# Modeling and Quantifying the Importance of Snow Storage Information for the Nordic Power System

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***Abstract*—This paper describes how snow storage information can be used to improve the hydro operation strategy in a newly developed hydrothermal market simulation model. The model was applied to a detailed description of the Nordic system, and simulation results show that the value of knowledge about the snow storage in Norway corresponds to an annual average increase in Norwegian hydropower generation of 440 GWh.**

***Index Terms*—Hydroelectric power generation, Power generation economics, Linear programming, Stochastic processes.**

## I. Introduction

About 50 % of the Scandinavian (including Finland) electricity generation comes from hydropower. Norwegian electricity generation is almost solely based on hydropower and is on average equal to 133.4 TWh, referred to 1981-2010 [1]. About 50 % of Swedish electricity generation is based on hydropower. Even though these countries are part of the larger European electricity market, weather-related uncertainty, and in particular inflow variations, are very important for the balance between supply and demand. The natural variation in yearly Norwegian hydropower generation is +/- 20 %. Yearly inflow variations are even higher but the large reservoirs smooth inflow variations. Because of the uncertainty and the reservoirs, hydropower scheduling models and hydrothermal market models are formulated as stochastic dynamic optimization problems [2]. Inflow uncertainty is typically represented by historical variations directly, or by parametric models calibrated to historical observations. In operation, utilities make short- and medium-term inflow forecasts based on the latest weather forecasts and updated information about the snow storage. Snow storage information is used in the late winter, spring and early summer periods to modify the inflow statistics. Snow storage information can be gathered using many different methods; e.g. model-based, manual measurements, and from radars or satellites. An HBV-type hydrological model [3] can estimate the snow storage and make spring inflow forecasts dependent on the current snow storage. Estimation of snow storage and inflow forecasting is also discussed in [4].

In the Nordic market hydrothermal market models are used for many different purposes:

- Price forecasting (utilities and consultants);
- Hydropower scheduling (utilities);
- Investment analyses, transmission and capacity (transmission system operator, regulator, utilities);
- Security of supply analysis (regulator);
- Different types of system analysis (e.g. consequences of new environmental constraints, taxes etc.).

In this paper a hydrothermal market model is used to quantify the benefit for the system of including snow storage information in the operational planning for the whole system. Including snow storage information makes the model decisions closer to reality and improves the model. Snow storage information has been included in a few other hydrothermal models [5]–[9], but we are not aware of any attempt at representing snow storage information in a detailed hydrothermal scheduling model at the same scale that we present in this work. The detailed Nordic system description includes more than 1000 individual reservoirs and more than 100 statistically different inflow series which all are influenced by individual snow storage information.

This paper describes briefly a new hydrothermal market simulation model [10] in Section II, focusing on how snow storage information can be modeled in Section III. In Section IV we estimate the benefit for the Nordic power system of using detailed snow storage information in Norway.

## II. Hydrothermal Market Model

The development of a new hydrothermal market model was motivated by stronger coupling between the Nordic and the continental European power markets, both facing an increasing share of generation from wind and solar power. The large storage capacities of the hydro reservoirs can be used to balance much of the variation in wind and solar generation. Storage capacity is distributed between a large number of reservoirs and the flexibility is limited by many physical and judicial constraints. A hydrothermal market model combining simulation and formal optimization was implemented as described in [10] to analyze the costs and benefits for the system in this new market context. An early version of the model applied to an aggregate representation of hydro storages was presented in [11].

The model works as a simulator repeatedly solving two-stage stochastic optimization problems using linear programming (LP). The first decision stage is assumed to be deterministic and represents the first week. The second decision stage represents the future and consists of a number of scenarios.

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Each scenario is constructed from a historical weather-year sequence. The weather years are used to keep correlations in time and space between weather-related uncertainties. Weather-related uncertainties include inflows to different reservoirs, wind and solar generation at different locations, and temperatures that affect the demand. All these uncertainties impact the balance between supply and demand for electricity. Weather statistics may have been modified to compensate for climate change, especially if long records are used. Other uncertain variables, e.g. market prices on bordering countries or thermal related generation costs, are modeled by scenarios that are tied to the weather years. Thus, the two-stage stochastic LP problem takes the form of a scenario fan. We refer to the model as *FanSi* (Fan Simulator) in the following.

