Financial risk management in the electric power industry using stochastic optimization

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Abstract

This paper describes a risk management tool for hydropower generators and its application to Norway's second-largest generation company and largest electricity consumer, Norsk Hydro ASA. The tool considers both operations scheduling and the utilization of financial contracts for risk management. Financial risks are accounted for by penalizing incomes below a reference income. The risk management problem is solved by a combination of stochastic dual dynamic programming and stochastic dynamic programming. Simulations demonstrate that lower income scenarios improve when risk aversion is introduced

Keywords: Risk management, generation planning, stochastic dual dynamic programming

1. Introduction

Deregulation of the Nordic power market has increased price uncertainty, and therefore stimulated a demand for risk management tools. Each generation company schedules by using self-dispatch at the power exchange (Nord Pool). Based on aggregate bids for purchases and sales, Nord Pool calculates the market clearing price for the spot market. The spot price is the reference price for the financial contract market. Nord Pool facilitates the trade of a wide range of contracts as futures, forwards, options, and Contracts for Differences (spatial risk hedging instruments). In the over-the-counter (OTC) market, bilateral contracts are traded. These may be forward contracts, options, or load factor contracts. System coordination, monitoring and operation of the Norwegian transmission network are the responsibility of the transmission system operator (Statnett). The Norwegian power market consists of 99% hydropower with its associated uncertainty in inflows. Therefore stochastic optimization tools are utilized for long-term generation planning [1]. The objective of these models is to find the optimal first-stage decision and simulate (forecast) optimal operation and income for the future. The most important risks that the Norwegian hydropower generators face are price uncertainty and quantity risks caused by uncertainty in inflows and demand. Risk management of both uncertainties is complex. Local area prices depend strongly on the precipitation and usually correlate with the local generation. There is also a correlation between the precipitation and temperature such that wet winters are warmer than normal. Hydropower generators with large reservoirs dominate the Nordic market, resulting in a sequential dependence in spot price. All of these correlations must be managed by using an appropriate risk management tool. A model for integrated risk management of hydropower scheduling and contract management in a stochastic dynamic optimization framework has been developed by Mo et al. [2] and [3]. Their model includes the possibility of future trading and use of reservoirs and futures contracts as risk management tools. The objective of the model is to utilize a time separable utility function to characterize the risk attitude of the company. The solution methodology is a combination of stochastic dual dynamic programming (SDDP) [4] and stochastic dynamic programming (SDP).

The latest version of the model accounts for the modeling of the spot price extremes and the long-term uncertainty of futures prices. As mentioned in [5] it suggests less trading when dynamic hedging is allowed (Dynamic hedging is a strategy that involves rebalancing hedge positions as market conditions change.). The test results also demonstrated that the reservoir discharge strategy depends upon the utility function of the company. An increased penalty term gives a more risk-averse operation of the reservoir. The tests showed that it is possible to reduce the risk considerably without reducing

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the expected income to the same extent. It implies that the income optimum is relatively flat. Gjelsvik et al. [5] demonstrated that the results are highly sensitive to the internal price model used in the optimization. This resulted in the development of the price model described in [6]. In this paper we describe the testing of the improved model on the power system of Norway's second largest generation company.

2. The model

The model has been developed by Mo et al. [2] and is an extension of an existing tool for medium-term hydropower scheduling described in [5], where new state variables are introduced to account for future trading. For an overview, we present the model in this section. The objective in the new model is to maximize the sum of net income from trading in the futures market, sales in the spot market and the value of the water at the end of the planning period, minus penalty terms for failing to fulfill income requirements. The penalty terms penalize progressively for incomes below a user-specified limit at the end of the period. The planning period is usually two or three years with a time resolution of one week. The spot price and inflow are assumed to be known in the beginning of the week. Generation, trading of standardized futures contracts and withdrawal of load factor contracts are decided at the beginning of the weeks (The state variables describing reservoir levels, position in the futures market and accumulated income are referred to the beginning of the week.). In Nord Pool the contracts are traded in one-week lots for the first 4-7 weeks (This is referring to the financial market structure existing until fall 2003). After this contracts are traded in 4-week blocks and beyond one year in seasons. The market features are implemented in the model and the time resolution is dynamic, so that blocks are resolved into weeks and seasons are resolved into blocks as time passes, as in the actual market. Future contracts are delivered at a flat MW rate. The important calculated values are:

- Generation schedules and marginal water values for each reservoir.
- Trading schedules and marginal contract values for each standardized future contract (traded at Nord Pool).
- Income forecasts that include a realistic measure of future uncertainty.

