used in the planning period. For a day in January 2015, the production schedule from the stochastic model shows no improvements. The total difference in objective function value is -40 NOK, which is not significant.

Results for other dates are given in Table 4-7.

Table 4-7: Results from the production schedule test for RSK East.

| Day | 1 | 2 | 3 | 4 |
|----------------------|--------|--------|---------|-------|
| Difference (NOK) | -40.02 | -5 672 | -16 994 | 72.18 |
| Difference (Percent) | -0.00 | -0.01 | -0.02 | 0.00 |

Day 2 and 3 show negative values, which should be impossible due to the design of the test procedure. The values are not large compared to the total objective function, but show that there are inconsistencies in the tests we perform. These effects may have been introduced by using common decision period which require that the stochastic production schedule must be feasible for all scenarios, as further explained in Chapter 5. With common decisions, the production plan is sensitive to particularly risky scenarios, and once again influenced by penalty costs that may not have been assigned the correct values.

4.5 Mandal river system

The system that has been tested is similar to the Mandal river system operated by Agder Energi Kraftforvaltning AS and is made up of 7 reservoirs and 6 plants. Some additional power stations and creek intakes also belong to the same river system, but a simplified description of the topology has been used for testing the stochastic model due to the initial limited functionality developed in SHARM. The tested topology can be seen in Fig. 4-10. The discharge from the large top reservoirs Návavn and Juvatn end up in the common smaller reservoir Ørevatn which releases its water through a string of smaller series-connected reservoirs and plants. The scheduling challenge is to produce from the top reservoirs without causing spillage

for the downstream reservoirs. Particularly, the handling of Ørevatn is thought to be improved by considering uncertainty.

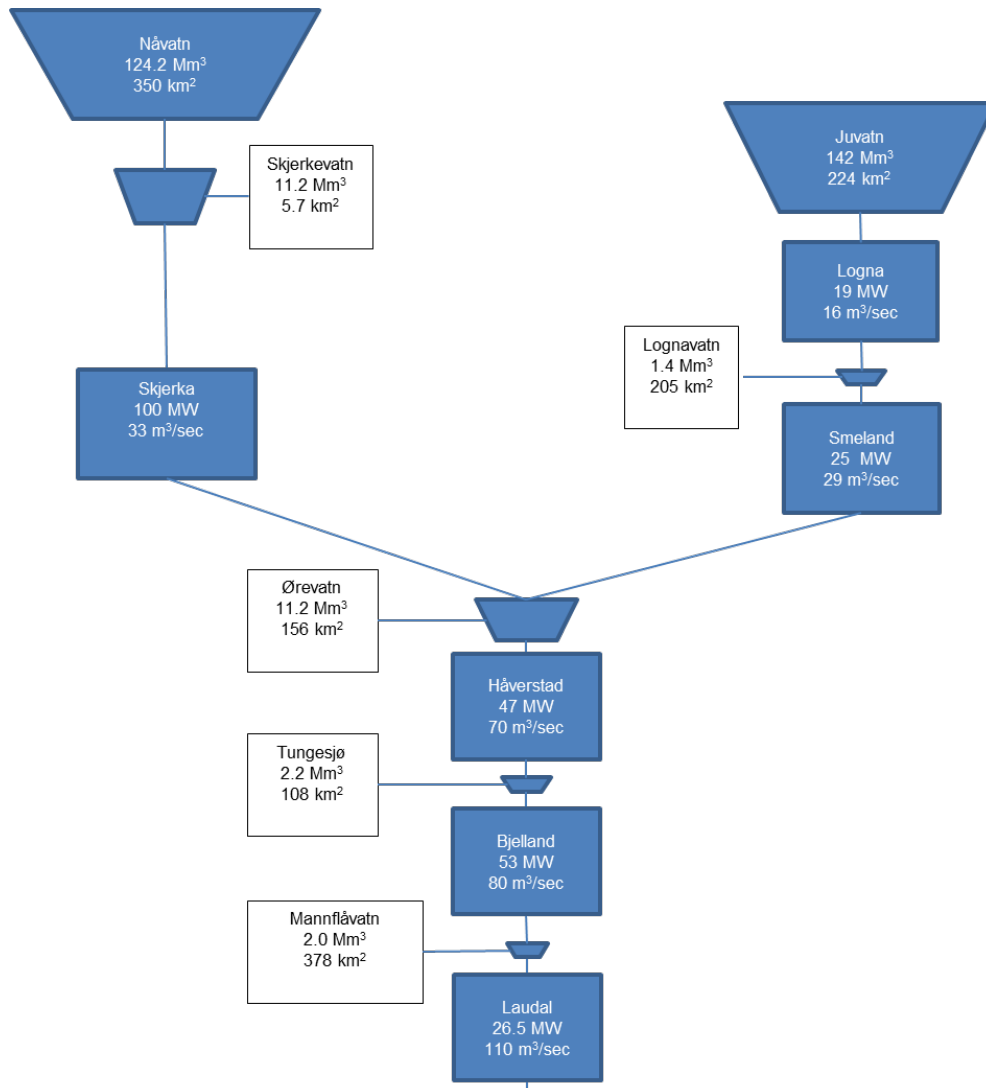


Figure 4-10: A schematic representation of the tested model for the Mandal reservoir system.

The operational deterministic SHOP model is used with safety limits on the reservoir level for some of the downstream reservoirs. This reduces the risk for spill as the reservoirs are not allowed to take on extreme values, but the production schedule is not optimized according to the uncertain inflow. The hope is that a stochastic model will produce a more conservative reservoir management strategy, avoid spill and give additional gains. These safety limits are removed for the case shown here.

The Mandal river system is tested for inflow uncertainty over the course of a week. The 51 inflow scenarios are generated by feeding the 50 ensemble results from the EC weather forecasts into the HBV model. The 51th scenario is generated from the main EC result. The Mandal system is the most complicated topology of all the SHARM test systems and it has proved difficult to get quality results, particularly for the mean trees test.

The contact person at Agder Energi has been Jarand Røystrand.

4.5.1 Results from the mean trees test

The tree structure used in the mean trees test and the values for the Ørevatn reservoir can be seen in Fig. 4-11. The inflow scenario tree is multi-dimensional and each of the reservoirs has its own inflow series except the two most downstream reservoirs Tungesjø and Mannflåvatn which share the same inflow series. Thus, there are 5 stochastic parameters at every node in the tree.

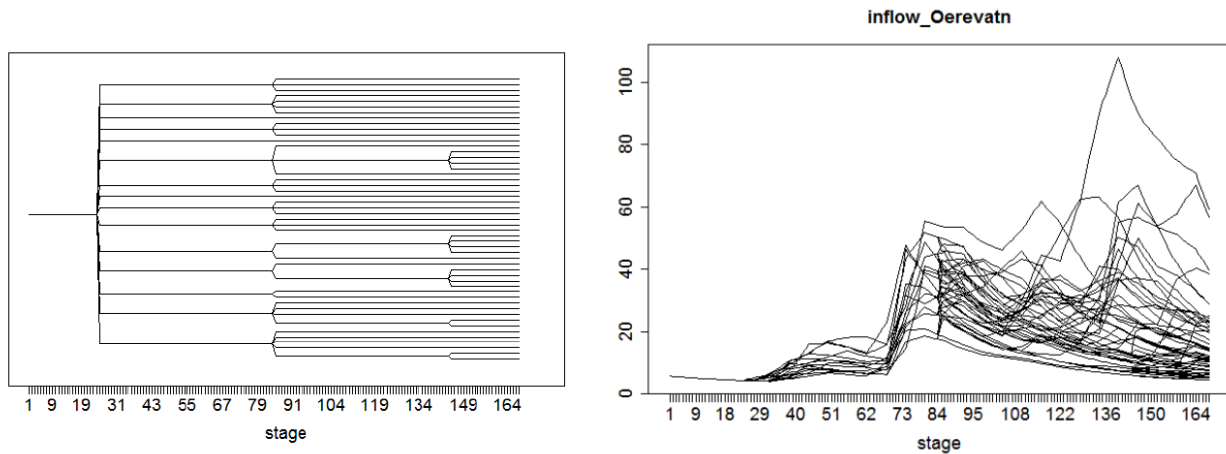


Figure 4-11: The scenario tree structure and the inflow time series values for Ørevatn.

The results show that the expected improvements occur at Ørevatn, as the plant below is run a bit harder in the beginning, thus reducing the spill when the peak inflow starts later on. This can be seen from the plot of the mean reservoir level over all scenarios for Ørevatn in Fig. 4-12.

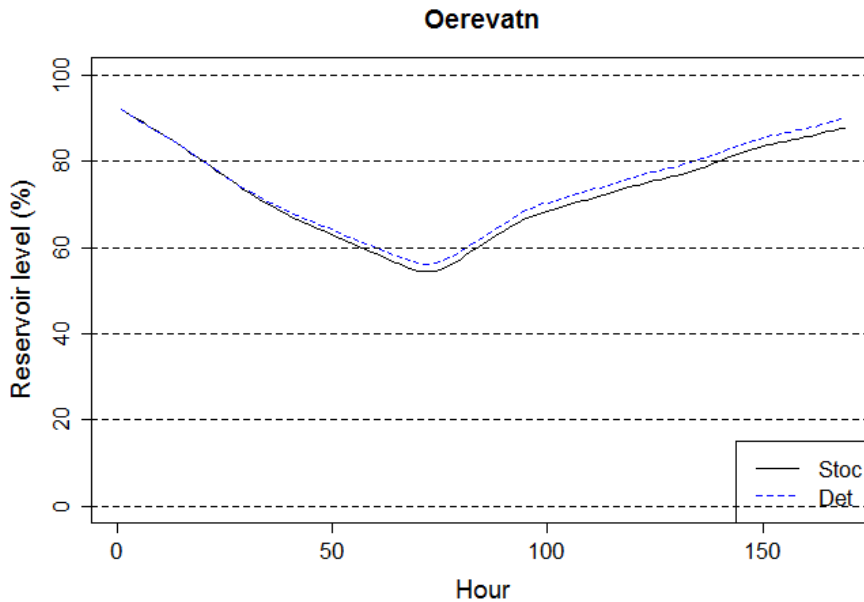


Figure 4-12: The mean reservoir level at Ørevatn for the stochastic and deterministic strategy.

In addition, there is less spillage when using the stochastic strategy than using the updated deterministic strategy, as seen from the plot of the percentiles of spillage from the most downstream reservoir in Fig. 4-13.