To begin with, we assume that all historical weather years are equally probable from any point in time. A scenario reduction technique similar to [12] is implemented to reduce the size of the fan.

For a given value in the first stage we make a smooth transition to independent weather years in the second stage using an estimated autocorrelation for individual series. The smoothing is given by (1). The smoothing can be seen to represent short-term forecasting.

$$T_j^{new}(t+k) = T_j(t+k) + [T_i(t) - T_j(t)]\,\frac{\sigma(t+k)}{\sigma(t)}a^k \quad (1)$$

Where:

| | |
|---|---|
| $t$ | Week number for first stage decision; |
| $i$ | Weather year for first stage decision; |
| $k$ | Week number in second stage; |
| $T_i(t)$ | Observed value for time $t$ in year $i$; |
| $T_j^{new}(t+k)$ | Smoothed value for week $t+k$ for year $j$; |
| $\sigma$ | Standard deviation; |
| $a$ | Autocorrelation. |

FanSi simulates sequences of two-stage stochastic LP problems. Only results from the first decison stage is stored and used. The reservoir volume by the end of the first (stage) week is input to a new two-stage LP problem. Simulations can either be performed in serial or parallel mode. In serial mode historical weather years are arranged in one consecutive sequence. FanSi simulates week-by-week along this sequence. In parallel mode different historical weather sequences are simulated in parallel. Serial mode is typically used for investment analyses and analysis that are independent of the current state of the system, while parallel mode is used for analysis that depend on the current state, e.g. price forecasting.

The new model has very long computation times, ranging from a few days to several weeks for a detailed description of the Nordic system. We use Benders decomposition to decompose the first-stage problem from individual second-stage scenario problems. The computation time depends on factors such as the level of details when representing the physical system, the time resolution for both the first-stage and along the second-stage scenarios, and the number of scenarios used in the second-stage. Parallel processing is utilized as much as possible and is especially effective for the parallel simulation mode where parallel processing is used in two layers [13].

## III. Modeling Snow Storage Information

The starting point for inclusion of snow storage information is simultaneous time series for snow storage and inflow for the whole historical sequence that are going to be used in the simulation. Typically, observed time series for snow storage do not exist but it is possible to generate such series from e.g. a HBV-type model based on observed inflows, temperatures and precipitation.

We assume that historical time series for inflow $T_j(t)$ and snow reservoir $S_j(t)$ in week $t$ for inflow year $j$ are available, and define $T_a$ as the last week of the melting season where the snow reservoir give significant information about future inflow. $T_a$ is calculated automatically with criteria to maximize the correlation between snow storage and future inflow for the whole snow accumulation period. $T_a$ is fixed for a given time series and is typically around week number 33 (August). We assume here that inflow data have weekly resolution but daily data are also available and may be used.

Further we define a new time series for accumulated inflow

$$T_{acc,j}(t) = \sum_{k=t+1}^{T_a} T_j(k), \quad (2)$$

where $T_{acc,j}(t)$ for week $t$ is the accumulated inflow from week $t+1$ to week $T_a$ for inflow year $j$.

The method is based on the estimated correlation between the time series for snow storage $S_i(t)$ and accumulated future inflow $T_{acc,j}(t)$. Correlations are estimated from normalized versions of $S_i(t)$ and $T_{acc,j}(t)$. The normalized time series are calculated by subtracting the average weekly value and dividing by the standard deviation for each week $t$. An example of estimated correlations for four different inflow and snow storage series are shown in Fig. 1.

For a given week $t$ and inflow year $j$ the normalized snow storage is given by $S_j^N(t)$. Positive values means snow storage above normal. Based on the estimated correlation it is possible to calculate the expected future accumulated inflow conditioned on known snow storage in week $t$, i.e. $S_j^N(t)$.

$$\bar{T}_{acc}(t)|S_j^N(t) = \rho(t)S_j^N(t)\sigma_{Tacc}(t) + \bar{T}_{acc}(t) \quad (3)$$

Where:

| | |
|---|---|
| $\bar{T}_{acc}(t)\|S_j^N(t)$ | Expected accumulated future inflow conditioned on known snow storage $S_j^N(t)$ in week $t$; |
| $\rho(t)$ | Estimated correlation between snow storage in week $t$ and accumulated future inflow $T_{acc}(t)$; |
| $\sigma_{Tacc}(t)$ | Standard deviation for accumulated inflow in week $t$; |
| $\bar{T}_{acc}(t)$ | Unconditional expected accumulated inflow from week $t+1$ to $T_a$. |

