

BENCHMARKING OF HYDROPOWER GENERATION SCHEDULING

Tarjei Kristiansen
KEMA Consulting¹
Bonn, Germany
Tarjei.Kristiansen@kema.com

Abstract – The objective of this paper is to find a method to evaluate ex post how good (or bad) the operation planning (short and medium term) of a hydro system has been for a certain period compared with the best state of the art planning methodology. We also want to help improve optimization methods and practice in this field.

We describe possible benchmarking tools for optimization of hydropower generation. Most hydropower generation companies use dynamic programming tools as decision support to decide when to generate. There is, however, a lack of appropriate methods for how to measure the quality of a scheduling method or the success of a management scheme. Any method is complicated by the reality that the company's maximum revenue varies with the inflows and the spot price, which are beyond management's control. These parameters are subject to stochastic variations and market mechanisms (spot price) and they are correlated. One approach for hydropower scheduling is to use hydropower generation scheduling model outputs in a regression model to calculate theoretical revenues. Another approach is to use market information such as forward or futures prices as a guide to decision making. Our results show a substantial potential for improvements in methods for benchmarking of generation scheduling.

Keywords: Hydropower generation scheduling, benchmarking, risk management

1 INTRODUCTION

Generation scheduling of hydropower plants is a complex task, particularly in a restructured market. The scheduling problem is divided into different planning periods:

- Long-term scheduling with a planning period of 1-3 years and a time increment of one week. Stochastic models are used.
- Medium-term scheduling with a planning period of 1 year and a time increment of one week. Stochastic and multi-scenario deterministic models are used.
- Short-term scheduling with a planning period of 1 day to 1 week and a time increment of one hour. Deterministic models are used.

Here, we focus on the short- and medium-term scheduling processes.

In the Nordic power market the day-ahead market provides the price reference for the next day generation plans. Dynamic programming medium-term models are used to calculate the opportunity cost of taking water out of the reservoirs. This opportunity cost or expected future

marginal value of water (hereafter called water value) is the expected cost of generation that can be replaced by an increment of water at some time in the future. Because the medium-term models utilize a time step of one week, the calculated water value applies for the whole of that week.

For the hours when the spot (day ahead) price is higher than the water value, generation is scheduled and vice versa. Ex post it is then easy to identify the hours to which generation should have been allocated. The challenges are to find an optimal plan or strategy in advance, and to evaluate the quality of actual performance. The most common benchmarking tool is to calculate the degree to which this optimization potential is utilized, compared to a worst possible plan or a naive approach (flat generation, historically highest priced hours/seasons etc.). The objective of this paper is to explore more appropriate benchmarking tools that could help to improve optimization methods and practices in this field. The paper focuses on ways of defining a reference plan reasonably close to the maximum revenue in realistic ex ante planning, without using 'potential' found in hindsight. It may be possible to apply our work to results from the stochastic dynamic programming model that are extensively used in generation scheduling [1] and forward/futures market data.

2 GENERAL ISSUES ASSOCIATED WITH BENCHMARKING OF HYDROPOWER SCHEDULING

Historically, not much literature is available on the subject of benchmarking of hydropower scheduling. This is probably because prior to the deregulation of the electricity industry the management of power companies were paid irrespective of performance. Today, management bonus schemes are more the norm, and this paper describes some of them and also some of the alternative schemes.

This paper is meant to be a starting point for discussion and is not exhaustive. First we discuss some philosophical and methodological questions about benchmarking of hydropower scheduling.

The main problem is to compare the actual revenue and profit margin observed for a particular period with what ideally should have been realized using the best of the

¹ The views in this paper are not necessarily those of KEMA Consulting.

existing methods to determine the possible stochastic outcomes of hydro inflows and prices. After all, management is compensated for the actual revenue and profit margin. Therefore, how can we assess how well the generation planners (and indirectly the managers) have done?

Hydropower generation planners must take into account the risk of overflows in the spring and spilling water in addition to other technical plant constraints. The technical constraints are usually considered when the generation planner tells the plant operators how much to produce. The plant operator's response might be that it is not possible to run so much generation on a certain plant or turbine because it is out of service or has reduced efficiency. The plant operator also communicates information about other constraints such as minimum and maximum flows of water or reservoir levels. Usually the plant operator cannot draw down reservoirs too much because of environmental concerns, or because people living nearby may complain.