Model definitions include:

period: the basic time step is one week so that a period may be one or more weeks

planning period: time from now up to the planning horizon (usually 2 to 3 years) used in the model

income period: the period used for measuring income, usually annually

k week in the planning period

t week in the futures market (contract period), $t > k$

N number of weeks in the planning period

$E_{P,v}$ expectation operator applied to the distributions of price (P) and inflow (v)

$Sp(k)$ energy exchanged at spot market price in week k (GWh)

$P(k)$ average spot price in week k (NOK/MWh)

N_{prof} number of income periods

$P_{st}(J)$ first week in income period J

$P_{sl}(J)$ last week in income period J

$I(k,J)$ accumulated income for income period J in week k (NOK)

$Pen()$ penalty function for failing to fulfill the income requirements

$R(x(N))$ value of water remaining in week N (NOK), estimate obtained from long-term scheduling

$S(k,t)$ sales committed in week k for future week t (GWh)

$K(k,t)$ purchase committed in week k for future week t (GWh)

$B(k,t)$ accumulated balance (sum of commitments) in week k for future week t (GWh)

$pf(k,t)$ contract price in week k for delivery in future week t (NOK/MWh)

Δp transaction costs (NOK/MWh)

$x(k)$ vector of reservoir levels in week k (Mm^3)

$x_{max}(k)$ vector of maximum reservoir levels in week k (Mm^3)

$x_{min}(k)$ vector of minimum reservoir levels in week k (Mm^3)

$u(k)$ vector of discharges in week k (Mm^3)

$u_{max}(k)$ vector of maximum discharges in week k (Mm^3)

$u_{min}(k)$ vector of minimum discharges in week k (Mm^3)

C matrix describing the system topology

$G()$ conversion function from discharge vector to generation (GWh)

$v(k)$ vector of inflows for week k (Mm^3)

$v_n(k)$ normalized inflow vector in week k

$\sigma_v(k)$ standard deviation of inflow week k

$\mu_v(k)$ expected inflow in week k

$\varepsilon_v(k)$ noise-term which is normally distributed $N(0,\Omega)$ where Ω is the covariance of the noise-term

A inflow matrix containing correlation in inflow between week k and k+1

The objective function is:

$$
\begin{aligned}
&Max\ E_{P,v}\Bigg\{\sum_{k=1}^{N} Sp(k)P(k) \\
&-\sum_{k=1}^{N-1}\sum_{t=k+1}^{N} K(k,t)(pf(k,t)+\Delta p) \\
&+\sum_{k=1}^{N-1}\sum_{t=k+1}^{N} S(k,t)(pf(k,t)-\Delta p) \\
&-\sum_{J=1}^{N_{prof}} Pen(I(P_{sl}(J),J)) + R(x(N))\Bigg\}
\end{aligned} \tag{1}
$$

The water balance, reservoir and discharge constraints are:

$$x(k+1) = x(k) - Cu(k) + v(k) \qquad k = 1,..,N \tag{2}$$

$$x_{\min}(k) \le x(k) \le x_{\max}(k) \qquad k = 1,..,N \tag{3}$$

$$u_{\min}(k) \le u(k) \le u_{\max}(k) \qquad k = 1,..,N \tag{4}$$

The contract balance for any future week t is updated for every week in the planning period k:

$$B(k+1,t) = B(k,t) + K(k,t) - S(k,t) \qquad k = 1,..,t-1 \tag{5}$$

The spot market balance equals:

$$Sp(k) = G(u(k)) + B(k,k) \qquad k = 1,..,N \tag{6}$$

Accumulated income caused by trading in the futures market (accounted as physical contracts) and income due to trading in the spot market are given by:

$$I(k+1,J) = I(k,J) + \sum_{t=max(P_{st}(J),k+1)}^{P_{sl}(J)} S(k,t)(pf(k,t) - \Delta p)$$
$$- \sum_{t=max(P_{st}(J),k+1)}^{P_{sl}(J)} \left(K(k,t)(pf(k,t) + \Delta p) \qquad k = 1,..,N \tag{7}$$
$$I(k,J) = I(k,J) + Sp(k)P(k) \quad \text{if } P_{st}(J) \le k \le P_{sl}(J)$$

The initial contract portfolio gives $B(0,t)$ and $I(0,J)$ for all t and J. Each load factor contract is modeled as a reservoir with a given initial energy amount and a power station efficiency of 1.0 and an upper MW rate. Equations (2) and (4) therefore apply. The inflow is zero except for the time of initialization or renewal. The model suggests the optimal use of existing load factor contracts, but does not give any decision support whether or not to enter into new load factor contracts. Accounting of futures contracts are as for physical contracts and affects which income states that are updated when trading occurs in week k for future week t.

