Integrated Risk Management of Hydro Power Scheduling and Contract Management

Birger Mo, Anders Gjelsvik, and Asbjørn Grundt

***Abstract*—The paper describes the implementation of a new integrated tool for risk management in hydropower systems. Earlier practice in Scandinavia has been to separate operations scheduling and contract management. In the present approach operation scheduling and hedging by future contacts are integrated in one model. The risk level is controlled by setting revenue targets. Revenues below target are penalized; this implicitly defines a revenue utility function to reduce risk. The possibility of dynamically changing the future contract portfolio is now represented.**

The resulting large stochastic dynamic optimization problem is solved using a combination of stochastic dynamic programming and stochastic dual dynamic programming.

Simulations for a test case show that the profit in the lower range is considerably improved with the new tool. The approach can be useful for hydropower companies that face price risks in addition to the inflow uncertainty, as is the case in a deregulated system.

***Index Terms*—Dynamic hedging, hydro scheduling, risk management, stochastic dynamic optimization.**

I. INTRODUCTION

RECENT liberalization of the electricity market in several countries has increased the need for risk management tools and methods that can be applied in the electricity market. Risk management is considerably more complex for market players that are exposed to both quantity (inflow) and price uncertainty.

Risk in economic theory is defined as an option where the profit is not known in advance with absolute certainty, but for which an array of alternative outcomes and associated probabilities are known [1]. The purpose of risk management is to deliberately adjust risk to the market situation at all times based on today's status and expectations regarding future outcome and the probability distribution associated to this.

The typical hydro-based producer faces different types of risk:

- Price risk
- Quantity risk caused by inflow uncertainty
- Quantity risk caused by demand uncertainty (in case of end use sales)
- Basis risk, credit risk etc.

The risk management tools commonly used in the Scandinavian market incorporate the first three types of risks.

Manuscript received January 27, 1999; revised October 16, 2000.

B. Mo and A. Gjelsvik are with SINTEF Energy Research, N-7034 Trondheim, Norway.

A. Grundt is with Norway Norsk Hydro ASA, P.O. Box 200, N-1321 Stabekk, Norway.

Publisher Item Identifier S 0885-8950(01)03784-1.

The price volatility has been considerable since deregulation in Norway, see [2]. Price risk is therefore of particular interest within the area of risk management.

Since the market price is strongly dependent on precipitation, the local producer's production capacity will usually be correlated with the market price. Some correlation also exists between temperature and precipitation. Wet winters are typically warmer than normal, and vice versa. It is important to account for any such correlation in risk management. The most commonly used risk management tools in the Scandinavian market have several drawbacks, the most important being:

- The possibility of future trading (i.e., changing the future contract portfolio) is not included.
- Reservoirs and load factor contracts are not used as tools for risk management. It may be cheaper to change the generation schedule than to do more trading in the market.

A new tool has therefore been developed for risk management for companies with hydropower generation. In this new tool scheduling of generation and utilization of load factor contracts as well as futures trading are all integrated in one stochastic dynamic optimization problem where the goal is to maximize a defined time separable utility function. This problem is solved by adaptation of a method used in [9]. The integrated model concept, which is based on a more general approach [3], was first described in [4].

This article has the following structure: The next section describes briefly the Scandinavian electricity market and the principles of the most commonly used risk management systems. Section III describes the newly developed integrated model for hydropower scheduling and contract management. Section IV describes the solution methodology, which is essential for application of the model to practical problems. Section V shows examples of application of the implemented model to a realistic case study.

II. BACKGROUND

A. Instruments for Risk Management

The participants of the Scandinavian electricity market have several instruments available for reducing their exposure toward risk to an acceptable level. Depending on whether the company has generation or is a pure distributor, different kinds of contracts may be used. The range of available contracts is growing, and comprises several financial and physical contracts to be traded bilaterally or with the power exchange Nord Pool. The main wholesale contract types are futures, options and load factor contracts.

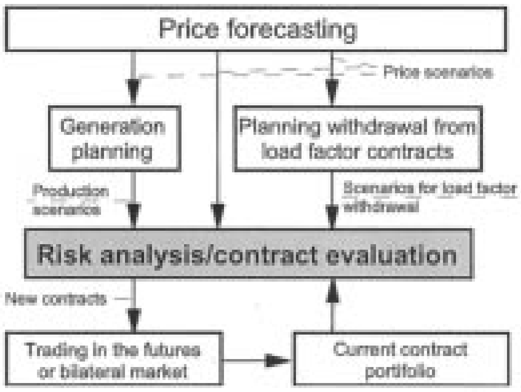

Fig. 1. Principle of risk analysis.