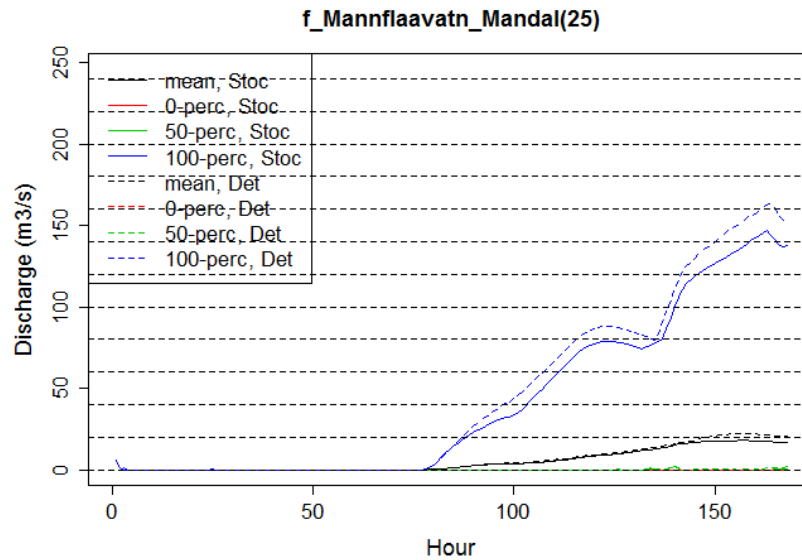


Figure 4-13: The percentiles for spillage from the most downstream reservoir, Mannflåvatn.

Regardless of the observed improvements described above, the objective function is actually less for the stochastic solution than for the deterministic. For the Mandal system we have not been able to get results where SHARM consistently gives better results than the mean tree comparison. In fact, quite the opposite happens: SHARM is evaluated to perform worse than the deterministic strategy in all cases run for this test system. According to the design of the test procedure, this is obviously an error. Even if production schedule and the reservoir management from SHARM seem like an improvement, the calculated objective favors the mean tree test.

The conclusion taken from the mean trees test for the Mandal system is that due to noise or errors in the calculations, we are unable to quantify the improvement from considering uncertainty – even if we to some extent can observe it as explained above. Unless these errors are adequately explained or sorted out, we must conclude that the improvement from stochastic modelling is drowning in noise, and thus must be rather small.

4.5.2 Results from the production schedule test

The production schedule test was run for the same data set as described for the mean trees test, and the results somewhat similar. The initial deterministic period is 24 hours and common decision constraint is used for the planning time steps in hours 35-48. The schedule from the deterministic model runs the Skjerka station more than the stochastic plan, while at the same time running the Håverstad station a bit less. This results in a higher reservoir level at Ørevatn prior to the higher inflow values. The production schedules for Skjerka and Håverstad are plotted in Figs. 4-14 and 4-15.

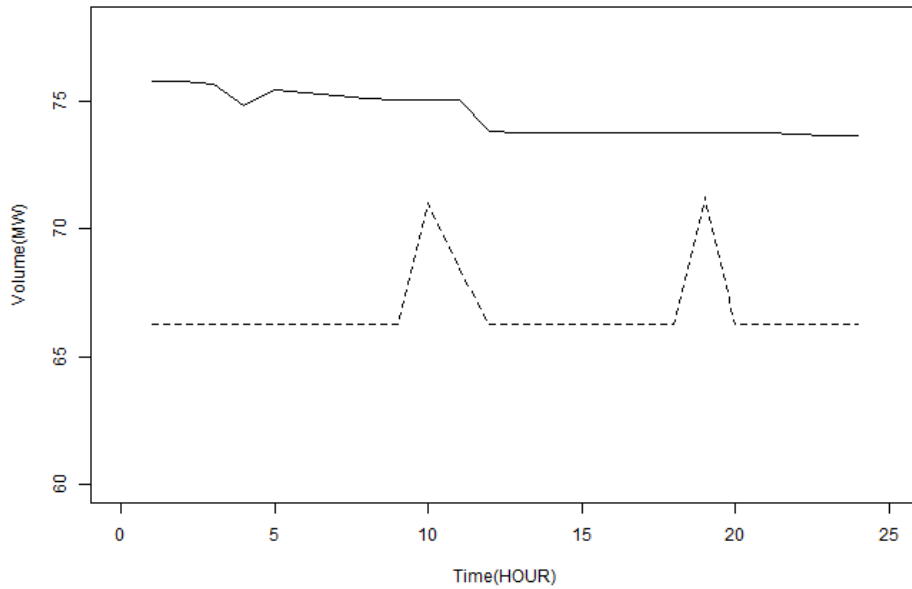


Figure 4-14: The schedules for Håverstad plant from the stochastic (straight line) and deterministic (dotted line) solution evaluated in the production schedule test.

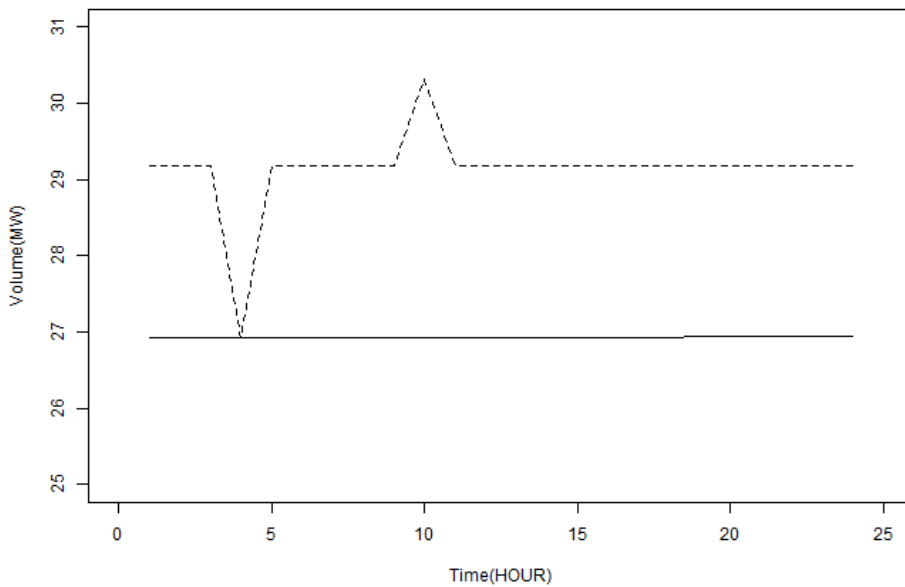


Figure 4-15: The schedules for Skjerka plant from the stochastic (straight lines) and deterministic (dotted line) solution evaluated in the production schedule test.

The objective function value show an improvement of 1300 NOK or 0.1% of the total objective function value less the value of the initial reservoir level. Considering the result of the mean trees test above, not much confidence can be put in this result.

5 Lessons learned

During the project period, working with SHARM and the test system resulted in new insight into the short-term production scheduling problem. This knowledge is particularly related to the use of penalty variables and subsequent costs and what these values actually represent in terms of real-world operation. We summarize some of the lessons learned in the rest of this chapter. All of these subjects have affected the results of our test procedures and some of them require further research in order to adequately assess the effects on our results.

5.1 Iteration logic and margins of error

Both the SHOP and SHARM software is based on successive linear programming where non-linear elements in the physical system are handled by iterative updating of the reservoir trajectory. The iterative procedure along with the linearization of curves describing for instance the efficiency of turbines and generators, the relationship between reservoir storage and head or the overflow function introduce errors to our modelling. These errors might sometimes be in the same order of magnitude as the values we are trying to measure for the improvement of stochastic modelling, and diminish or diffuse the validity of some of our results.

These errors might contribute to the fact that some of the test results presented in Chapter 3 show that the deterministic strategy performs better than the stochastic strategy in both the mean trees and the production schedule test. This should not be possible due to the design of the test procedures. When these negative values occur, it might be because measurement errors in the same size as the gain tip the result in the wrong direction. If this is the case, the gain from stochastic modelling must be rather small, and improvements in other facets of the modelling of the physical system might be just as important. It is important to remember that also the results that are in favour of the stochastic model are affected by the same errors. There is some noise to all of our measurements and tests on several watercourses for longer periods of time should be conducted to reach a certain significance level.

In order to avoid the errors related to linearization of curves, a few test runs have been made for system descriptions where all linearized curves are replaced by a single value. For instance, the efficiency is set to 100% and the reservoir is described as a flat surface instead of a relation between volume and height. The system description clearly no longer describes any accurate physical system, but these tests have been useful for assessing the effect of errors related to linearization.

A test case showing 300 NOK *loss* from SHARM in the production schedule test using the original system description showed a 15 NOK improvement when using the modified system description. These values are not large and the tests performed are not enough evidence to draw any valid conclusions, but gives an indication of how much the linearization error might affect the results. For larger systems, the margin of error will be even larger as small discrepancies are accumulated for all elements in the system. Hopefully, the gain from SHARM will also be larger, but this is in no way certain and we have not seen consistent prove that it is.

Even if there is some margin of error related to the linearization of curves, the test are designed so that both the stochastic and deterministic strategy are determined based on the exact same system description. The linearization errors are not larger for the stochastic model, except that it may be accumulated for all scenarios. This might introduce larger errors when determining the plans in the mean trees or production schedule test. However, when the plans and objective function value are evaluated, both strategies are evaluated for the full scenario tree and errors will be accumulated for the same number of time steps and scenarios for both strategies. Thus, these errors alone do not explain the observed inconsistencies.

The iteration procedure in itself has also caused some trouble. As each iteration is a refinement of the solution from the previous iteration, the decisions are successively better. It is therefore possible that the

solution from the last iteration is not a valid starting point for a new optimization on the same data set. This has occurred a few times in the mean trees test framework, where decision variables for earlier time steps are locked to schedules from earlier branching points. When more and more variables are locked, the problem becomes infeasible and the test cannot be performed as wanted.

To overcome this obstacle of infeasibility, slack variables for maintaining the schedules generated throughout the mean trees test has been implemented. These slack variables can be utilized to get a feasible solution for a certain costs. Slack variables already established in SHOP/SHARM are also used to overcome infeasibility. In principle, all past decisions are irreversible, and hence the penalty costs for breaking schedules should be high. Some decisions, however, such as the power sold to the market, can be changed closer to real-time by trading the intra-day market.

All in all, the problem of infeasibility between different branching time steps in the mean trees test introduces errors due to the slack variables and penalties introduced. Keeping track of the penalty costs, why they occur and if they favour/disfavour the deterministic strategy is difficult for large systems and large trees. The value of penalty costs also greatly influence the value of the measured gain. As more and more decision variables are locked to schedules from previous branching steps, errors might be introduced in the calculation of the objective functions as there are some inconsistencies in SHOP/SHARM regarding how scheduled versus optimized decisions are evaluated.

A last error related to the method in SHOP/SHARM is inaccuracies due to MIP and the allowed size of the MIP-gap. The MIP-gap is the difference between the best objective value for the integer-relaxed problem and the MIP-objective value, and should be very close to 0 in order to not affect the results. The allowed value of the MIP-gap is set by the user, and can be increased to shorten calculation times. Some of the results for the added value of SHARM are smaller than the MIP-gap used in the test runs, which indicate that the gain from stochastic modelling is smaller than the accepted stopping criterion for deviation between the relaxed optimal solution and the MIP objective function value.