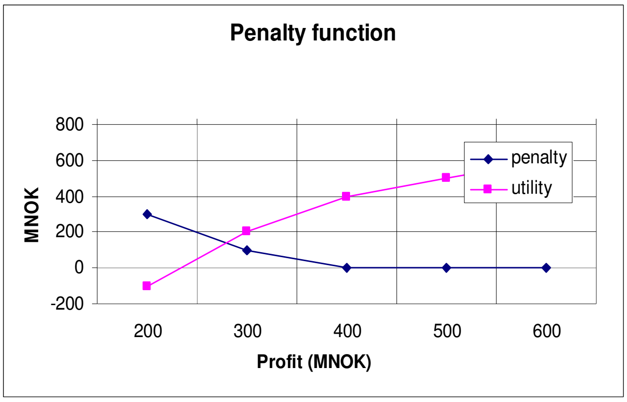

Fig. 1. Example penalty function and the associated utility function for a risk-averse agent.

The penalty function describes the risk attitude of the company and corresponds to a utility function. It is illustrated in Fig. 1. Incomes below a reference income (the income target of the company) in each income period are penalized in the objective function by subtracting a penalty cost. The cost is zero for incomes above the reference income. The penalty function must be defined by a reference income and marginal penalty (i.e. the slope of the function) for all income periods and may differ from one income period to another. It may also have two or more segments as illustrated in Fig. 1. If the penalty function is subtracted from the income, the result is a utility function demonstrating that the company is risk neutral for incomes above a certain level. The penalty function is assumed to be convex and must be specified and calibrated by the user of the model. In this paper incomes below the 25 percentile are penalized with different marginal penalties. We only include two segments in the penalty function.

Hydropower plants have an infinite horizon and therefore a function that values the water at the end of the planning period is needed. The function is constructed from an aggregated long-term model system and is a function of total storage.

Inflow Model

Uncertainty is taken into account by assuming stochastic future spot market prices and inflows to reservoirs. The inflows to the reservoirs are modeled as a multivariable first order autoregressive model. Input data are historical inflows. The model described in [7] introduces additional state variables to Equations (1)-(7). With a weekly resolution there will usually be a certain autocorrelation in the inflow, $v_n(k)$. A simple model describing this is the lag-one autoregressive process. A normalized inflow model is used:

$$v(k) = \sigma_v(k)v_n(k) + \mu_v(k) \tag{8}$$
$$v_n(k+1) = A \cdot v_n(k) + \varepsilon_v(k+1) \tag{9}$$

A is the auto-regression matrix, and $\varepsilon_v(k+1)$ is a stochastic term that is uncorrelated from one week to the next. With no auto-correlation $v_n(k+1) = \varepsilon_v(k+1)$. This inflow model is easily handled by the SDDP algorithm. The elements of A and the distribution of $\varepsilon_v(k+1)$ must be determined from the observed inflows. To apply the SDDP algorithm, a set of discrete inflow values are used at each week resulting in a finite number of possible reservoir sequences. Inflow series for regulated and unregulated inflows are treated similarly.

Price Model

A first order discrete Markov price model is simple and applicable in a stochastic optimization framework. The price in one time step depends on the price in the previous time step. However, the Markov price model does not always capture all of the statistical properties of the price scenarios. In some cases it is observed that the mean reverting properties of the Markov model are stronger than what is observed for simulated extreme prices.

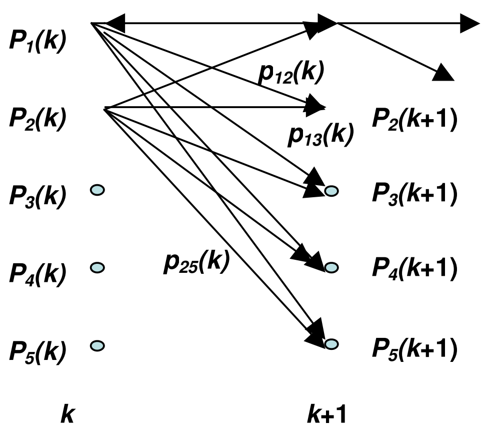

Fig. 2. Price model structure.

The general price model structure is shown in Fig. 2. For every time step, there is a given number of price nodes, $P_i(k)$. Transition probabilities $p_{ij}(k)$ are linking the price nodes where $p_{ij}(k)$ is the probability that the price is $P_j(k+1)$ at time step k+1 given that it was $P_i(k)$ at time step k. A process identifies what prices belong to the same node and estimates the transition probabilities from Norsk Hydro's statistical price forecast [6].

An important assumption is that the price of the futures contract equals the expected spot price in the delivery week t conditioned on the spot price in trading week k:

$$pf(k,t) = E(P(t) \mid P(k)). \tag{10}$$

Here it is assumed that the futures market gives an unbiased estimate of the expected future spot market prices. The spot price model is used to compute the conditional probability distribution of $pf(k,t) = E(P(t) \mid P(k))$ and therefore the futures market price at decision time step k and future delivery week t.