- *Future contracts* can be divided into two main categories, *futures* and *forward*. Both are agreements on delivery of a quantity of electricity at a predetermined price in the future, at a flat MW rate. Futures are normally cleared every day, while forward are cleared at the time of delivery. For futures the value of each participant's contract portfolio is calculated daily, and there is a daily settlement through Nord Pool between the buyer and the seller. In this way contract losses are quickly exposed and realized at the same time as profits are realized and paid out.
- An *option* gives the buyer or seller a right, but no obligation, to buy or sell a forward contract at a certain time at a predetermined price.
- A *load factor contract* is a physical or financial contract between two parts where price, energy volume and maximum power (load factor) is predetermined, but utilization is to a certain extent flexible, determined by the buyer during the defined period.

Bilaterally traded contracts, often by means of brokers, consist of both standardized and nonstandardized forward, options and load factor contracts.

Contracts can be combined in several ways so that the risk exposure is reduced in accordance to the company's attitude toward risk. A contract can have completely distinct effects on two different portfolios. The total portfolio of contracts for purchase and sale has to be evaluated in combination with the possibilities of own generation, which are uncertain. All this makes portfolio analysis an important and difficult task to handle in managing the company's risk.

B. Current Method of Risk Analysis

The basic principle of how many hydro producers have implemented risk analysis is illustrated in Fig. 1.

A price forecast is given by a number of scenarios representing possible future spot market prices. These price scenarios are the basic input to risk analysis and together with the inflow uncertainty they represent all the uncertainty included in the risk analysis.

The price and inflow scenarios are input to the long and mid-term hydro scheduling. This scheduling results in production schedules corresponding to each input scenario. The price forecast is also input to utilization scheduling of the load factor contracts. Each load factor contract can be represented as single-reservoir hydro module, when seen from the buyer. This gives long or mid-term utilization schedules for each price scenario. The other contracts in a portfolio, except options, are assumed to be independent of the price/inflow scenario.

Increased trading of options makes it necessary to include also these contracts in risk management tools. One method, which integrates the evaluation of options with the rest of the portfolio, is based on assuming that options are exercised depending on the price in each price scenario. Options are otherwise evaluated using adaptations of the Black and Scholes model [10], although this model is not very well adjusted to the electricity market.

Risk analysis is performed using a simulation technique where the objective function, which represents the users risk aversion, is inspected before and after a new contract is included in the simulation. The contract is traded if the objective function increases when the new contract is included in the simulation. This method can also to some extend calculate the "optimal" amount to trade (buy or sell) for a given contract price and period, or "optimal" trade as a function of contract price.

The objective function represents the user's utility function, usually specified quite simply as:

- A function of a number of the lowest accumulated results over the planning period.
- A function of the expected result and some kind of down-side measurement.

III. Integrated Model

A. General

In the integrated model that has been implemented, the modeling of the physical production system is the same as in the medium-term scheduling model described in [5] and [9]. However, additional state variables must be introduced to account for trading balances for each future trading period (week, block or season). There is one state variable for each future trading period. The state variables are updated with the decisions for trading during the same periods. The current contract portfolio gives the initial balance for each contract period.

The objective function contains progressive penalty functions for income below user specified limits. The penalty comes into effect if the profit for the given period is below the user specified limit at the end of the period.

The most important output from this model will be:

- Generation schedules and marginal water values for each reservoir
- Trading schedules and marginal contract values for each standardized future contract
- Income forecasts which include a realistic measure of future uncertainty.

The following definitions are used:

k	Week in the planning period
t	Week in the futures market, $t > k$
N	Number of weeks in the planning period
$E_{p,v}$	Expectation operator, with respect 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 profit periods
$P_{st}(J)$	First week in profit period J
$P_{sl}(J)$	Last week in profit period J
$I(k, J)$	Accumulated profit for profit period J in week k (NOK)
$Pen()$	Penalty function for not fulfilling the profit requirements
$R(x(N))$	Value of water remaining in week N (NOK), obtained from long-term scheduling
$S(k, t)$	Sales committed in week k for delivery in 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)
$x_{\max}(k)$	Maximum reservoir levels in week k (Mm^3)
$x_{\min}(k)$	Minimum reservoir levels in week k (Mm^3)
$u(k)$	Vector of discharges in week k (Mm^3)
$u_{\max}(k)$	Maximum discharge in week k (Mm^3)
$u_{\min}(k)$	Minimum discharge in week k (Mm^3)
$v(k)$	Vector of inflows for week k (Mm^3)
C	Matrix to describe system topology
$G()$	Conversion function from discharge vector to production (GWh).