5.2 Quality scenario tree input

The solution from a stochastic model is highly dependent on the values of the input scenario tree. As the strategy is determined by evaluating the consequences of the decisions for all scenarios, there is balancing between the possible adverse consequences for one scenario and the possible beneficial consequences for another scenario for each decision. This is what makes the decisions from stochastic models more robust. However, it also makes the results from the stochastic model more influenced by alternative or penalty costs of making any decision. Both the scenario tree and the penalty cost should therefore be given thorough consideration.

A main assumption in the framework used throughout the project has been that price and inflow are independent variables. This has allowed us to generate scenario trees by combing the set of inflow scenarios with the set of price scenarios all against all, which is a simple and straightforward way of making input to the SHARM model. However, this may not be a good representation of the true distribution of the future states of these important input parameters. Inflow and price is thought to be inversely correlated, and some combinations of for instance high inflow and high prices are quite unlikely. An example of this might be when the inflow to the reservoirs is large over time and a likely alternative is flooding. The dam owners are obligated to regulate the water flow, and they will be held responsible for damage caused by flooding. When a sufficient amount of power generators enter such a state, the system price might decrease substantially, making such periods particularly volatile.

The SHARM Toolbox offers options for the user to assign different probabilities to both the individual series for price and inflow, and also for each combination. If a specific combination is given a low probability, this

scenario will be removed from the tree even with a small degree of tree reduction. Another alternative that has been implemented in the Toolbox is the option for the user to specify that only certain combinations should be included in the initial scenario tree. Both these options has the main goal of limiting the scenario tree to only include combined inflow-price scenarios that the user finds likely to occur at the given state of the power system. This method for generating the tree relies on users with some experience in hydropower scheduling.

How much influence the user should have over the structure of the tree is a question for debate. Altogether, scenario generation has not been any large part of this project as input data mainly has been left to the partner companies. Generation of input to the stochastic model should be given more attention in future development of the stochastic model for short-term production scheduling.

Scenario tree reduction has also been governed by the users. The reason for wanting to limit the tree size is twofold. First, the calculation time is increased when using large trees and hence we want to use only the scenarios that are important. Secondly, we do not want the results of the stochastic model to be too influenced by scenarios that will never happen, as this, combined with an unbalanced level of penalty costs, may distort the results from the stochastic model under certain conditions.

The goal is to make a flexible production schedule, but we cannot be overly concerned about what will happen in extreme or highly unlikely scenarios. In some cases, extreme downsides (or upsides) could influence the resulting schedule and in effect make the plan suboptimal for the more normal cases. This effect may occur in our tests due to often very high default penalty costs. The production schedule test might be particularly influenced by extreme scenarios due to the common decision constraint.

However, since both the mean trees test and the production plan test evaluate the value of stochastic modelling assuming that the scenario tree is the true distribution of the uncertain variables, i.e. in-sample, the loss sometimes observed by using SHARM cannot be explained by a non-representative scenario tree. Stability and robustness of the stochastic solution should be evaluated in out-of-sample tests. This has not been done in this project partly due to lack of available data and partly due to focus on other aspects of the testing.

The value of optimization models and stochastic modelling in particular is highly dependent on the input given to the model. In order to get decision support that is applicable in the real situation, the input to the model must reflect real events. Future use of SHARM will require methods for forecasting and scenario generation and reduction that adequately describe the information structure and any correlations between the stochastic variables.

5.3 The effect of using common decision period

As explained in Chapter 3.3, an option of obtaining *one* production schedule from SHARM even if the underlying scenario tree has several different branches for the scheduling time steps has been implemented. This was done in order to yet usable results from SHARM even for structured trees, and was thought to mitigate problems of how to interpret the output data from the stochastic model. With this option, operators could get *one* physically feasible production plan for a prescribed number of hours independent of the structure of the scenario tree.

This resembles the use of the deterministic model; with a single scenario there is really no scenario tree to be concerned about and the tree structure is not an issue. With distributional information on price and/or inflow as input in the form of a scenario tree, the structure of the tree very much influence the results from the optimization model and the user should have some knowledge of the tree structure. Particularly, SHARM

produces schedules for each scenario in the tree which are optimally adapted to the input values of each scenario. With a fan tree structure, this is more similar to multi-scenario runs of a deterministic model than actual stochastic modelling. The results for each scenario in the tree were therefore seen as quite useless in the sense that without knowledge of the realization of uncertainty there is no way of knowing which scenario solution to implement in practice.

This could be solved by letting the first-stage of the tree be deterministic, as in Fig. 5-1. In this manner, a single schedule is obtained for the 24 first hours of the tree anticipating uncertainty at the following stages. This schedule could be implemented as the actual scheduling decisions, but assumes that there is no uncertainty for the period of time the schedule is made for.

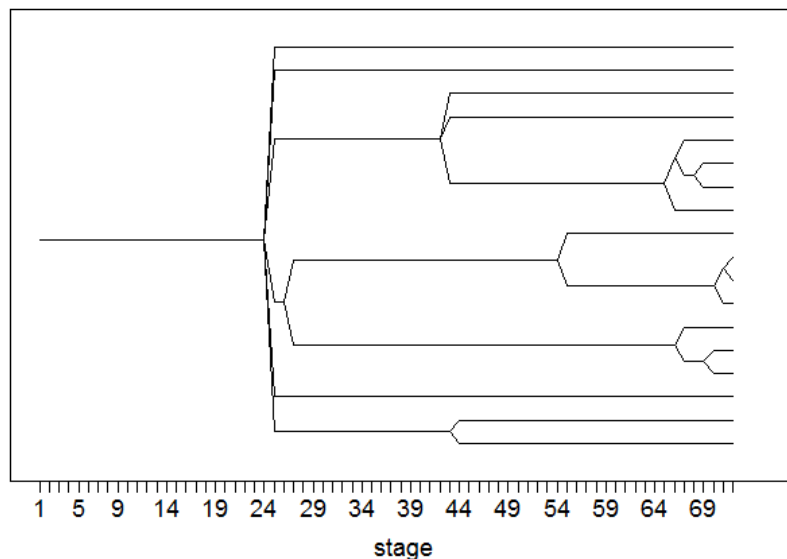


Figure 5-1: Scenario tree structure with deterministic period until hour 24.

This is not the case in real operations due to inflow uncertainty. The day-ahead market is cleared once every day, and hence prices are known with certainty for 24 hours at a time. For price uncertainty, a scenario tree structure with 24-hour branching period represents the true picture of uncertainty. Since the stochastic model is run with updated information each day, the plan obtained for the first (deterministic) 24 hours would be usable. Inflow uncertainty, however, does not follow any structure and the final structure of the inflow scenario tree will be determined by the forecast distribution which again will vary depending on time of year, weather conditions and all other variables that determine the inflow. Inflows are naturally uncertain, and will thus also vary within the time steps covered by the scheduling decisions. The tree in Fig. 5-1 is therefore too simplified, and we want to solve SHARM for scenario trees of any structure while at the same time being able to obtain results that are usable in practice. Fig. 5-2 shows a scenario tree with branching from time step 1. We still want to obtain a single schedule for time steps 1-24.

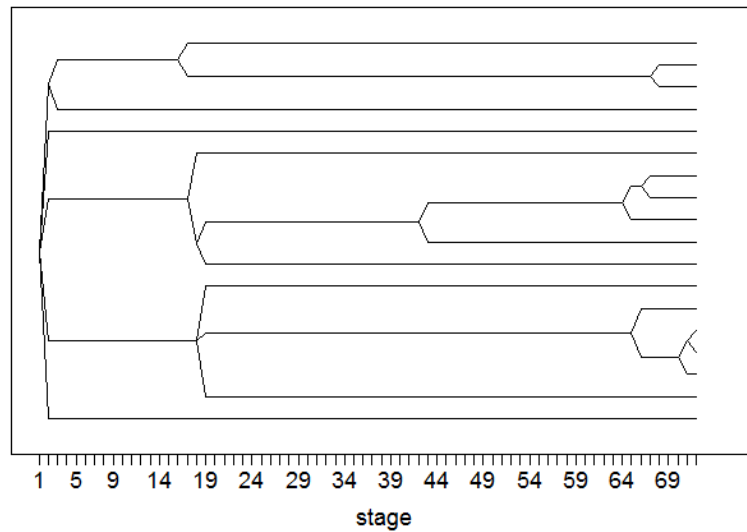


Figure 5-2: Scenario tree structure with stochastic values from hour 1.

This objective was accomplished by adding constraints specifying that the scheduling decisions should be equal for all time steps and scenarios covered by the scheduling period. Implementation details can be found in project memo Introducing common decision variables in SHARM and is referred to as *common decision period* or *the common decision constraint* in this report.

Even though motivated by obtaining usable results, common decision period proved too have some unintended purposes. Adding an additional constraint to the optimization problem limits the solution space and could decrease the objective function, which we have seen in some cases. The interplay between common decision period and penalty costs has also proved interesting. Any decreases in the objective function due to the common decision period can be seen as the cost of obtaining results from a stochastic model that can be implemented in practice. However, the value of penalty variables inherited from SHOP often lead to an overestimation of this cost.

Table 5-1: Results for deterministic tree and stochastic tree with and without common decision.

| | Objective function value |
|---|--------------------------|
| 24 hour deterministic period | 106 050,65 |
| 1 hour deterministic period | 105 714,99 |
| 1 hour deterministic period, 24 hour common decision period | 105 257,49 |

Table 5-1 shows the objective function values from running SHARM for a tree structure with a 24-hour deterministic period at the start of the optimization and for a tree with more than one scenario within the first 24 hours with and without the additional constraint of common decision period. The underlying tree structures can be seen in Figs. 5-1 and 5-2. There is a decrease in the objective function value by using the common decision constraint.

The loss is related to the plans generated from the model. Figs. 5-3 to 5-5 show the production schedule for the first 24 hours for the 24-hour deterministic tree, and for the tree with branching from time step 1 with and without common decision period.

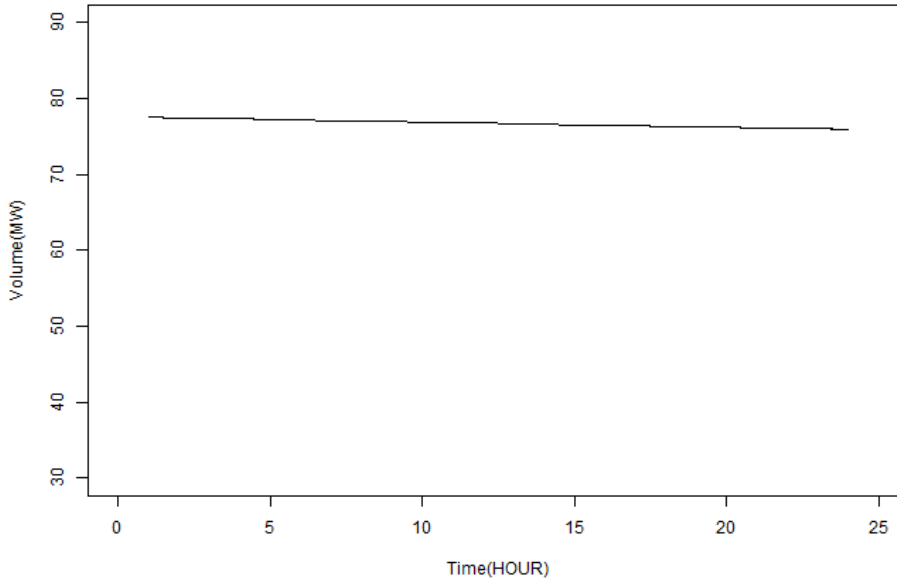


Figure 5-3: The obtained production schedule for the tree structure with a 24-hour deterministic period. All scenarios result in the same production since the tree is deterministic for the first 24 hours.