In the forward market, prices of contracts with delivery up to several years ahead vary from week to week. To incorporate this, the price model has been expanded with new nodes and transition probabilities that model the probability of shifts in futures prices [6]. The price nodes consist of the original nodes and new nodes calculated as the original ones plus/minus a price shift. The new transition probabilities are calculated by combining the original ones and the probability of a price shift. The price shift model is symmetric with expected value zero so that the expected price of the original price model is unchanged. The improved price model is similar to a multi-factor price model.

3. Solution methodology

The model formulation in Equations (1)-(7) is a stochastic dynamic optimization problem. The solution methodology is a combination of SDDP [4] and SDP [5] adapted to the model extensions. There is no reduction of the state space, and a power system with many reservoirs and load factor contracts will have a substantial computational time.

A system state vector in week k is defined as:

$$z(k) = \left[x^T(k), B(k,k+1),.., B(k,N), I(k,1),...I(k,N_{prof}), P(k) \right]^T \tag{11}$$

and a decision vector as:

$$y(k) = \left[u^T(k), S(k,k+1),...., S(k,N), K(k,k+1),...K(k,N) \right]^T \tag{12}$$

With these definitions the objective is written as:

$$Max\ E_{P,v} \left\{ \sum_{k=1}^{N} L_k(z(k), y(k)) + R(z(N)) \right\} \tag{13}$$

where $L_k(z(k), y(k))$ is the immediate return from stage k, including penalties represented by Equation (1). Assuming that transition probabilities at stage k are independent of the previous states $z(k\text{-}1)$, $z(k\text{-}2)$, ..., the problem can be solved by dynamic programming. The Bellman recursion equation is:

$$\alpha_k(z(k)) = E_{P,v} Max\left\{ L_k(z(k), y(k)) + \alpha_{k+1}(z(k+1)) \right\} \tag{14}$$

and is solved subject to Equations (2), (5), and (7) which define $z(k+1)$, and to other relevant constraints. $\alpha_{k+1}(z(k+1))$ is the expected future return function from state $z(k+1)$ to a feasible final state in the optimum manner. For the last interval we have the relationship $\alpha_N(z(N)) = R(z(N)) + Pen(z(N))$. The objective function in Equation (1) contains non-linear terms, making it non-convex. To utilize a hyperplane (or cuts – a set of linear constraints) representation of the future income $\alpha_k(z(k))$, 5-7 discrete price levels are used. The methodology is analogous to traditional stochastic dynamic programming with respect to price state. The solution algorithm is iterative. Each main iteration consists of a backward recursion using Equation (14) where the strategy is updated for all weeks in the planning period and a forward simulation based on the last operating strategy (described by hyperplanes). As in the SDDP method sampling in the tree of outcomes is essential. SDDP differs from SDP in that expected future incomes are represented by hyperplanes and not tables.

At each time step one builds a strategy given by hyperplanes in the "z-space." The hyperplanes are represented as constraints of the type:

$$\begin{aligned} &\alpha_{k+1} - \left(\mu_{k+1}^{j1}\right)^T z(k+1) \le \gamma_{k+1}^{j1} \\ &\dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \\ &\alpha_{k+1} - \left(\mu_{k+1}^{jR}\right)^T z(k+1) \le \gamma_{k+1}^{jR} \end{aligned} \tag{15}$$

where $\mu_{k+1}^{j1}....\mu_{k+1}^{jR}$ and $\gamma_{k+1}^{j1}....\gamma_{k+1}^{jR}$ denote the coefficients that define the R hyperplanes representing the expected future income function at the price point $P^j(k)$. Moreover, $z(k+1)$ includes all state variables except price. The vector μ is the mean dual variable of some of the constraints in the sub-problem of Equation (14) while γ is the right-hand side constant in the cuts.

A single-transition sub-problem of Equation (14) under the assumption of a hyperplane representation together with the cuts Equation (15) and the respective constraints in Equations (2), (5), and (7) constitute a standard linear programming problem (with associated dual variables), which is easily solvable and gives the expected income in week k based on the hyperplanes in week k+1. In the backward recursion an upper limit on the income is obtained. To solve the single-transition sub-problem, a relaxation procedure is utilized. This is an effective strategy if relatively few constraints are binding at optimality. In the sub-problem $x(k)$ is known while $x(k+1)$ in the cuts (Equation (15)) and the bounds Equation (3) can be eliminated by using Equation (2) as described in [7]. Bounds on the reservoirs are seldom binding and may be relaxed. Also when many cuts are present most of them may be relaxed. Thus, the number of iterations in the relaxation procedure is relatively small.