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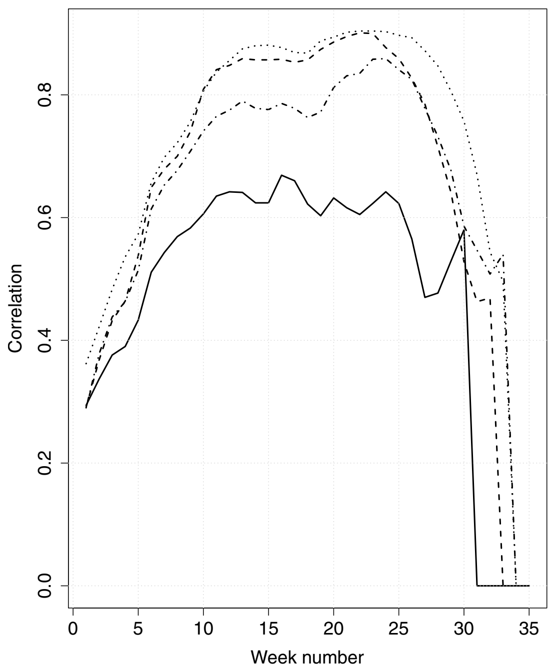


Fig. 1. Estimated correlations between normalized snow storage $S_j^N(t)$ and accumulated future inflow $T_{acc,j}(t)$ for four different inflow and corresponding snow storage series.

We see from (3) that snow storage above normal gives more than normal future inflow, and that higher correlation gives higher dependency on the snow storage. We have chosen to base the uncertainty estimates on +/- 2 standard deviations.

$$T_{acc}^{max} = \bar{T}_{acc}(t)|S_j^N(t) - 2\sqrt{1-\rho^2(t)}\sigma_{Tacc}(t) \quad (4)$$

$$T_{acc}^{min} = \bar{T}_{acc}(t)|S_j^N(t) - 2\sqrt{1-\rho^2(t)}\sigma_{Tacc}(t) \quad (5)$$

Eqn. (3) gives the average accumulated inflow for the scenarios that are going to be used in the second stage problem when solving the first-stage problem for week $t$, inflow year $j$ with known snow storage $S_j(t)$. All weather years that have inflows between limits given by (4) and (5) are included in the second-stage scenarios. Weather years with inflows outside the limit are excluded. The chosen scenarios are scaled to the average given by (3). The process is done individually for each inflow series, and consequently different weather years may be excluded for different inflow series. All weather years are always used to keep as much as possible of the correlations in time and space, but inflows that are outside the limits are substituted with inflows from a year that are within limits, i.e. some inflows are duplicated. We limit the use of the snow correction method to periods where estimated correlation factor $\rho$ is higher than 0.4.

Equations (3), (4) and (5) modify the inflow scenarios used in the second stage. The first-stage decision is done for known inflows and known snow storage that is the basis for the inflow modifications.

The described method for generation of snow storage dependent scenarios could be substituted by direct use of HBV-type models. For every time step and initial snow state a full set of scenarios could be generated on the fly or made available from preprocessing based on weather scenarios representing temperatures and precipitation. For a typical Nordic dataset more than 100 GB of preprocessed inflow data is then needed. Such data have not been available for us in this work.

## IV. Case Study

### A. System Description

The snow correction method was applied to a description of the Nordic system provided by the Norwegian transmission system operator (Statnett). The modeled hydropower system consists of 1265 individual hydro reservoirs of which 737 have storage capacity larger than 2 Mm$^3$. The description includes 26 price zones in 7 countries. Bordering countries, e.g. Germany, Poland and the Netherlands, are modeled by exogenously given stochastic price-series. The simulations were done for the historical weather years 1962 to 2012 and include 228 unique inflow series, 85 wind power series and 15 temperature series. The actual system is referred to year 2020 and a serial simulation mode was used. The FanSi model was run with 5 load periods within the first stage and weekly resolution along the second-stage scenarios. The number of scenarios in the scenario fan was reduced to 19. The FanSi model was run on a Windows cluster using 20 cores on Intel Xenon ES-26400 processors with 2.50 GHz. CPLEX 12.6 was used to solve the LP problems, and the total calculation time was 52 hours.