B. The Objective Function

The objective is to maximize the following expected sum:

$$Q = \text{Max}\left\{E_{p,v}\left[\left(\sum_{k=1}^{N} Sp(k)p(k)\right) + \text{Sales} - \text{Purchase} + \sum_{J=1}^{N_{prof}} Pen(I(P_{sl}(J), J)) + R(x(N))\right]\right\} \tag{1}$$

where

$$\text{Purchase} = \sum_{k=1}^{N-1}\sum_{t=k+1}^{N} K(k, t)(pf(k, t) + \Delta p) \tag{2}$$

$$\text{Sales} = \sum_{k=1}^{N-1}\sum_{t=k+1}^{N} S(k, t)(pf(k, t) - \Delta p). \tag{3}$$

Thus the objective function is net income from trading in the futures market plus sales in the spot market minus penalty for not fulfilling profit constraints plus value of the water by the end of the planning period.

We use a basic time step of one week. In Scandinavia the actual contracts are traded in one week lots for the first 4–7 weeks only. Beyond that, the contracts are traded in 4 week blocks and beyond one year in seasons. For simplicity, we neglect this in the presentation here. In the implementation, however, the time resolution is dynamic, i.e., blocks are resolved into weeks and seasons are resolved into blocks as time goes, as in the actual market. Future contracts are delivered at a flat MW rate.

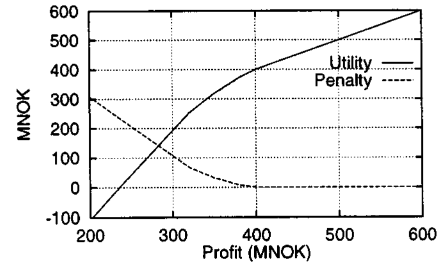

Fig. 2. Example of penalty function $(Pen())$ and corresponding utility function describing the users risk aversion.

The penalty functions are used to describe the user's attitude to risk and can be seen as an inverse utility function as shown in Fig. 2. The penalty functions are assumed to be convex. The user of the model must specify these functions.

The future market price is assume to be given by the expected spot price at the given future week conditioned on the spot market price in the trading week as described by equation (4). That is, it is assumed that the futures market gives an unbiased estimate of expected future spot market prices. The spot market model mentioned in Section III-D below can therefore be used to compute the conditional probability distribution of $pf(k, t)$ and consequently the futures market prices at decision time step k and future delivery weeks t.

$$pf(k, t) = E(p(t) \mid p(k)). \tag{4}$$

All contracts are accounted as physical contracts (forward), i.e., billing in the delivery period. This affects which profit state (J) is updated when trading in week k for future period t.

C. Model Constraints

The water balances and the reservoir limits can be written as:

$$x(k+1) = x(k) - Cu(k) + v(k) \tag{5}$$

$$x_{\min}(k) \le x(k) \le x_{\max}(k) \tag{6}$$

$$u_{\min}(k) \le u(k) \le u_{\max}(k). \tag{7}$$

The contract balance for any future period t is updated for each trading period k:

$$B(k+1, t) = B(k, t) + K(k, t) - S(k, t). \tag{8}$$

Spot market balance

$$Sp(k) = G(u(k)) + B(k, k). \tag{9}$$

Accumulation of profit due to Trading in the futures market, accounting as physical contracts.

$$I(k+1, J) = I(k, J) + \sum_{t=\text{Max}(P_{st}(J), k+1)}^{P_{sl}(J)} \cdot (S(k, t)(pf(k, t) - \Delta p) - K(k, t)(pf(k, t) + \Delta p)). \tag{10}$$

For the current profit period trading in the spot market must be added.

$$I(k,\, J) = I(k,\, J) + Sp(k)p(k) \qquad \text{if } P_{st}(J) \le k \le P_{sl}(J). \tag{11}$$

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 of efficiency 1.0 and an upper MW rate, and is thus described by (5) and (7). The inflow is zero, except for the time of initialization or renewal. The present model analyzes the optimal use of existing load factor contracts, but does not give support for decisions whether to enter into new load factor contracts or not.