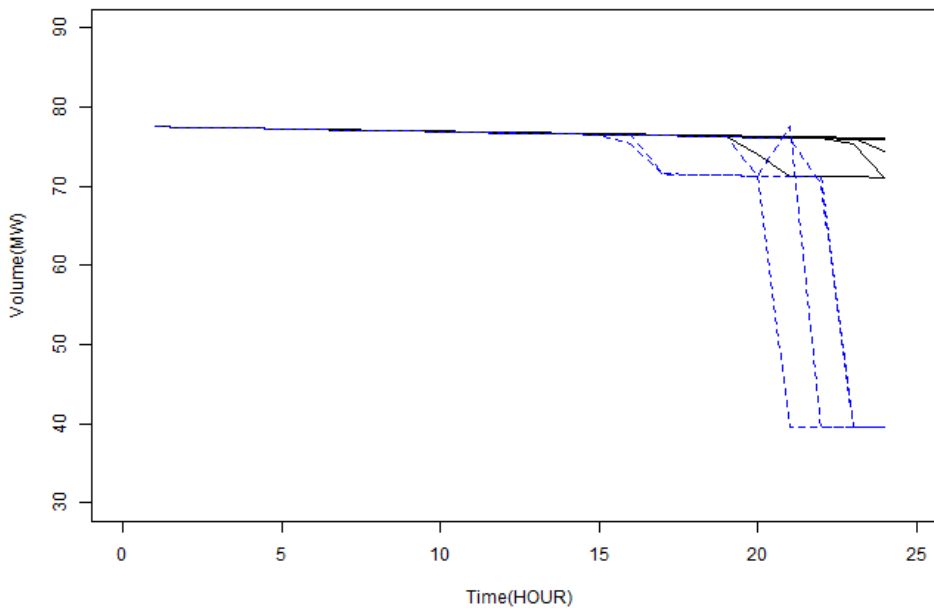


Figure 5-4: The obtained production schedules for the tree structure with different scenarios from hour 1. Most scenarios result in a production around 77 MW for all hours (black lines), but the last 4 scenarios finds it optimal to reduce production for the last hours of the day (blue, dotted lines).

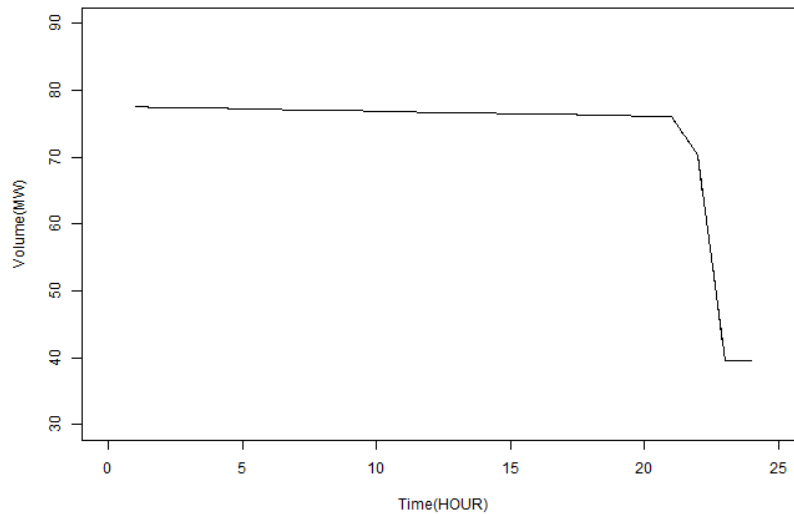


Figure 5-5: The obtained production schedule for the tree structure with different scenarios from hour 1 and common decision period forcing the production schedule to be equal for all scenarios.

The plan shown in Fig. 5-3 is generated based on the average values for the first 24-hours, and indicate that production should be kept around 77-76 MW for all hours. The plans in Fig. 5-4 are the results for all scenarios in the tree independently from each other. It is optimal to produce around 77-76 MW for all scenarios except for three scenarios with low inflow and thus lower production in the last hours. In Fig. 5-5, the plans for all scenarios are forced to be equal due to the common decision constraint. Production is low for the last two hours. The low inflow values of scenario 18-21 dictate that the solution for *all* scenarios must decrease production in order to avoid running dry if one of the low inflow scenarios are realized. If any of the other scenarios are realized, we would be better off by being allowed to produce at a higher level also for the last hours. The penalty for running dry which would be incurred in the low scenarios if the production level is not decreased is set so high that SHARM will avoid this cost by all means. The penalty value can hence be seen as the level of risk-aversion of the producer, as it influences the willingness/aversion for generating a schedule that might result in running dry for the worst scenarios. Being overly risk-averse (that is, using unrealistically high penalty values) and using common decision period may result in a production schedule from the stochastic model that performs less than the schedule from a deterministic model using the mean values. This is shown in the results from the production schedule test for the tree structures in Figs. 5-1 and 5-2 given in Table 5-2. The results from using common decision period are worse than using the plan generated from the mean values.

Table 5-2: Results from the production schedule test using common decision variables and default penalty costs.

| 24 hour deterministic period, no common decision | | | |
|--|------------------------|------------|----------------|
| Stochastic schedule | Deterministic schedule | Difference | Difference (%) |
| 106 093,50 | 106 093, 50 | 0 | 0 |
| 1 hour deterministic period, 24 hour common decision | | | |
| Stochastic schedule | Deterministic schedule | Difference | Difference (%) |
| 105 231,21 | 105 493,93 | -262 | -0,25 |

Rather than letting the traditional large values for penalty costs dictate the solution from the stochastic model and the common plan, the penalty costs should be set at a level that represent the real-world cost by violating a constraint. The practical alternative for having too little water to cover commitments is to buy the same volumes in the intra-day market. Setting the penalty cost at a level that represents the intra-day market price gives the results in Table 5-3 where the two alternative ways of obtaining *one* schedule from SHARM both perform equally well as the deterministic plan generated from the mean values.

Table 5-3: Results from the production schedule test using common decision variables and penalty costs representing the intra-day market prices.

| 24 hour deterministic period, no common decision | | | |
|--|------------------------|------------|----------------|
| Stochastic schedule | Deterministic schedule | Difference | Difference (%) |
| 106 093,50 | 106 093, 50 | 0 | 0 |
| 1 hour deterministic period, 24 hour common decision | | | |
| Stochastic schedule | Deterministic schedule | Difference | Difference (%) |
| 107 789,72 | 107788,68 | 1,04 | -0,00 |

The effect of using common decision period without proper concern for the penalty costs is thought to be the reason for some of the inconsistencies in the results from the production schedule test. The test is designed so that the results from the stochastic model always are equal to or better than the deterministic solution, but we have seen that this is not always the case in the testing performed during the project period.

5.4 Sensitivity for tree reduction

Using the production schedule test, we wanted to investigate the sensitivity of the improvement from the stochastic model for different degrees of scenario tree reduction. Referring to Fig. 5-6, we wanted to test if the plan generated from different sized trees would perform better than the deterministic plan when evaluated for the full tree, even if the trees were small. This is a step towards testing the benefit from the stochastic model out-of-sample, because we do not use the true distribution (the full tree) of the stochastic variables when generating the stochastic plan. For this analysis, the four runs of the production schedule test were repeated for increasing tree reduction when generating the stochastic plans. All plans were evaluated for the full scenario tree.

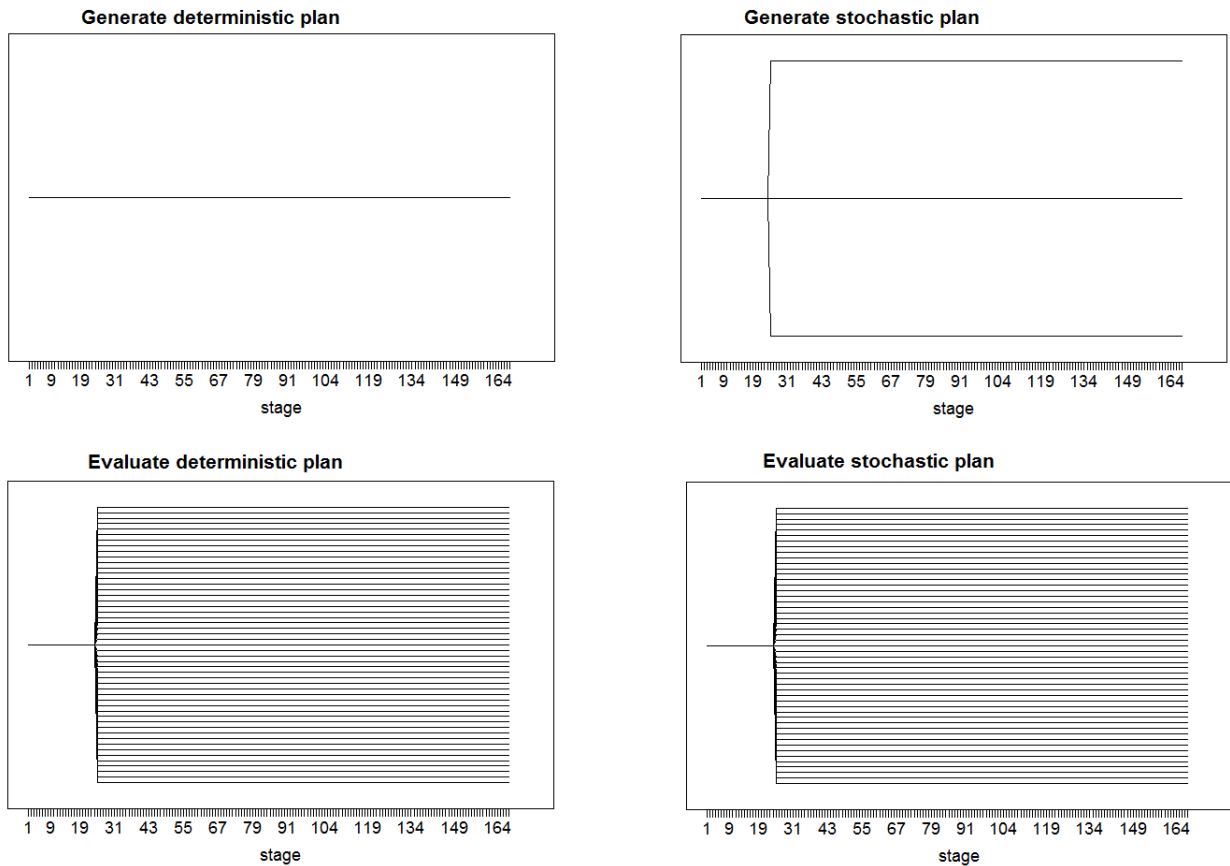


Figure 5-6: The underlying scenario trees for the four runs of SHARM to perform the production schedule test for different degrees of tree reduction.