The forward simulation is performed for all inflow and price scenarios. Optimal weekly generation is determined from the single-transition sub-problem, given inflow and price. The expected future income is calculated from the last backward iteration. The objective function is:

$$E_{P,v} Max\left\{\text{Income}(k) + \alpha_{k+1}(z(k+1))\right\} \quad (16)$$

The forward simulation gives possible non-optimal solutions that are used to calculate an indicative lower limit on expected future incomes. The same scenarios are simulated but with different state values. A cut generated for one reservoir and price level may be used by the other scenarios at the same price level because of the Markov assumption. The model includes a heuristic based on observed inflows in the forward simulation.

Convergence may be obtained when the absolute value of the difference between the upper and lower limit is comparable to the standard deviation of the upper limit. However, in practice a specified number of iterations are carried out.

4. Lagrange multipliers and marginal market signals

The marginal cost values determined from this model cannot be directly compared to the market price when penalty functions are active. Let the Lagrange multipliers associated with the contract balance (Equation (5)) and the accumulated income due to trading in the futures market (Equation (7)) be $\Pi_B(k,t)$ and $\Pi_I(k,J)$ respectively. For a sale of contracts $S(k,t) > 0$ a necessary condition is:

$$\Pi_B(k,t) \leq (pf(k,t) - \Delta p)(1 + \Pi_I(k,J)) \quad (17)$$

or

$$pf(k,t) \geq \Pi_B(k,t)/(1 + \Pi_I(k,J)) + \Delta p \quad (18)$$

Similarly for a purchase of contracts $K(k,t) > 0$, a necessary condition is:

$$pf(k,t) \leq \Pi_B(k,t)/(1 + \Pi_I(k,J)) - \Delta p \quad (19)$$

$\Pi_I(k,J)$ is called the income penalty multiplier associated with week *k* in the planning period and *J* is the index of the income period that contains week *t*.

Associate λ with the spot market balance (Equation (6)). To sell in the spot market we must have:

$$P(k) \geq \lambda/(1 + \Pi_I(k,J)) \quad (20)$$

In the case $\Pi_I(k,J) = 0$ we find the usual condition for sales in the spot market. When the market price is higher than the water value, sales are suggested. When $\Pi_I(k,J) > 0$, the Lagrange multiplier associated with the spot market balance (λ) is modified such that risk adjusted water values are obtained.

5. Test system description

Norway's second-largest power producer, Norsk Hydro ASA operates 21 power stations and has ownership in 25 others. The total installed capacity is 1740 MW; the average annual generation is 8.6 TWh (11.3 TWh in 2000). Fig. 3 shows the respective yearly generation in the main five watercourses.

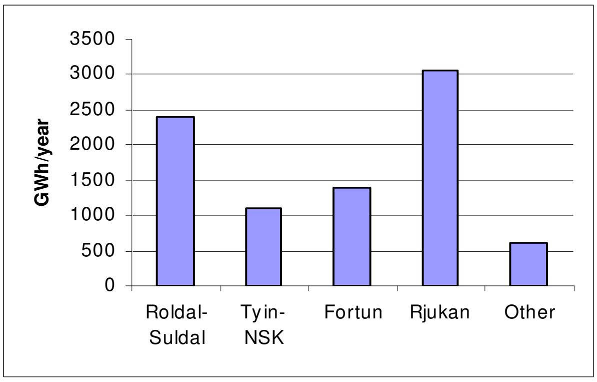

Fig. 3. Norsk Hydro's annual total power generation.

Norsk Hydro's fictive contract portfolio consists of a flat sales contract with a volume of 8.76 TWh/year and a price of 21.49 EUR/MWh, and three load factor contracts with the specifications shown in Table 1. The load factor contracts span different income periods (i.e. the years 2001, 2002, and 2003) and seasons, which makes the problem complex to solve. The user of the model is free to specify the length of the contract durations.

LFC	Period	Price (EUR/MWh)	Initial volume (GWh)	Min volume (GWh)	Max volume (GWh)
1	44-78	22.08	491	0	491
2	79-130	22.08	664	0	664
3	131-156	22.08	332	0	332
	Min rest volume (GWh)	Max rest volume (GWh)	Min withdrawal (GWh)	Max withdrawal (GWh)	
1	0	0	0	15.288	
2	0	0	0	15.288	
3	0	0	0	15.288	

Table 1. Load factor contract specifications.

Parameter	
Generation cost	5844160 EUR monthly
Transaction cost	0.195 EUR/MWh
Maximum weekly transaction	50 GWh/week
Probability of price shift	0.1
Value of price shift	0.481 EUR/MWh
Initial contract balance in each week	-168 GWh/week

Table 2. Different parameters used in the model.