D. *Modeling Uncertainty*

The future spot market price and the inflow to the reservoirs are assumed to be uncertain.

The spot market price is modeled as outlined in [9]. For each future week we consider the spot price $p(k)$ as a stochastic variable. We constrain $p(k)$ to a number (5–7) of discrete values. For a given price in week k the probability distribution of possible prices in week $k+1$ is given directly by transition probabilities. There is one matrix of transition probabilities for each week. This price model can be seen as a time discrete Markov model with discrete set of prices in each time period. This way, the price in the next time step depends on the price in the previous time step. This is important since hydro producers with large reservoirs dominate the market in Scandinavia, leading to sequential dependence in the price. The choice of price model is done to facilitate solution by dynamic programming.

The price forecast data are given in the for of a number of price scenarios. These data can be obtained from the EMPS model, which is a long term market simulator [6]. The transition probabilities are estimated from these scenarios, which are assumed to have equal probabilities.

The inflows to the different reservoirs are modeled as a multivariable first order autoregressive model, that is estimated from historical inflow series. This model, described in [7], introduces new state variables that are not explicitly shown in the description (1)–(11).

IV. Solution Methodology

The model described by equations (1)–(11) is a stochastic dynamic optimization problem. The solution method is similar to the combination of stochastic dual dynamic programming (SDDP) [8] and stochastic dynamic programming (SDP) that was used in [9], adapted to deal with the model extensions.

We define the system state vector in week k as:

$$\begin{aligned} z(k) = \big[&x^T(k),\, B(k,\, k+1),\, \ldots,\, B(k,\, N),\\ &I(k,\, 1),\, \ldots,\, I(k,\, N_{prof}),\, p(k)\big]^T \end{aligned} \tag{12}$$

and a decision vector

$$\begin{aligned} y(k) = \big[&u^T(k),\, S(k,\, k+1),\, \ldots,\, S(k,\, N),\\ &K(k,\, k+1),\, \ldots,\, K(k,\, N)\big]^T. \end{aligned} \tag{13}$$

The objective can be written as

$$Q = \operatorname{Max} E_{p,\, v} \left\{ \sum_{k=1}^{N} L_k(z(k),\, y(k)) + R(z(N)) \right\} \tag{14}$$

where $L_k(z(k),\, y(k))$ is the immediate return from stage k, including penalties, as obtained from (1)–(3).

Provided that transition probabilities at stage k are independent of the previous states $z(k-1),\, z(k-2), \ldots$, the problem can formally be solved by dynamic programming, and the Bellman recursion equation becomes:

$$\alpha_k(z(k)) = E_{p,\, v} \operatorname{Max} \left\{ L_k(z(k),\, y(k)) + \alpha_{k+1}(z(k+1)) \right\} \tag{15}$$

subject to (5), (8) and (10) which define $z(k+1)$, and to other constraints that apply. $\alpha_{k+1}(z(k+1))$ is the expected future return function in going from state $z(k+1)$ to a feasible final state in an optimal manner, with for the last interval

$$\alpha_N(z(N)) = R(z(N)) + Pen(z(N)). \tag{16}$$

Product terms in (1)–(3) such as $Sp(k)p(k)$ in (1) make the objective function nonconvex, so a hyperplane representation of $\alpha_k(z(k))$ as in SDDP cannot be used directly. But for each discrete price value in the price model, we can represent $\alpha_k(z(k))$ with hyperplanes, since the price is fixed, [9]. This is analogous to traditional stochastic dynamic programming with respect to the price state. We note that now the new state variables $B(k,\, k+1), \ldots, I(k,\, N_{prof})$ enter the hyperplanes. Like SDDP, our solution algorithm is iterative. Each main iteration consists of a forward simulation with the most recent operating strategy (given by the hyperplanes), and a backward recursion using (15) where new hyperplanes are added to update the strategy. As in the SDDP method, sampling in the tree of outcomes is essential; here we go further and have as a heuristic used observed inflows on the forward simulation. Time-saving techniques similar to those in [7] have been implemented.

The marginal cost signals from the model cannot be directly compared to market prices, if profit penalty functions are active.