The sensitivity analysis is carried out for a one-reservoir, one-plant system with inflow uncertainty for a 168-hour period. The common decision restriction is used to generate a single plan for the scheduling time steps in hours 19-42 where the underlying tree structure is stochastic.

The initial hypothesis was that the value of SHARM would decrease for increasing degrees of tree reduction, but that even a small number of scenarios would yield good results. Earlier research using the mean trees test has found this to be the case, see Follestad, Wolfgang and Belsnes, 2011 which give an example where the scenario tree can be reduced by 30% and the added value of SHARM over the deterministic strategy is only reduced by 0.02 % of the maximum added value of 1.3% when using the full tree. Even a degree of reduction of 90% (2 scenarios) yielded a benefit from SHARM of 0.5%. We wanted to see if these results could be recreated using the production schedule test with common decision period.

Fig. 5-7 shows the results for added value of stochastic modelling measured by the production schedule test when the stochastic plan is generated using scenario trees reduced to smaller and smaller sizes.

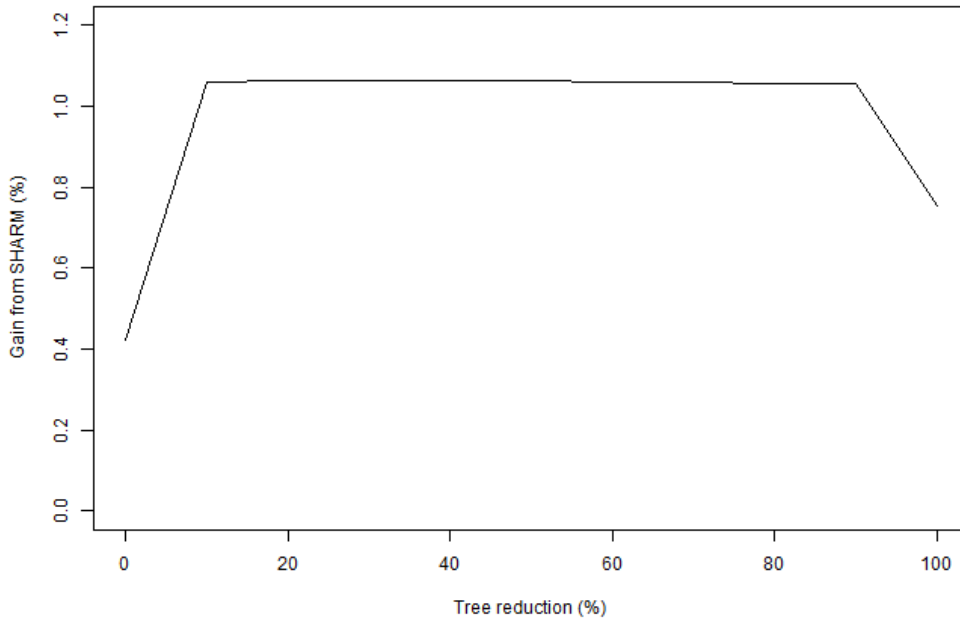


Figure 5-7: A plot of the obtained gain from SHARM measured by the production schedule test for increasing degrees of tree reduction.

The results are somewhat counterintuitive, as they show a larger gain as soon as the tree is reduced. Since all schedules are evaluated for the full scenario tree, it should not be possible to perform better than the plan generated from the full tree – but this still happens. This may be due to the effect of imposing the common decision constraint. For the full tree, some extreme scenarios and high penalties may force the common plan in an adverse direction. When the tree is reduced, these extreme scenarios are taken out and no longer affect the plan.

In the two runs with the full tree for evaluating the plans, the decision variables within the plan period are locked to the previously obtained schedules. However, the penalty cost for not producing according to the schedule is something else (often a lower value) than the penalty seen for running dry when the plans were scheduled. The plans are therefore not evaluated under the same conditions as when they were generated.

The same sensitivity analysis has been conducted for the same data set using a 42 hour deterministic period. That is, there is only one realization in the tree for hours 0-42 which we are making scheduling decisions for, and we avoid usage of the common decision constraint. The results from this test are shown in Fig. 5-8 .

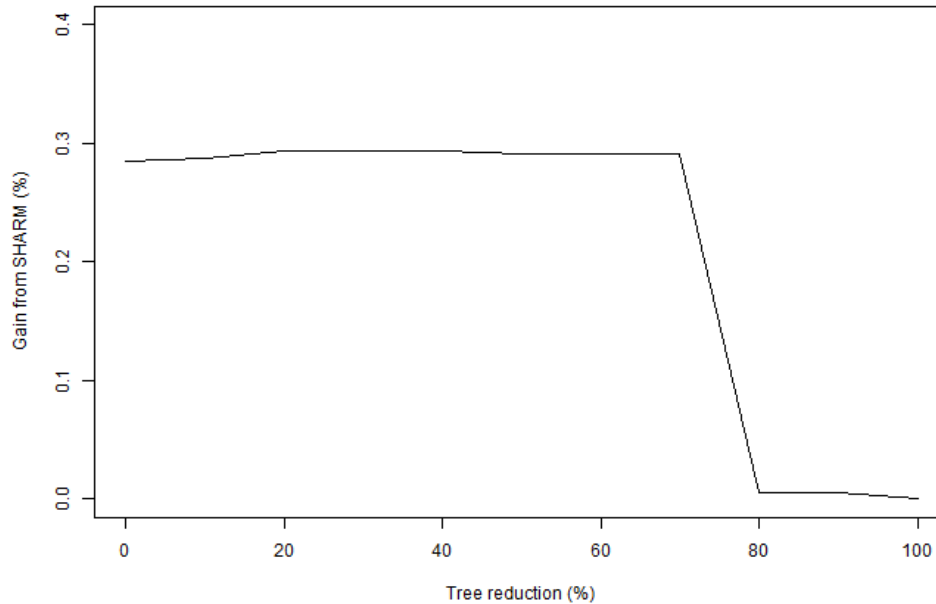


Figure 5-8: A plot of the obtained gain from SHARM measured by the production schedule test for increasing degrees of tree reduction and no common decision period.

The results now show the expected behavior, and SHARM gives good results even for 70% tree reduction. The obtained added value here (0.3%) is less than the added value obtained when using common decision period for the smaller trees (1.1%).

Even if the results in Fig. 5-8 suggest that the unexpected result is due to the common decision constraint, this is not sufficient for any conclusions. When the stochastic plan is generated and evaluated for the full tree, it should not be possible for the deterministic plan to perform better.

5.5 Simulation, not optimization

The results observed in Chapter 3 may be due to that fact that we use an optimization model where we in principle only want to simulate operation of the system according to already obtained schedules. In the production schedule test, production plans for the first day are obtained in the first two runs and it should be no need for re-optimizing these time steps in the two runs for evaluating the plans. Hence, the evaluation step should be performed by simulating the first day and then optimizing the remaining time steps. A similar methodology should have been used in the mean trees test where only the decisions after the current branching time step should be optimized – all prior decisions should only follow the already determined plan.

Unfortunately, at the start of the validation project we had no framework for performing simulation according to already given schedules. A choice was therefore made of implementing the test procedures directly in the optimization model. Simulation functionality for the SHOP model has later been developed, but this has not been utilized in this project.

In principle, it should not cause problems to use the optimization model for simulation given the options for locking decisions to schedules already present in SHOP/SHARM. However, due to feasibility issues throughout the iterations, some of the schedules are only implemented as soft constraints. This opened possibilities for utilizing a large range of slack variables with belonging penalty costs. The value given to the penalty costs needed unprecedented consideration and judgment calls regarding what opportunities the slack variables actually represent.

Particularly in the updated deterministic strategy in the mean trees test, the optimizations in successive branching points sometimes utilized different penalties in order to make up for bad decisions taken at an earlier time step. These decisions would in reality be irreversible, and in the cases where they are not the cost of using penalty variables should reflect the true cost of breaking the constraint and not some imaginary (and often too high) value. The water released through different gates is irreversible decisions that cannot be changed at later time step and these schedules should be imposed as hard constraints. An example of a reversible decision taken at an earlier time step is the production volume, which can be changed closer to real-time by trading in the intra-day market. The penalty cost of breaking the production schedule should hence be the intra-day market price.

In some cases we observed that the deterministic strategy "cheated" by utilizing slack variables for earlier time steps that should have been treated as irreversible decisions. For instance, if the initial plan from the deterministic strategy turned out to result in penalty costs as more and more of the tree was revealed, the optimization would move this penalty to other (and cheaper) slack variables in earlier time steps as the water then could be utilized for several time steps. For large topologies and large trees, this behavior became too complicated to handle. If the previous decisions had been simulated, not optimized, this behavior had not been possible and we might have been better able to measure any differences in revenues by operating the system according to the stochastic and deterministic strategies.

It is clear that the deterministic strategy benefitted from this behavior, but we are not sure of the extent and if it completely has diminished the measurable gain from stochastic modelling. For similar verification projects in the future, we recommend that test procedures are validated on a principle level before implementation in the full scale model. Above all, we recommend that simulation is used to a far greater extent than in this project, as this increases precision of all calculations and rule out the possibilities of optimization of being too smart.

5.6 Penalty costs should reflect the cost of the real-world alternative

Within the framework used in this project, where the evaluation of the value of stochastic modelling is evaluated by test procedures implemented into the optimization model as explained in Chapter 5.5, penalty costs are of crucial importance. The aim was to develop test procedures that to a large degree represented how the stochastic and the deterministic model would be used in real operations. This would measure the gain obtainable to producers by switching to the stochastic model. Unfortunately, no consistent results have been obtained for the watercourses and data sets tested.

The lack of quality results is due to the combined effect of all subchapters of Chapter 5. The behavior from Chapter 5.5 is an area where more caution should have been exercised, as this is thought to be the main reason of the observed inconsistencies. However, the updated deterministic strategy should be allowed to make up for bad decisions as long as this can be interpreted as some sort of action in reality. This is most transparent by considering violations of the schedules on generators from previous time steps in the mean

trees test as mentioned above. However, also the common decision constraint should be a soft restriction where the cost of using slack variables is equal to the intra-day price. This will likely limit some of the adverse effect of using this option.