The model parameters are given in Table 2. There are three income periods, one for the period weeks 44-52 (the rest of year 2001), and one each for weeks 53-104 (2002) and 105-156 (2003). The locked income in the futures market for each of the income periods is EUR 16.56, 102.26, and 102.40 million, respectively. The value of the price shift was estimated from the seasonal forward Summer 2001 contract prices at Nord Pool in the period 02.05-29.12.2000. The average price of the forecast used in the simulations is shown in Fig. 4. The price forecast has 240 scenarios.

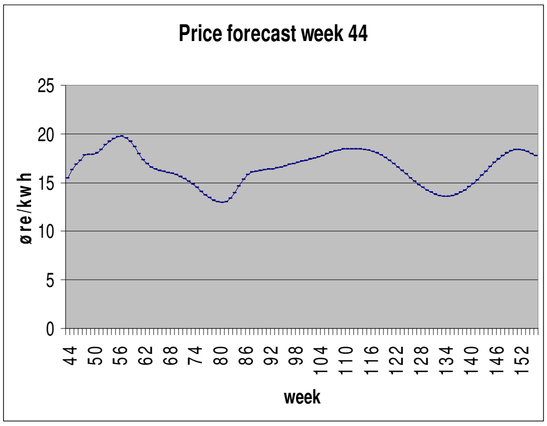

Fig. 4. Future price forecast at week 44 used in the simulations. The average price of 240 scenarios is shown (1 øre/kWh is approximately equal to 1.3 EUR/MWh).

6. Model studies

The integrated risk management model calculates values used for making decisions today, such as discharge of water and hedging in the futures market. It also simulates forecasts for possible futures given by price scenarios and associated local inflow scenarios after the optimal strategy is found.

We have run the model for five different cases for the penalty function. The penalty function is similar in all income periods. A marginal penalty of 1.0 means that if the expected income is 100 EUR million below the reference income, the company is charged a penalty of EUR 100 million. We use a two-segment penalty function with different marginal penalties or slopes corresponding to different risk preferences.

Case 1: Risk neutral
The base case is the risk neutral case. In this case it is unnecessary to optimize the generation and the contract portfolio simultaneously.

Case 2: Risk-averse, marginal penalty 0.5
In this case we penalize income results below the 25 percentile with marginal penalty 0.5.

Case 3: Risk-averse, marginal penalty 1.0
In this case we penalize income results below the 25 percentile with marginal penalty 1.0.

Case 4: Risk-averse, marginal penalty 5.0
In this case we penalize income results below the 25 percentile with marginal penalty 5.0.

Case 5: Risk-averse, without dynamic hedging
The penalty function is the same as in case 2 but trading in the futures market is not allowed.

In each run we received income results for 240 different scenarios (with equal probability) based on Norsk Hydro's price forecast. The calculated expected income for each of the periods is given in Table 3. The results for income period 3 should not be overemphasized, since the planning period is rolling. Only the simulation results for weeks 1-52 are used in practice.

The risk neutral case (case 1) has the highest expected total income, EUR 379.49 million, followed by cases 2 and 5. The expected income does not change substantially in the different cases, so the optimum is relatively flat. The standard deviation for the first period has decreased by half the amount from the risk neutral case for all the other cases. The decrease is less in other periods; cases 4 and 5 show the most significant change. The end reservoir is highest for the risk neutral case and decreases with increasing risk aversion (except case 3).

	Case 1	Case 2	Case 3	Case 4	Case 5
Average income period 1	28.61	30.25	31.93	30.92	31.83
Std. dev.	8.85	4.86	5.40	4.96	4.86
Average income period 2	140.70	139.98	136.35	142.11	140.96
Std. dev.	25.81	22.46	19.60	20.60	21.56
Average income period 3	130.78	130.46	129.72	126.68	130.03
Std. dev.	29.70	27.73	26.40	25.69	23.51
End reservoir	79.35	74.77	76.70	72.73	73.16
Expected total income	379.49	375.44	374.68	372.43	375.31
Min income period 1	3.03	23.04	25.12	24.91	23.05
Min income period 2	85.54	88.13	109.09	107.89	96.09
Min income period 3	43.77	26.01	10.62	25.51	75.18
Max income period 1	43.79	42.86	46.01	43.34	43.90
Max income period 2	208.86	207.06	199.26	205.94	205.15
Max income period 3	221.50	221.31	217.22	211.66	217.25
Expected trading income	0.00	-2.10	-1.42	-1.40	0.00
Expected transaction cost	0.00	0.44	0.45	0.55	0.00
Expected penalty	0.00	1.57	1.42	12.52	0.95

Table 3. Simulated income (MEUR) for cases 1- 5.