Let $\Pi_B(k,\, t)$ be the Lagrange multiplier for (8) and $\Pi_I(k,\, J)$ the multiplier for (10), respectively. From the objective function gradient we can deduce that to sell contracts, $S(k,\, t) > 0$, it is necessary that

$$\Pi_B(k,\, t) \le (p(k,\, t) - \Delta p)(1 + \Pi_I(k,\, J)) \tag{17}$$

or

$$p(k,\, t) \ge \Pi_B(k,\, t)/(1 + \Pi_I(k,\, J)) + \Delta p. \tag{18}$$

Similarly, to buy contracts, $K(k,\, t) > 0$, we must have

$$p(k,\, t) \le \Pi_B(k,\, t)/(1 + \Pi_I(k,\, J)) - \Delta p. \tag{19}$$

Here J is the index of the profit period that contains week t.

If λ is the multiplier for (9), we find that to sell in the spot market $(Sp > 0)$

$$p \ge \lambda/(1 + \Pi_I(k,\, J)). \tag{20}$$

In the case $\Pi_I(k,\, J) = 0$, the above inequalities give the intuitive results.

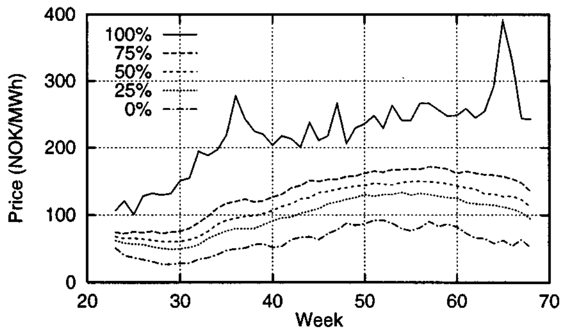

Fig. 3. Price forecast at week 23, percentiles.

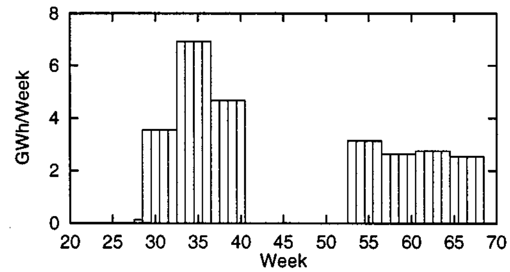

Fig. 4. Trade for future weeks in first week, as function of future week.

TABLE I
MARGINAL COST OF POWER GENERATION (NOK/MWh)

Station	Case 1	Case 2	Case 3
1	53.4	71.0	81.3
2	97.4	120.4	137.8
3	149.8	172.5	194.3
4	92.9	110.9	126.4
5	75.6	95.5	109.5
6	239.5	273.1	302.9
7	68.4	81.2	91.0

TABLE II
MARGINAL VALUES OF FUTURE CONTRACTS AT WEEK 23 (NOK/MWh)

	Case 1	Case 2	Case 3
Week 24	72.3	86.4	97.1
Week 25	70.3	84.3	95.1
Week 26	69.0	83.0	93.8
Week 27	67.0	80.9	91.6
Week 28	65.9	79.9	90.4
Block 29–32	69.2	84.1	95.1
Block 33–36	95.5	115.7	130.4
...	...	...	...
Block 13–16	129.4	146.8	162.6

V. CASE STUDY

The purpose of the case study is to illustrate some properties of the model. The model results consist of two different types of results:

- Results describing today's decisions, such as water releases and hedging in the futures market
- Simulated (forecast) results for possible futures given by price scenarios and corresponding local inflow scenarios (hydro production, trading etc.). These are found by simulations after the optimal strategy has been found.

The simulations carried out to find average profit etc. from the optimal strategy calculated, are "parallel" simulations of different scenarios from a given initial state. The strategy thus reflects the information available at the initial time. So although the strategy has feedback from the system states, the simulations do not capture the updating of the strategy as time goes that is possible in real operation, for instance by moving the horizon. Ideally, to fully evaluate the new approach, one should simulate sequentially a number (say 60) of contiguous years, rerunning the present algorithm (almost) every week to find the decisions and update the system state accordingly, moving the horizon as necessary. However, this is not computationally feasible at present, so we have to be content with the parallel simulations.