The main point is that much more attention must be paid to the cost of penalty variables in a stochastic model than in a deterministic model, particularly when the same penalty costs are used for evaluation of the value of stochastic modelling. Penalty costs are included in both SHOP and SHARM to tell the user that the system is pushed to its limits, and to maintain the opportunity for getting a valid solution in a broad range of cases. Some of the penalty costs are incurred due to the use slack variables which are necessary in order to get feasible solutions. The idea is to first get a solution and then tell the user that boundaries have been exceeded with subsequent costs. Other penalty costs are incurred due to violations of limits specified by the user, such as penalty for breaking tactical limits on reservoirs or generator schedules. These penalties are set in order to get the model to operate according to a specific pattern or to avoid unfortunate results. Regardless of the source of the penalty, the cost should reflect the real-world alternative to the corresponding slack variable in the model. For the purposes of evaluation, only penalties that have a readily easy interpretation should be allowed. Applying penalty costs and variables without proper concern for what alternatives they represent and how they compare to other alternatives may diminish the value of stochastic modelling.

5.7 Full potential by implementing multiple markets

What the increased attention to penalty costs has taught us, is that the value or costs of alternatives are much more important in stochastic than in deterministic models. As the stochastic model is able to weigh different alternatives against each other, the cost of these different alternatives will influence the final strategy. Balancing the profits and costs of each decision in all scenarios is what makes the decisions from a stochastic model more robust. If a certain decision has a beneficial outcome for some scenarios, this is balanced by the possible adverse outcome in other scenarios. For this to yield a sensible schedule outcome, the cost of the different outcomes should adequately reflect the cost incurred in the real-world situation.

For instance, consider a situation where the flexibility of the reservoir is low and price is expected to be increasing throughout the optimization period. In addition, inflow is expected to take on possible high values causing a risk of spillage if the reservoir level is not adjusted accordingly. The typical strategies from a deterministic and stochastic model for this situation are shown in Fig. 5-9.

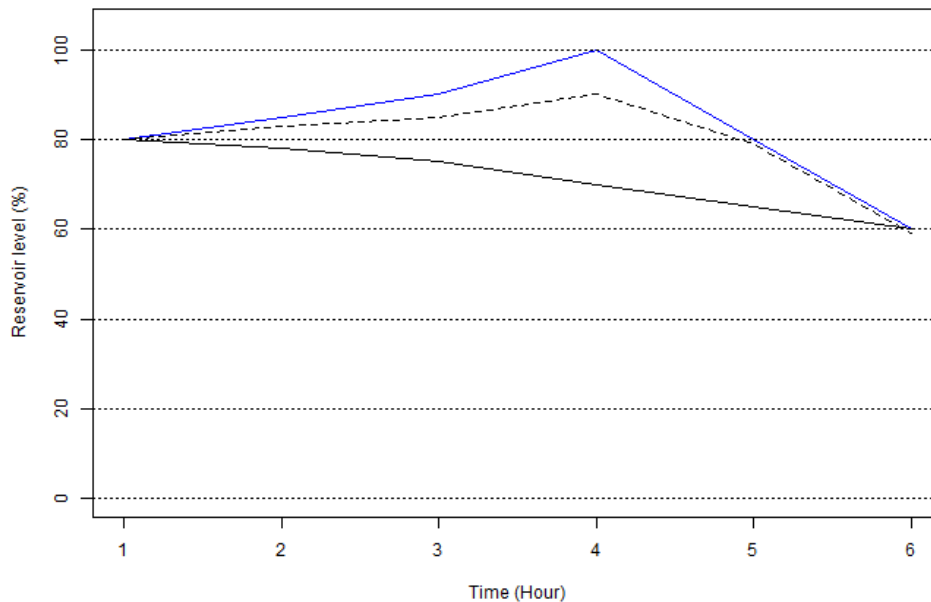


Figure 5-9: Illustration of reservoir management strategies for a simple case. High prices are expected in hours 4, 5 and 6. Inflow may be high for the same hours. The deterministic strategy (blue line) fills up the reservoir prior to the high prices and fails to see that this involves a risk of spillage. The stochastic strategy with high penalties (straight, black line) is too risk averse and immediately starts lowering the reservoir level in order to avoid spillage. With more appropriate penalty costs (black, dotted line), the stochastic model is able to balance profit and risk.

The deterministic strategy, failing to see the risk of overflow, fills up the reservoir prior to the highest prices towards the end of the period. It then has a high head and is able to produce with high efficiency for high prices. The stochastic strategy, however, sees the high inflow scenarios and also the cost associated with overflow. If the penalty cost is set too high reflecting a very high level of risk-aversion, the stochastic strategy is too eager to release water early in the period where prices are lower in order to avoid spill. This is a good strategy only if the cost of overflow is truly larger than the loss by producing at lower prices now instead of higher prices later. This is a judgment call for the system operator. On the other hand, if the penalty cost of overflow is set too low, the stochastic strategy may not be any different from the deterministic strategy. A moderate level of penalty costs in the stochastic model will yield a strategy that accounts for both profit and overflow, resulting in a more modest reservoir trajectory. Stochastic modelling have the ability to balance profit and risk, but the level of risk-aversion must continuously be assessed in order to reap any benefits.

Instead of interpreting the penalty costs as a level of risk-aversion, they should rather be interpreted as real-world actions. Consider Fig. 5-10 which show the reservoir management strategy for a small reservoir which for simplicity is optimized against a given load. Unfortunately, the load is so large that the reservoir empties towards the end of the period. This situation would incur penalties in both model and the real-world situation. However, the operators of the system would never let the reservoir run dry (or below the minimum allowed level) and would trade their way out of the load obligation using the intra-day market. The reservoir level is kept at a sound level throughout the optimization period.

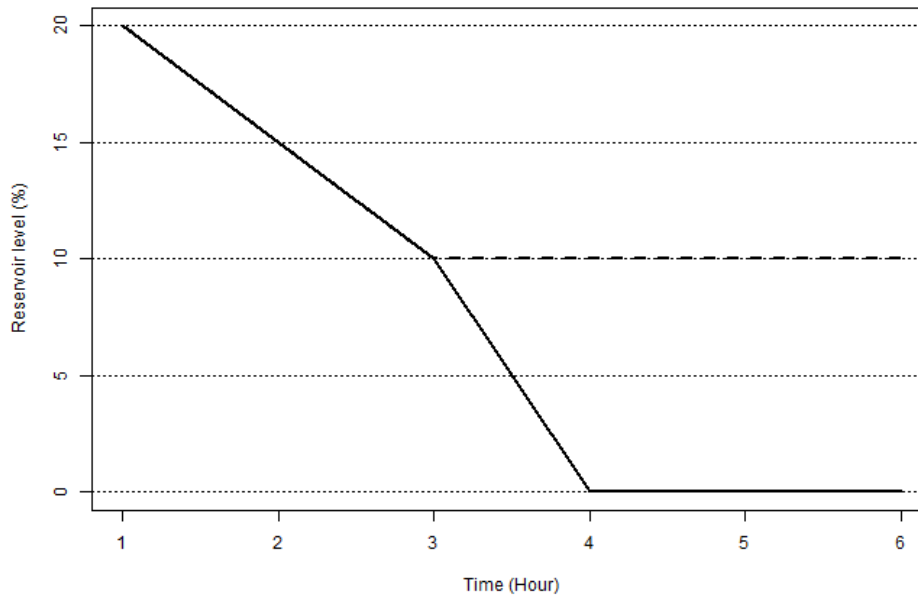


Figure 5-10: Illustration of how the reservoir trajectory is improved by using the intra-day market. The black line shows the results of the optimization model when no intra-day market is modelled and the penalty for not meeting the load is too high. The dotted line shows the results when the penalty for not meeting the load is set equal to the intra-day market price.

However, in the current implementation of the SHARM model, the possibility of trading in the intra-day market is not present. The only alternative the stochastic model sees is to empty the reservoir and incur the very high penalty. The strategy is adjusted accordingly. In real-operations, the operator might be satisfied with a strategy that gives good performance in most cases because it is known that if a particularly adverse situation should occur, it is still possible to take some measure to get out. The operator has more alternatives than are evaluated by the stochastic model!

The examples above are too simplified and stylized to be realistic, but they still prove a valid point. In order for the stochastic model to give valuable decision support for the operator, the optimization should be able to evaluate the same options that the operator is faced with. It may not be possible to model every facet of the decision situation, but a minimum requirement should be that alternatives are properly valued even if they are not explicitly modelled. This is even more important in a stochastic model than in a deterministic model, as these alternatives are balanced against each other and hence affect the final strategy to a larger extent.

In order to get the full potential out of a stochastic model for short-term production scheduling, it is recommended that several of the physical markets for power are modelled in the optimization tool. This would of course make the model more complex, but would also hopefully yield better decision support in an increasingly complex situation. With a model that to a larger extent reflects the actual situation, it would also be possible to measure the added gain of stochastic modelling with greater accuracy.

Another point is that the testing performed in this project has been on current data for price and inflow. In a future where market prices across several short-term markets expected to become more volatile, the added value of stochastic modelling is expected to increase. The tests performed in this project should have been applied to data representing a future market situation in order to assess the future potential benefit from SHARM.

6 Operationalization of SHARM

So far the report has dealt with methodologies and results for calculating the added economic value of SHARM. This has been the main activity in the project. Any value from SHARM must however be compared with any increased costs for implementing and using SHARM in the hydropower companies. An assessment of the changes in the production scheduling process and the associated costs is made in this chapter. In addition, the industrial impact of the SHARM model is assessed, along with some thoughts on how to further develop the prototype.

6.1 Challenges of operationalization

Three main challenges have been identified for operationalization of the SHARM software. These are discussed below.

6.1.1 Generation of valid input

The results from any optimization model are dependent on the input data. For a stochastic model, input is given in the form of distributions of the stochastic parameters and for SHARM this is required to be in the form of a scenario tree. The generation of forecast distributions for price and inflow as well as the generation and possible reduction of scenario trees are fields of study in their own right. These issues are interconnected with the stochastic model and are hence a more integrated part of the scheduling process.

Forecasts could be obtained from fundamental or statistical models. In Nordic hydropower companies, meteorological and hydrological models are used for inflow and power system models such as the EMPS model is used for price. Statistical models are not that common. The generation and use of forecasts vary across companies. Some have good data for inflow but not for price and vice versa. Data for price and inflow often come from different analysis departments in the companies, and there may arise new needs for coordination. The generation of input to the stochastic model may therefore come at an increased cost.

6.1.2 Easy access

Even if quality input could be obtained, the current use of the SHARM software and interface is cumbersome. The software is still a research prototype and not suited for operational use. The rudimentary "user interface" of the SHARM Toolbox only includes the bare necessities for running the test procedures and not much more. It would be beneficial if the functionality from SHARM could be accessed from the user interface and system developed for the SHOP model. In principle it should be possible to switch back and forth between deterministic and stochastic versions of the production scheduling tool. If this was the case, the operationalization costs of SHARM would be very limited, and there would also be opportunities for benefitting from the strengths of both models. The deterministic version could be used when uncertainty is limited or of limited value or for fast rescheduling within the day. The stochastic version could be used when uncertainty is large or the system is close to its limits or for the main daily scheduling decisions.