Table 3 shows that the minimum income scenarios[2] have improved in income periods 1 and 2. For income period 1, cases 3 and 4 show the most improvements: from EUR 3.03 million to about EUR 25.12 and EUR 24.91 million respectively. For income period 2, case 3 shows the best improvement of the minimum value from EUR 85.54 to EUR 109.09 million. In short all minimum income scenarios in income periods 1 and 2 have improved significantly from the risk neutral case, while the minimum income in period 3 decreased in most cases, except for case 5. The maximum income scenario in period 1 is highest in case 3, and in the other periods the maximum income scenario has the same order of magnitude in most of the cases.

The expected trading income (or loss) is lowest in case 3 (moderate penalty) and zero in cases 1 and 5 because there is no trading in the futures market. The transaction and penalty costs are highest in case 4.

The hydropower generation in the different cases and periods is given in Table 4. The total generation is lowest in case 1 and highest in case 5. This is as expected because

[2] The minimum income scenario is the value of the scenario with lowest income of the 240 scenarios.

hedging is not allowed in case 5. The only way the producer can fulfill the income requirement is to use physical generation. With increasing risk aversion the generation in the period Winter 2 2001 is increasing relative to case 1. The reason is that when a penalty for failing to fulfill the income requirement is introduced, it is cheaper to use hydropower generation than hedging in the futures market to meet the budget for the year 2001. The results are more ambiguous for the other seasons.

Period	Case 1	Case 2	Case 3	Case 4	Case 5
Winter 2 2001	1840.4	1949.2	1935.6	1970.6	2001.7
Winter 1 2002	3255.7	3150.1	3153.3	3134.8	3155.7
Summer 2002	3912.0	3927.1	3916.9	4041.8	4018.1
Winter 2 2002	2191.6	2254.3	2230.9	2263.3	2297.0
Winter 1 2003	2966.3	2900.9	2877.1	2653.5	2783.8
Summer 2003	3871.6	3939.9	3935.6	3997.1	3899.2
Winter 2 2003	2371.5	2468.1	2488.9	2511.0	2500.4
Total	20409.1	20589.5	20538.2	20572.1	20656.0

Table 4. Simulated generation (GWh) for all cases.

	Income period 1	Income period 2	Income period 3
Case 1	0	0	0
Case 2	0.036	0.020	0.003
Case 3	0.024	0.002	0.017
Case 4	0.030	0.015	0.019
Case 5	0.030	0.023	0.041

Table 5. Income penalty multipliers for the initial week.

The income penalty multipliers for our runs are shown in Table 5. The multipliers are highest in the first period for cases 1-4, meaning that the model emphasizes the fulfillment of the income requirement more in this period compared to the other periods.The marginal risk adjusted water values and contract values for some of the most important reservoirs in Norsk Hydro's total system in the initial week are shown in Table 6. To use the marginal water values as a decision support tool, they must be divided by one plus the income penalty multipliers for income period 1.

As for the marginal water values the marginal future contract values shown in Table 7 must be adjusted with an income penalty multiplier referred to the actual income period. Trading of futures contracts in the model occurs when the difference between the corrected marginal contract value and the market price for that specific futures contract exceeds the transaction cost. A positive difference indicates purchase; a negative difference indicates sale.

	Case 1	Case 2	Case 3	Case 4	Case 5
Møsvann	19.09	20.77	20.05	20.73	18.40
Middyrvann	20.52	20.88	21.45	19.65	18.82
Votna	19.92	20.13	20.67	18.64	17.82
Valldalen	19.49	19.53	20.21	17.51	19.90
Røldalsvann	19.82	19.56	20.36	16.48	19.84
Sandvann	21.49	22.81	21.99	20.82	22.35
Tyinsjøen	19.12	19.45	19.92	17.99	18.44
Øvre Herva	22.02	23.05	22.80	23.62	22.84
Storevatn	21.59	23.08	22.63	22.96	22.65
Herva	22.14	23.43	22.79	22.97	23.01
Skålavatn	22.14	23.43	22.79	22.97	23.01
Fellvann	19.16	20.04	19.46	16.79	18.40
Sokumvann	18.33	19.39	18.76	15.61	17.61
LFC 1	17.93	18.20	18.28	18.29	18.42
LFC 2	17.13	17.44	17.40	17.35	17.48
LFC 3	18.14	18.18	18.40	18.45	18.83

Table 6. Marginal water values and marginal values of load factor contracts (LFCs) in EUR/MWh in week 44 for all cases.