The Røldal/Suldal hydro system which consist of 11 reservoirs and 7 hydro plants is used. In the test data, the planning period starts at week 23 in 1999 and ends with 68 (week 16 in 2000). The futures market as seen from the beginning of week 23 consists of weekly contracts for weeks 24–28 and eight blocks of four weeks each for the remaining 40 weeks. (The block structure is dynamically changed during simulations.) There are two profit periods, one from week 23 to week 52 in 1999 and the other from week 1 in 2000 to week 16 in 2000 (or week 53 to 68, as we shall write), so that $1 \leq J \leq 2$.

The spot market price forecast consists of 240 different scenarios, coupled to historical inflow records, made available to us from the owner of the test system. These scenarios are used to estimate the transition probabilities in the Markov model for price. Fig. 3 shows some percentiles for the distribution of price scenarios.

The test system has been run for three cases, differing only in the profit penalty functions. Case 1 is risk neutral (zero penalty). In Case 2, the penalty function for profit period 1 is as shown in Fig. 2, which also shows the corresponding utility function. In Case 3, the penalty is twice that of Case 2. The desired minimum profit is 400 MNOK (million NOK) in the first period and MNOK 170 in the second period.

As an example of the results, the futures market transactions $(S(23, *) + K(23, *))$ in the initial week for Case 2 are shown in Fig. 4. The initial contract balance was around -90 GWh/week. This means a commitment to delivery of 90 GWh/week, which is comparable to the capacity of the system. The positive values in Fig. 4 show buying; the action is thus mainly to reduce the future commitment to delivery. Case 3 give similar results, but with still more buying. For Case 1 there are no transactions.

Marginal cost for each of the 7 power stations in the initial week are shown in Table I. The values are calculated from the marginal water values of the reservoirs that are found from multipliers of (5) Table II shows the marginal value of the different contracts in the futures market for the different cases, taken at the initial week.

As expected, Tables I and II shows that the marginal contract values and marginal water values increase with increasing profit penalty (provided the profit targets are not always met). The marginal values of water and of future contracts cannot be directly compared to the corresponding market prices, as discussed at the end of Section IV. Equations (17)–(20) are examples of marginal value relationships at optimum. The values of the profit constraint multiplier $\Pi_I(k, J)$ at the initial week are given in Table III.

TABLE III
PROFIT PENALTY MULTIPLIERS FOR INITIAL WEEK

	Profit period 1	Profit period 2
Case 1	0.00	0.00
Case 2	0.187	0.120
Case 3	0.329	0.238

TABLE IV
SIMULATED PROFIT (MNOK)

	Case1	Case2	Case3
Average profit period 1	409.24	411.43	411.40
Standard deviation	(37.2)	(29.2)	(27.5)
Average profit period 2	172.00	169.10	168.23
Standard deviation	45.9	38.9	37.9
Total average profit	581.24	580.54	579.63
Standard deviation	66.0	60.6	58.3
Least profit period 1	310.08	323.69	328.69
Least profit period 2	-83.76	-9.73	-12.22
Least total profit	276.07	374.35	379.38
Average 10 lowest profits period 1	327.36	348.99	353.7
Average 10 lowest profits period 2	38.70	62.99	62.65
Average 10 lowest total profits	391.48	420.11	425.59

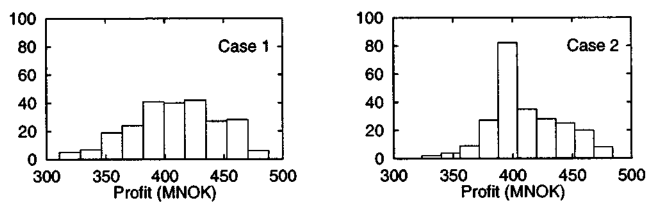

Fig. 5. Histograms of simulated profit, profit period 1.

The main goal of the present method is to avoid very low profits. How this is accomplished in the test case simulations, is summarized in Table IV, which gives averages over a sample of 240 scenarios. The numbers in the table do not include penalties.

The table shows that the lowest profits have improved in both profit periods, as well as for the whole planning period. This is illustrated in Fig. 5, which shows histograms for the profit in profit period 1. One sees that with profit penalty (Case 2), the distribution has narrowed, especially downside, as expected. The penalties applied in Case 3 are very high; Table IV shows that they do not make much improvement over Case 2. Examination of the results for the individual scenarios for all cases show that there are cases with a high net profit from hedging with future contracts, but large losses may also occur. As expected, profit is also evened out by redistributing water releases in time compared to the risk-neutral case. For the present case, this only slightly affects average sum generation in the whole planning period. The average sum generations in Cases 2 and 3 are 0.5 per cent lower than the average in Case 1.