Steps have been taken towards achieving this goal. The stochasticity-related functionality in SHARM has been re-implemented in the operational model SHOP. At the current state, this is only done for inflow uncertainty, but a stochastic market description is pending. When this work is finished, the stochastic version of SHOP will be available as a licensed version of the SHOP software. If generation of forecasts and generation of scenario trees also could be implemented in the same software package and the interface adapted to also the stochastic version of SHOP the cost of considering uncertainty would be negligible.

6.1.3 Computation time

So far the computation time has been the main challenge during testing and is expected to remain the main challenge also for operationalization. Due to the time constraints of the electricity market, decisions must be made fast. There is limited time in the morning hours after receiving updated results from the forecasting and

analysis department before the spot market decisions must be sent to the market operator. The decision support tool should give fast responses. The calculation time of SHARM is already substantially increased compared to SHOP. This naturally depends on the number of scenarios, but even a small number of scenarios will give too long calculation times for large systems. There will hence be a trade-off between getting results in time and getting results that are based on an adequate description of the uncertainty involved. With MIP the calculation time is even worse, and this has sometimes even been abandoned for testing purposes where time restrictions are more relaxed.

Measures to improve the calculation time must be taken if the SHARM-concept should be considered for operationalization, especially if several short-term markets are to be implemented in the future.

6.2 Process and costs for using SHARM

The stochastic model will be used in a similar way as the deterministic model is used today. The process for obtaining a final production schedule is illustrated in Fig. 6-1. The production scheduling process starts with generation of forecasts for price and inflow for the coming days or week. Information of the future values for price and inflow are inputs into the optimization model together with the current system state. The optimization model gives results in the form of schedules for the next day's operation. Operators at the hydropower companies evaluate and adjust the schedules from the optimization model based on experience and company strategies. Not all information or constraints can be modelled in the optimization model and some manual adjustments may be necessary before a final production schedule is obtained. New information about the current system state or new forecasts might induce rescheduling or re-optimization. The process of forecasting, monitoring the system, optimization, evaluating and adjusting plans is performed in a continuous loop throughout the week.

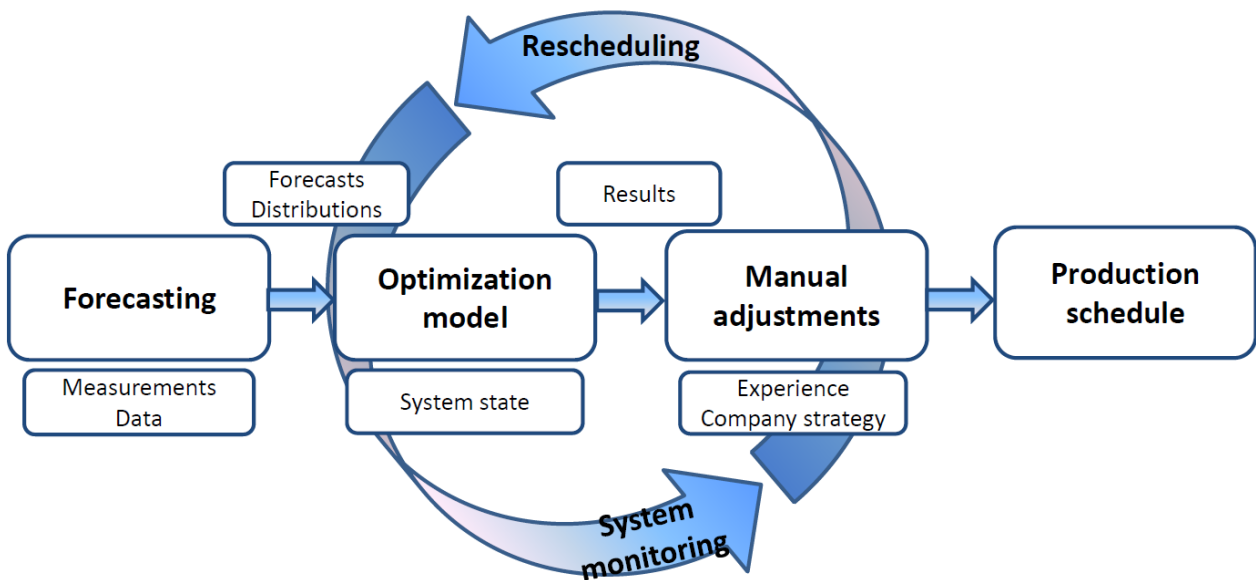


Figure 6-1: The process for determining the final production schedule.

We will now try to pinpoint where and how this process might change by advancing to a stochastic model, and also assess the associated costs.

As already noted in Chapter 6.1.1, generation of input is important when using a stochastic model. As of now, the forecasting and the scenario generation algorithm are independent from the optimization model.

Tight connections exist between forecasting and the scenario tree, and between the scenario tree and the results from the optimization model. It may thus seem that a stronger relation between Forecasting and the Optimization Model is necessary when using a stochastic model. Should the scenario generation algorithm be an integral part of the SHARM software? Or is it more beneficial to have this as a stand-alone tool that can be used by other departments than the production planning department? This will depend on the organization and work flow at the individual power company. Evaluation of the scenario tree structure could perhaps be a joint effort between the forecasting department which know the distribution, and the production planners who have experience with the (wanted) final result. It is expected that the cost of generating and evaluating input to the optimization model will require more resources when using a stochastic model. It is however not certain how much these costs will increase, as the forecasting tools in use today already span out a possible sample space for the uncertain price and inflow. The input to the deterministic model is made with concern for the total forecast distribution, and hence also involves some judgements calls and associated costs. If the output from the forecasting models could be used more directly in the stochastic model, this may in fact reduce costs. However, scenario tree generation, which is not needed for a deterministic model, require attention and thus introduce some added costs.

On the other side of the Optimization model, on the output side, the costs are expected to decrease. Operators at the hydropower companies have expert knowledge about their systems and experience about the possible impact of uncertainty, and take measures to adapt the solution from the deterministic optimization model in order to avoid too risky production schedules. The optimization model offers decision support, but is only an element the total process for generating a final production schedule. The manual adjustments are costly in terms of time and personnel with high skill levels. The stochastic model has the ability to determine schedules that do not need as much manual adaptation, and will thus save some of the costs associated with the production scheduling process. Even if we are not able to determine any monetary benefit from the stochastic model due to inconsistencies and errors as elaborated in Chapter 5, the production schedules and reservoir management from SHARM is judged to be better for the test cases reported in Chapter 3. Therefore it is expected that the the need for manual adjustments will decrease along with the accompanying costs.

It is the opinion of the SHARM project participants that the above described changes in cost structures are expected when switching to a stochastic model. That is, some added costs are expected on the input side but the largest change is related to the expectation of less need for manual adjustments to the results from the optimization model, which results in a reduction of the total costs involved in production scheduling for hydropower.

There are other costs that are not as easily related to the production scheduling process. This mainly involves training of personnel. The indications form the participating hydropower companies is that a more complicated model require more skilled staff, which again require training and education. This would include costs for sending employees to relevant courses and seminars, or even increased salaries for higher educated personnel.

6.3 Industrial impact of the SHARM model

The SHARM model is not finished in the sense that the prototype can be re-implemented or directly applied in the industry in the current state, then applied for 5-10 years until a new model concept or an revised version is established.

Stochastic short-term scheduling is not finalized in terms of challenges of where stochasticity is applied or how it should be modelled, neither has the use of the model or the application of results found its final form. As for short-term scheduling in general, changes in boundary conditions, either driven by step-change in IT hardware or software techniques or by changes in the energy system, will trigger or has triggered new

demands of the software solution implemented. Some boundary conditions that affect the optimal utilization of hydro resources are illustrated in Fig. 6-2.

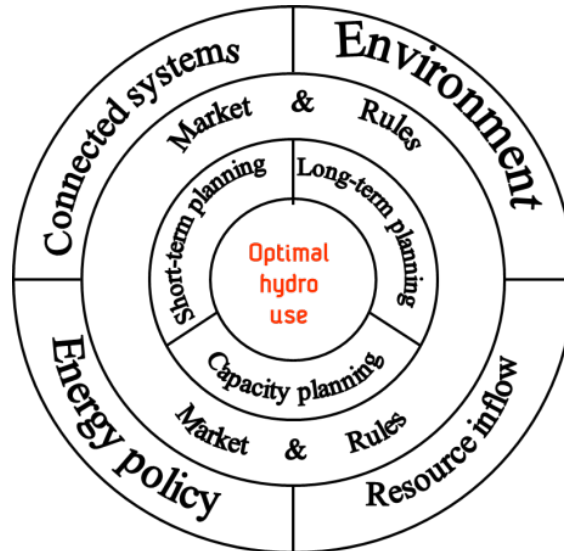


Figure 6-2: Boundary conditions that impact on hydro power utilization.

As with the SHOP model (Fosso and Belsnes, 2004) enhancement and further development is needed for the model to reach its full potential. The elements that have resulted in the success of the SINTEF models, EMPS, Samlast, EOPS, ProdRisk and SHOP are experience that we will bring with us when working towards implementation of the results from the KPN and IPN project on the SHARM prototype. The critical factor has always been to be able to maintain and expand competence on the specific models by continuous activity.

SINTEF Energy is a project organization. The team of scientists that develop scheduling models for the power industry works in three tracks to create activity that helps industry, software houses, power companies and consultants to create revenue and added value from the chain of models mentioned above. These tracks are:

- Public funded research with high risk through KPN, I-SIP, IPN, FME programs
- Industry funded research based in industry initiated projects and through activities initiated to licensing and supporting the specific models.
- Analysis projects where the models are used in research projects of common or industrial relevance

These activities are illustrated in Fig. 6-3 and aims to deliver the best possible optimization kernels to the industry with respect to methods and functionality with short lead times from ideas and specifications to value creation in the industry.