Futures contracts	Case 1	Case 2	Case 3	Case 4	Case 5
Week 45	21.90	22.66	22.55	22.52	22.53
Week 46	22.62	23.38	23.37	23.24	23.25
Week 47	23.18	23.92	23.83	23.79	23.79
Week 48	23.86	24.57	24.47	24.44	24.43
Block 1	24.00	24.57	24.58	24.55	24.55
Block 2	25.49	25.99	25.94	25.86	26.05
Block 3	25.34	25.83	25.78	25.70	25.90
Block 4	22.51	22.95	22.89	22.82	23.00
Block 5	21.16	21.57	21.52	21.45	21.62
Block 6	20.47	20.86	20.80	20.74	20.91
Block 7	19.04	19.39	19.34	19.27	19.43
Block 8	17.34	17.65	17.61	17.56	17.69
Block 9	17.32	17.62	17.59	17.53	17.66
Block 10	20.09	20.40	20.38	20.31	20.43
Block 11	21.12	21.43	21.39	21.35	21.45
Season 1	22.08	22.39	22.35	22.31	22.39
Season 2	23.62	23.69	24.01	24.06	24.64
Season 3	19.36	19.40	19.62	19.68	20.06
Season 4	23.18	23.22	23.43	23.51	23.83

Table 7. Marginal future contract values (EUR/MWh) in week 44 all cases.

Period	Case 1	Case 2	Case 3	Case 4	Case 5
Week 45	0	-5.21	-5.21	-3.96	0
Week 46	0	-10.21	-10.00	-8.96	0
Week 47	0	-21.67	-20.00	-15.83	0
Week 48	0	-29.32	-27.50	-25.62	0
Week 49	0	-35.19	-31.04	-30.0	0
Week 50	0	-35.19	-31.04	-30.0	0
Week 51	0	-35.19	-31.04	-30.0	0
Week 52	0	-35.19	-31.04	-30.0	0

Table 8. Expected trade (sale GWh/week) for future weeks in the first week (week 44), as function of future weeks for all cases.

The expected trade (sale) of futures contracts in the first week (week 44) for all future weeks is shown for all cases in Table 8. The trade is zero for all weeks in 2002 and 2003, and is highest for cases 2 and 3 in the rest of the weeks in year 2001. When risk aversion and hedging are introduced, there is trade (sale) in the end of year 2001.

The withdrawal from the load factor contracts illustrated in Fig. 5 shows that the withdrawal is typically high in periods with high prices (winter) and low in periods with low prices (summer). The withdrawal profiles for the different cases are relatively similar.

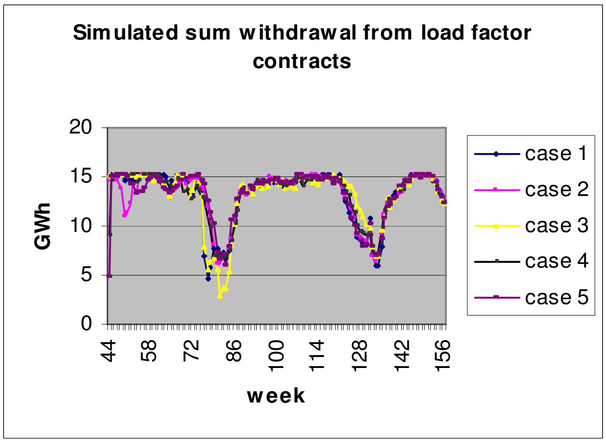

Fig. 5. Simulated sum withdrawal from load factor contracts (GWh).

7. Practical issues

Practical issues should be given high priority when the system will be run in parallel with today's risk management tools. The inputs for the model simulations on Norsk Hydro's total power system and portfolio are comprehensive. For the weekly runs, the following data are needed: reservoir levels; contract and income balance for the entire planning period; revision plans; options data; load factor contract data; and the weekly price forecast. A special program is used to extract the contract portfolio data from two databases. During testing it usually takes 1-2 hours to update all of the mentioned data. The running time for the model is about 15-20 hours on a 1 GHz CPU PC.

8. Discussion and conclusions

Our tests have demonstrated that it is possible to apply the model to realistic cases. The case results have shown that hydropower generation and trading in the futures market change with the risk aversion.

In general we found that the expected income decreased with increasing penalty as we expected. The minimum income scenarios in the closest income periods are reduced when risk aversion is introduced. When no hedging in the futures market is allowed, the water is moved between the different time periods (seasons) to meet the income targets.

The model gives risk adjusted water values as output and these can be used as a condition for sale in the spot market. Another result of the simulations is that the marginal contract values, when properly adjusted, can be used as signals for buying or selling in the futures market.

The expected trading observed from week 44 occurs in weeks 45-52 of year 2001 for the cases with risk aversion and hedging. Most of the withdrawals from the load factor contracts occur in the periods with high price, and the withdrawal profiles are relatively unaffected by risk aversion if the transaction costs are small [3].

When dynamic hedging is introduced, the simulated income uncertainty is reduced and the model offers a more realistic forecast of the associated income for a portfolio of physical generation, futures contracts, and load factors contracts. An optimization of both physical generation and the contract portfolio is necessary because the information about reservoir levels and rest volumes gives signals about changes in future position and reduces inflow risks.

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