"Historical" time series for snow storages for all the Norwegian inflow series was generated by The Norwegian Water Resources and Energy Directorate [14], [15]. Snow storage series for the other countries was not available and were therefore not included in the case study. Fig. 2 shows an example of snow storage for a given reservoir in western Norway.

### B. Simulation Results

Figs. 3 and 4 show simulated reservoir operation for a reservoir that is connected to the catchment area shown in Figure 2. The figures compare simulated reservoir filling for two strategies; with and without information about snow storage. Fig. 3 is from weather year 1989 with high levels of snow storage, and Fig. 4 is from weather year 2004 with low levels of snow storage in this part of Norway. The figures clearly show that the operation strategy takes advantage of information about the snow storage to adapt reservoir operation. High snow storage levels give more generation in the spring period, leading to lower reservoir levels before snow melting start as in Fig. 3. In the case with little snow, summer generation is lower and the winter period is started with higher reservoir levels, as shown in Fig. 4. Average simulated filling for the same reservoir also changes slightly. With snow storage

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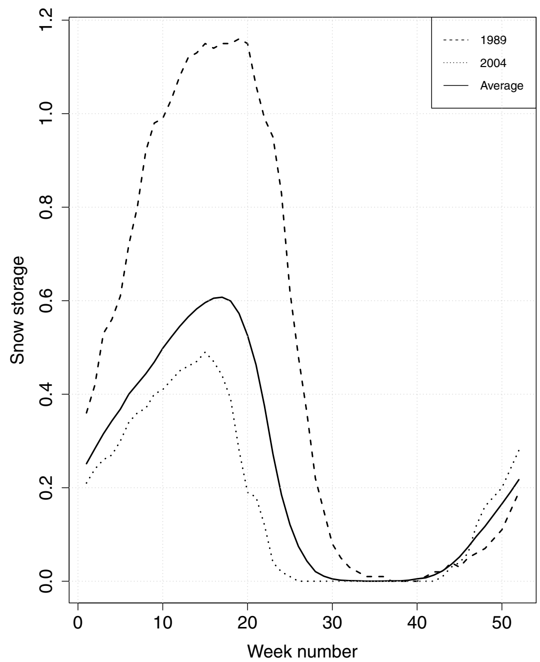


Fig. 2. Snow storage, average and two specific weather years for a catchment area in western Norway.

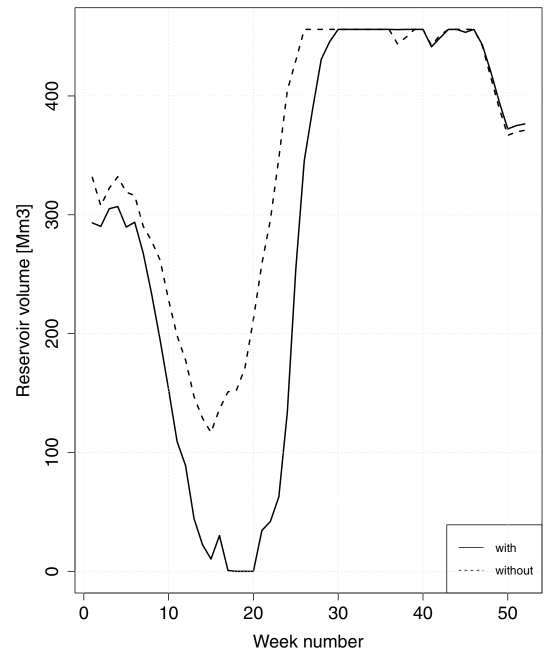


Fig. 3. Simulated reservoir filling for weather year 1989 with and without information about snow storage.

information included, summer filling is on average approx. 15 $Mm^3$ lower and winter filling 15 $Mm^3$ higher than without use of snow storage information.

Table I shows aggregated results for simulated hydropower generation and overflow for the whole system. Results are split between Norway and the rest of the market because snow storage information is only available for Norway. The results show that including snow storage information increases on average sum hydro generation in Norway with 440 GWh. Sum overflow us reduced by 421 GWh. Overflow (GWh) are calculated based on constant plant efficiency (kWh/m3), sum generation is based on individual plant generation that include discharge and head efficiency dependencies. Hydropower generation increases in all Norwegian price areas. Swedish generation is reduced because snow storage information is not included for the Swedish hydropower. Norway and Sweden are part of the same market, and we observe that the entire increase in generation cannot be utilized due to transmission constraints.