Table IV shows that the average total profit is slightly reduced in Cases 2 and 3. This is to be expected, and is the price that we pay to improve the lower profit range. The reduction is small, however, indicating a considerable freedom of choice. Small differences have been observed in other test cases as well.

The program is tested on a HP UX 9000/861 and the computation time (CPU) is about 3–4 hours for the test cases. This is acceptable for this type of decision support tools.

VI. CONCLUSION

This article has presented a new approach to risk management in hydro dominated power system. Hedging by future contracts and the medium-term generation scheduling is dealt with simultaneously. It is demonstrated by "parallel" simulations of a set of inflow/price-scenarios that the approach helps to reduce the occurrence of very low profit, at a low average loss.

The model is currently being tested by one of Norway's largest producers. The test results so far are very promising. The largest system tested so far consists of 38 reservoirs and 30 load factor contracts.

Future improvements of the model include modeling of options within the same framework as with the standard products of the futures market. Other improvements we are working on will reduce the computation time and improve the price modeling.

REFERENCES

[1] H. Levy and M. Sarnat, *Capital Investment and Financial Decisions*, 3rd ed. Englewood Cliffs, NJ: Prentice Hall International, 1986.

[2] N. Flatabø, A. Haugstad, B. Mo, and O. B. Fosso, "Short term and medium term scheduling in the Norwegian hydro system under competitive power market structure," in *EPSOM '98, (International Conference on Electrical Power Systems Operation and Management)*. Zurich, Switzerland, Sept. 23–25, 1998.

[3] S.-E. Fleten, W. T. Ziemba, and S. W. Wallace, "Portfolio management in a deregulated hydropower based electricity market," in *Proceedings Hydropower 1997*, A. A. Balkema, Ed., Rotterdam, 1997, pp. 197–204.

[4] A. Grundt, B. R. Dahl, S.-E. Fleten, T. Jenssen, B. Mo, and H. Satness, *Integrated risk management* (in Norwegian). Lysaker: Norwegian Electricity Federation.

[5] A. Gjelsvik and S. W. Wallace, "Methods for stochastic medium-term scheduling in hydrodominated power systems," Norwegian Electric Power Research Institute, Trondheim Technical report A4438, 1996.

[6] A. Haugstad and O. Rismark, "Price forecasting in an open electricity market based on system simulation," in *Proceedings from EPSOM'98*, Zurich, Switzerland, Sept. 1998.

[7] T. A. Røtting and A. Gjelsvik, "Stochastic dual dynamic programming for seasonal scheduling in the Norwegian power system," *IEEE Trans. Power System*, vol. 7, no. 1, pp. 273–279, Feb. 1992.

[8] M. V. F. Pereira, "Optimal stochastic operations scheduling of large hydroelectric systems," *Electrical Power and Energy Systems*, vol. 11, no. 3, pp. 161–169, July 1989.

[9] A. Gjelsvik, M. M. Belsnes, and A. Haugstad, "An algorithm for stochastic medium-term hydrothermal scheduling under spot price uncertainty," in *Proceedings 13th Power Systems Computation Conference*, Trondheim, Norway, June 28–July 2, 1999, pp. 1079–1085.

[10] J. C. Hull, *Options, Futures and Other Derivatives*, 3rd ed. London: Prentice Hall International, 1997.

Birger Mo received the M.Sc. degree in 1986 and the Ph.D. degree in 1991 in engineering cybernetics from the Norwegian Institute of Technology. He has since 1986 been employed at SINTEF Energy Research. His main interests are short-term forecasting, production planning and risk management.

Anders Gjelsvik received the M.Sc. degree in physics from the Norwegian Institute of Technology (NTH) in 1970. From NTH he also received the Ph.D. degree in engineering cybernetics in 1981. Since 1976, he has been with SINTEF Energy Research. His main interests are in large-scale optimization and numerical analysis.

Asbjørn Grundt received the M.Sc. degree in operations research in 1989 from the Norwegian Institute of Technology (NTH). In the period 1990–1994, he worked as a Researcher at the Norwegian Research Defence Establishment, and from 1994 he has been working at Norsk Hydro. Currently, he is responsible for the company's hydropower scheduling and its development of a new risk management system. His main interest is risk management for hydropower producers.