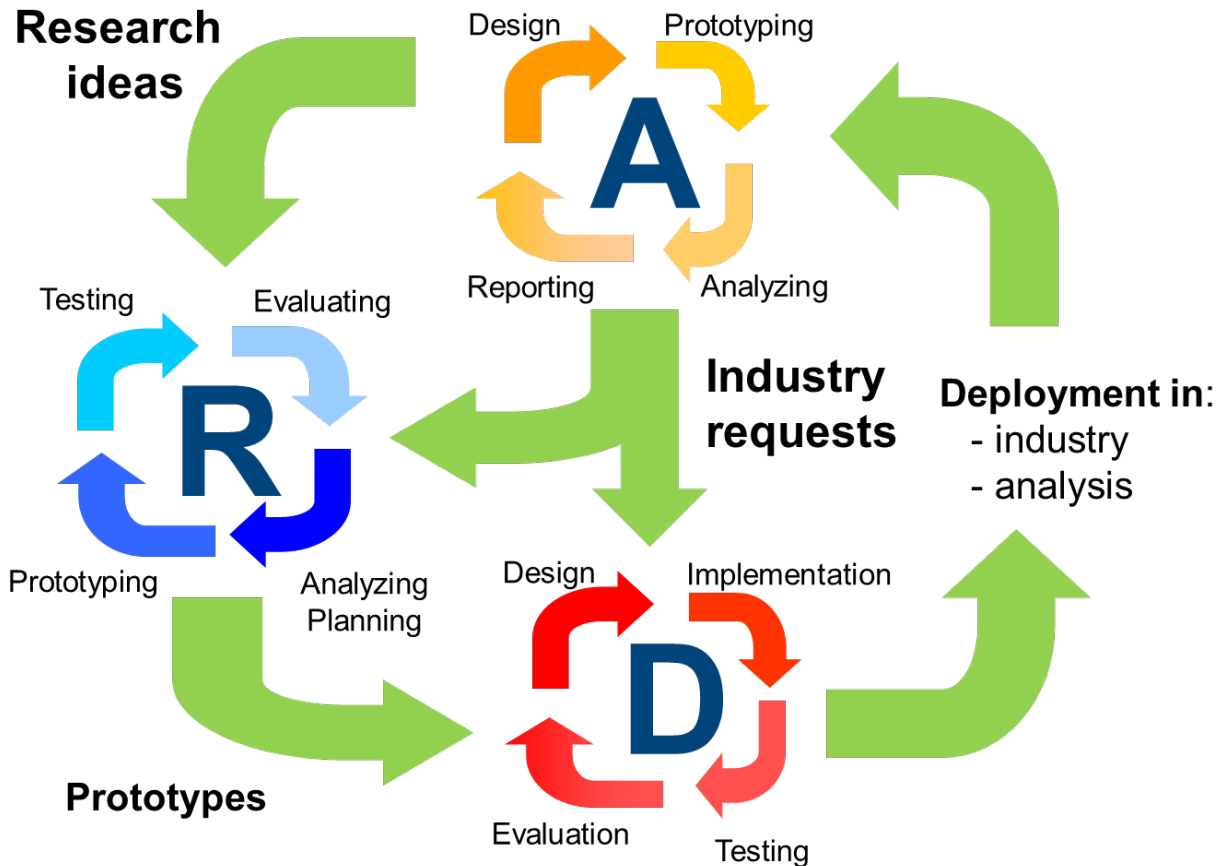


Figure 6-3: R&D approach for models with research needs that gives short lead times for industrial application.

SINTEF has taken steps to establish further utilization of the SHARM result. Examples of enablers getting the SHARM result into broader use are:

- The SHARM prototype is operated without exclusive rights. Parties not yet included in the research or without access to already established SHARM results will be able to license the results and are encouraged to enter in order to get access to the results and application in the future. One such offer has been issued to a large Nordic player.
- Software houses will be able to integrate the SHARM results into their applications if they feel that it is relevant. The industry partners in the project will be advisers regarding choice and conditions for software houses to get access to the SHARM prototype. SINTEF Energy will support the project partners' individual integration of the result into operation if they so choose.
- The step taken to minimize future operation cost of the SHARM model and at the same time include more functionality by leaning more heavily on functionality from the SHOP model also enable modern API solutions reducing integration cost of the concept.
- We are starting a new project with funding from the Norwegian Research Council in the research (R) loop as shown in Fig. 6-3 that will address the multimarket challenge and optimal bidding possibilities that is possible to implement in the SHARM concept.

We expect the utility value of SHARM to increase as new challenges can be solved by the model and the current low price level and low variability that we currently are experiencing in the energy markets subside.

Results from the project in terms of the possibility to buy into the model will be marketed to current and new SHOP-users. It is unknown to which extent SHARM will compete with SHOP and what other competition from stochastic short-term models in the market SHARM will have to face. We believe that our developed method can compete with short-term models from PSR in Brazil or the HotShot model owned by Powel.

To put some tentative numbers on the potential of SHARM, it is possible to compare to some key numbers for SHOP. The number of unique customers of SHOP is approximately 20 and growing. The number of end-users is higher than 200. More than 170 TWh of hydropower in Scandinavia, Asia, Europe and South America is scheduled by the use of SHOP. SHOP users represent the customer base for application of the SHARM model.

At the moment, we calculate 4-5 full time positions for industrial research tied to SHOP at SINTEF Energy. We estimate that there are about 8-10 positions for consultants at the software houses supporting SHOP. The value of improved energy efficiency and better planning is estimated to 1 billion NOK/year.

We will expose the SHARM concept through our web pages and software brochures under the SHARM logo which we have used in all presentations in the SHARM projects, as seen in Fig. 6-4.



Figure 6-4: The SHARM logo

We will actively and together with the project partners look for software companies that can add value to the results from the SHARM project and take part in the value creation from the SHARM model.

We will actively and together with the industry follow opportunities for creation of new projects founded on the SHARM concept. This includes different types of projects as illustrated in Fig. 6-2. This work as already concluded in one new KPN project.

7 Discussion

The primary aim of this project was to obtain sufficient knowledge to decide whether to proceed with implementation of the SHARM prototype for short-term optimization in the industry or to use the concept as a research prototype. The SHARM project participants agree that implementation of the stochastic short-term model should continue. The largest step taken in this direction is to incorporate the SHARM-specific functionality into the code base of the operational SHOP model. This work is still in progress, but the goal is that users should be able to switch effortlessly between the deterministic and stochastic version of the short-term scheduling tool and benefit from the strengths of both alternatives.

The introduction of stochasticity directly into the SHOP software had not been possible without the knowledge obtained in the SHARM projects. For the research side, experience with the SHARM model has been necessary for making an efficient solution that can accommodate users' needs and continued development of the stochastic model towards multi-market decision support. For the industry partners, experience with the SHARM model has lowered the barriers for using stochastic models and even led to

improvements in the utilization of the deterministic SHOP software. The participating hydropower companies believe that the stochastic model will be the industry standard at some point in the future, but disagree if this is in a perspective of 2 or 10 years.

To achieve the primary objective, some secondary objectives were stated. These have been addressed throughout this report, and our findings are summarized below.

1) Calculate added economic value from using SHARM based on extensive testing in the individual utilities and at SINTEF Energy Research.

From the outset, testing was intended to be the main activity in the project and this has also been the case. The test procedures were developed as a joint effort between SINTEF and the partner companies. However, the tests did not give consistent results. This is largely due to calculation noise and imprecise test procedures. If we could have anticipated that the gain from the stochastic model would be very small, more accurate test procedures could have been chosen. However, it is through the formulation and gradual improvement of the test procedures that insight into the stochastic model and short-term production scheduling has been obtained.

2) Identify and mitigate the challenges of implementation of the stochastic model for operative decisions in the utilities.

The main challenge for implementation was the increased amount of input and output required for the stochastic model. This has been mitigated partly by increased experience with the model, and by implementing new formats for output of results and the alternative of obtaining a common production plan even if the underlying tree structure have more than one scenario. Some of the challenges still remaining are generation of scenario trees that adequately describe the decision situation and the calculation time. For operational use, more experience with tree generation and a clear relation between input and output is necessary for trusting the results from the model. In addition, calculation time is an issue when running the model with a high number of scenarios or for all water courses in an area.

3) Generate an overview of the process required for operationalizing the model on partner level and in general.

The SHARM model has been on a prototype level throughout the project period. A user interface has been absent, and it was never the intent of this project to develop such features. Improvements of the code itself have also been done throughout the project. If the model is to be used in real operations, a user interface must be developed by the companies themselves, SINTEF or a third-party. As stated, integration of the SHARM and SHOP code is a large step towards operationalization, as this substantially decreases the costs of switching between deterministic and stochastic formulations. Continued testing and evaluation of the results from the SHARM model is necessary before making the switch, and the implementation in each partner company may be best undertaken as bilateral projects between partner companies and SINTEF.

4) Estimate the intra utility cost of implementing SHARM.

The cost of implementing SHARM has been difficult to assess, and will vary from company to company. A shift in the cost structure for the total production scheduling process has been suggested, where costs are shifted from verification of results and manual adjustments to obtaining good forecasts and generating scenario trees. How much the costs will change is difficult to say in explicit terms.

A few concluding remarks have been made by each participating hydropower company. These are given below.

TrønderEnergi Kraft

In the current state is not possible to use SHARM for operational scheduling at TrønderEnergi Kraft. The software lacks a proper GUI and tools for developing and evaluating input and output.

Statkraft

The SHARM project has shown that consideration of both price and inflow uncertainty has measurable gains. Due to inconsistencies in the results, there has been no real assessment of the size of potential added gains or if this gain make up for the efforts required for operationalization. The project has resulted in increased knowledge about stochastic optimization and given valuable input for future research projects.

E-CO Energi

We have observed that the benefit from SHARM seems to be highest when the system is close to its limits. In the test system, this is when reservoir levels are high and there is large uncertainty in inflow. We expect the value of SHARM to be larger for more complicated systems than the test system used during the project. In the future, we believe that stochasticity will become increasingly important due to larger shares of renewables and more extreme weather conditions due to climate change.

Hydro

There is little doubt that inflow and spot price are best modeled as stochastic processes. The numerical simulations presented show that in some situations there might be a substantial value of using the SHARM model compared to an updated deterministic alternative. We believe that the possible earnings generated by using SHARM will outweigh the costs associated with implementing it in Hydro, but there are, at this point, still some requirements related to robustness and consistency that remains to be satisfied. The SHARM-model as of today does not meet the requirements needed to be fully operational.

Agder Energi

The tests have so far not been successful. We have not been able to get results where SHARM consistently gives better results when we compare the objective function values. However, we see that the reservoir management strategy is slightly improved when using the stochastic model. Due to noise in the calculations we are unable to quantify the improvement, and we must thus conclude that the improvement is rather small.

The assessment of gains obtainable by using a stochastic model has proved difficult. The chosen test procedures have not been able to yield quality results that consistently point in one direction. Overall, the values measured for the added value are often too small to be significant compared to other measurement errors. This must mean that the added value is small, and that other improvements in the modelling may be just as important. Some results are also clearly inconsistent, and cannot be explained by measurement errors. At this stage, the conclusion is that we are not able to measure any stable improvements from SHARM for the tested watercourses. On the other hand, even if we are not able to measure any gain from stochastic modelling, the decisions and the reservoir management strategy from SHARM is often preferable to the strategy from the deterministic model. In these situations, we are sometimes able to observe the improvement from stochastic modelling, but not able to measure it by the chosen test procedures.

The test procedures have drawbacks related to the fact that they are based on repeating optimizations where some decisions are locked to results from previous time steps. This causes problems in terms of feasibility and utilization of slack variables that not always are priced correctly. This has distorted many of our results, and simulation would perhaps been a better choice of test procedure. Regardless, the increased attention paid to penalty costs and what they represent has led to greater insight into the short-term production scheduling problem and also pointed out a direction for further development of the stochastic short-term model.

The collaboration between SINTEF and the partner companies has added value to the project, and has contributed to the development of the test procedures. Getting experience with the input and output data from the stochastic model have also identified some of the challenges for implementation. Particularly, new formats for output data have been developed. How the process of determining a final production schedule will change have been discussed with the project participants, and the conclusion is a slight shift in focus from post-processing of the results from the optimization model towards more attention to generation of input in the form of forecast distributions and the scenario tree. The costs will change accordingly.

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