Fig. 5 shows simulated sum yearly overflow for Norway, including bypass, sorted in decreasing order of simulated overflow for the case without snow information. Overflow reductions are of course highest for years with high inflows. The maximum yearly reduction in overflow is equal to 5.2 TWh and the maximum increase is 1.4 GWh. Increase in overflow happens for weather years where snow storages are below normal and summer rain is much higher than normal. The strategy that is best on average will in this case be worse than a strategy without snow storage information.

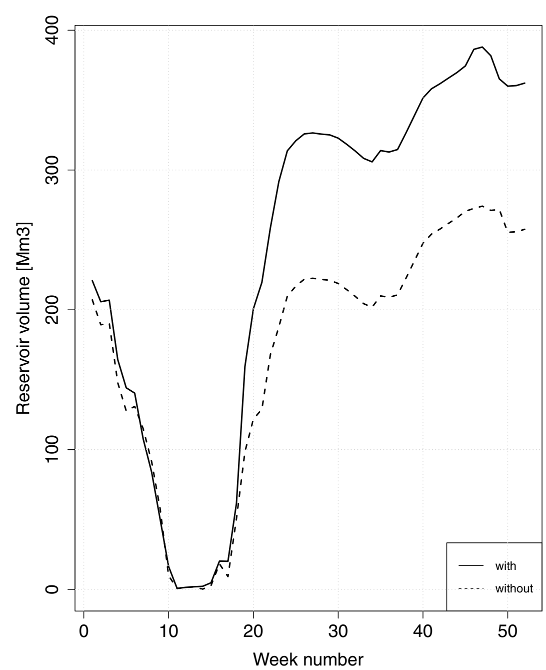


Fig. 4. Simulated reservoir filling for weather year 2004 with and without information about snow storage.

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as reference and application of different simulation tools.

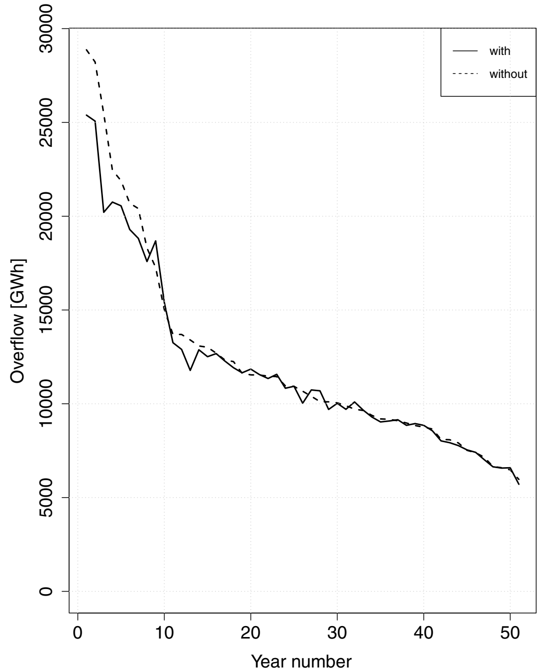


Fig. 5. Sum yearly overflow in Norway. Values sorted in decreasing order of simulated overflow without snow information.

Table I also shows socioeconomic surplus for the whole system. Note that the nominal value of the consumer surplus is proportional to the modeled curtailment price, and thus leads to high numbers. Based on the differences between the two surpluses the yearly average value of snow storage information is estimated to 9.4 M(million)€ for the whole system. Even if Swedish hydropower generation is reduced, use of Norwegian snow storage information is beneficial because of lower prices that give increased consumer surplus. Average power prices in Norway is on average reduced by about 0.02 cent/kWh.

TABLE I
SOME SIMULATIONS RESULTS WITH AND WITHOUT SNOW STORAGE INFORMATION, YEARLY AVERAGES FOR THE PERIOD 1962-2012.

| | **Without** | **With** | **Change** |
|---|---|---|---|
| Sum overflow Norway [GWh] | 12289 | 11868 | -421 |
| Sum hydro generation Norway [GWh] | 139204 | 139644 | 440 |
| Sum overflow Sweden & Finland [GWh] | 2902 | 2958 | 56 |
| Sum hydro generation Sweden & Finland [GWh] | 84524 | 84610 | -86 |
| Socio-economic surplus whole system [M€] | 2099463.9 | 2099473.3 | 9.4 |
| Socio-economic surplus Norway [M€] | 89117.4 | 89123.4 | 6.0 |

The average generation for Norway shown in Table I deviates from the number referred to in the introduction. This is because it refers to different stadiums (2012 and 2020), because of modeling differences, use of different weather years as reference and application of different simulation tools.

## V. CONCLUSIONS

The paper describes how snow storage information can be utilized to improve hydropower operational strategies in a hydrothermal market simulator. The market model is formulated as a simulator of two-stage stochastic LP problems. Adding snow storage information increases memory use, but does not increase the computation time.

A case study of the Nordic power market with detailed snow storage information for one country (Norway) was presented. We found that by adding snow storage information, the average increase in annual hydropower generation in Norway was 440 GWh. The average power price in Norway decreases when taking advantage of snow storage information. For the entire system, we found that the socio-economic surplus increases with 6 M€ when using snow storage information, and that the benefit is primarily seen for consumers through lower power prices.

## REFERENCES


[1] [Online]. Available: https://www.nve.no/energiforsyning-og-konsesjon/vannkraft/vannkraftpotensialet

[2] O. B. Fosso, A. Gjelsvik, A. Haugstad, B. Mo, and I. Wangensteen, "Generation scheduling in a deregulated system. The Norwegian case," *IEEE Transactions on Power Systems*, vol. 14, pp. 75–81, 1999.

[3] G. Lindström, B. Johansson, M. Persson, and M. G. S. Bergström, "Development and test of the distributed HBV-96 hydrological model," *Journal of Hydrology*, vol. 201, no. 1-4, pp. 272–288, 1997.

[4] D. J. Druce, "Insights from a history of seasonal inflow forecasting with a conceptual hydrologic model," *Journal of Hydrology*, vol. 249, no. 1-4, pp. 102–112, 2001.

[5] J. Kelman, J. R. Stedinger, L. A. Cooper, E. Hsu, and S. Q. Yuan, "Sampling stochastic dynamic programming applied to reservoir operation," *Water Resources Research*, vol. 26, no. 3, pp. 447–454, 1990.

[6] J. A. Tejada-Guibert, S. A. Johnson, and J. R. Stedinger, "The value of hydrologic information in stochastic dynamic programming models of a multireservoir system," *Water Resources Research*, vol. 31, no. 10, pp. 2571–2579, 1995.

[7] M. Hindsberger, "Modeling a hydrothermal system with hydro- and snow reservoirs," *Journal of Energy Engineering*, vol. 131, no. 2, 2005.

[8] P. Côté, D. Haguma, R. Leconte, and S. Krauc, "Stochastic optimisation of Hydro-Quebec hydropower installations: a statistical comparison between SDP and SSDP methods," *Canadian Journal of Civil Engineering*, vol. 38, no. 12, pp. 1427–1434, 2011.

[9] T. W. Archibald, K. I. M. McKinnon, and L. C. Thomas, "Modeling the operation of multireservoir systems using decomposition and stochastic dynamic programming," *Naval Research Logistics*, vol. 53, no. 3, pp. 217–225, 2006.

[10] A. Helseth, B. Mo, A. L. Henden, and G. Warland, "Detailed long-term hydro-thermal scheduling for expansion planning in the Nordic power system," *IET Generation, Transmission and Distribution*, vol. 12, no. 2, pp. 441–447, 2018.

[11] A. Helseth, B. Mo, and G.Warland, "Long-term scheduling of hydro-thermal power systems using scenario fans," *Energy Systems*, vol. 1, no. 4, pp. 377–91, 2010.

[12] N. Gröwe-Kuska, H. Heitsch, and W. Römisch, "Scenario reduction and scenario tree construction for power management problems," in *IEEE PowerTech Conference*, Bologna, Italy, 2003.

[13] G. Warland and B. Mo, "Stochastic optimization model for detailed long-term hydro thermal scheduling using scenario-tree simulation," *Energy Procedia*, vol. 87, pp. 165–172, 2016.

[14] N. R. Sælthun, "The "Nordic" HBV model," Norwegian Water Resources and Energy Directorate, Tech. Rep. 7, 1996.

[15] D. Lawrence, I. Haddeland, and E. Langsholt, "Calibration of HBV hydrological models using PEST parameter estimation," Norwegian Water Resources and Energy Directorate, Tech. Rep. 1, 2009.



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