In Norway, the best practice in generation planning uses scheduling models such as the EMPS-model [1] and the Vansimtap model which is a one-area model of the EMPS-model (see [2] for details). The models operate with a planning horizon of 2-3 years and therefore can account for inter-seasonal variations in hydro inflows and prices. The operating strategy uses marginal water values from the models for the coming week. Hence, planning occurs on a short-term basis but is based on water values that incorporate the long-term effects of uncertainty in hydro inflows and prices. The quantity outputs (i.e. how much to generate) from the models are not used in practice. The ultimate generation decisions are made by using the scheduling models in combination with the judgments made by experienced generation planners.

A generation company can assume a risk neutral, risk-averse or risk-seeking attitude, depending on how its management formulates its risk-taking policy. Usually power plants are run on a risk-neutral basis, but the planning and market departments may overrule the decisions of the plant operators when commercial or risk issues are deemed more important. In a risk-neutral strategy the company wants to maximize its profit.

Generally, however, a company's investors are risk averse, and may want to receive a stable pay-out. A power company in this situation may employ a risk-averse strategy to achieve stable, lower revenue.

Because hydropower scheduling consists of making decisions in an uncertain environment, one may assume that a best practice is to benchmark the decision made in advance with the verified outcome of the market, or by using traditional min-max regret. This would be true if the decisions were made based purely on model outputs. However, because decisions are reached by using the combination of model outputs and experienced judgment described above and because models only approximate reality, we believe planning should include this "soft" element.

3 GENERATION SCHEDULING IN A RESTRUCTURED MARKET

The traditional approach in medium-term scheduling is to aggregate the system into a one-reservoir model, for which an operating strategy can be found by using stochastic dynamic programming (SDP). A popular approach is

stochastic dual dynamic programming (SDDP) [2] and [3] which makes it possible to utilize a simultaneous stochastic optimization of several reservoirs rather than aggregating all reservoirs, and then perform a draw down calculation for each individual reservoir based on heuristics (rules based on experience). The objective in the medium-term is to find an optimal scheduling strategy for stochastic inflows and spot price forecasts. Inflow forecasts are based on historical data. Spot price forecasts including correlations (e.g. between price and inflow, and autocorrelation) are made using scenario forecast models.

The objective for the generation companies in a restructured market is to maximize their expected revenue over the planning period subject to the relevant plant constraints. The revenue consists of electricity sales/purchases to the power exchange (Nord Pool) and the value of reservoir changes during the planning period.² The maximization of the expected revenue is based on the assumption that the generator is a risk neutral agent acting as a price taker.³

The most important plant constraints are:

- Minimum and maximum flows of water
- Minimum and maximum reservoir levels

The necessary inputs for the simulation models are prices, inflows, reservoir levels, and turbine/generator availabilities. Reservoir levels at the end of the planning horizon are either specified end levels/bounds or water values. Additionally, a short-term generation planner must account for transmission constraints when plants are located in a price area where the price may differ from the system price.

The most important simulation outputs used in the scheduling process are the expected inflows and the water values for the reservoirs. The water values are outputs from simulation tools like the Vansimtap model and they are functions of the expected future inflows, expected future spot prices and the likelihood of draining reservoirs or of spillages.

Two available scheduling options are either to use the water values combined with experienced judgment by generation planners or to use short-term scheduling models. After the weekly water value calculation on the first weekday (i.e. on Monday), these values are used (perhaps with adjustments) for the bidding into the day-ahead market for the remainder of the week. When the spot price is higher than the water value, generation is scheduled and vice versa. The next decisions may be how to allocate the generation among plants along the same watercourse, perform schedules for maintenance and plant outages, and minimize the consequences of outages and unexpected events.

² We do not consider payments for ancillary services in this paper. The Norwegian hydro-based power system includes the following ancillary services: primary reserves (frequency control), secondary reserves (manually controlled), reactive power, frequency activated load shedding and generation shedding.

³ The companies do not take into account any influence their own generation might have on the market price. This assumption seems reasonable for small producers, but may be questionable for larger ones. A price taking behaviour is a reasonable assumption for a financially strong market player where the hydropower revenue is an insignificant fraction of the total revenues.

3.1 Earlier Used Benchmarks

In a Norwegian generation company a previous benchmark (KPI) has been:

$$KPI = \frac{(AR - PR)}{(OR - PR)}$$

where AR is the actual (or realized) revenue, PR is the worst possible revenue (or naïve approach revenue), and OR is the optimal revenue. Three possible alternatives OR are:

1. The revenue from a flat generation profile.
2. The revenue from a generation profile that equals the average of the total hydropower generation in Norway.
3. The optimal revenue from a hydropower scheduling model.

The disadvantages of these measures are:

- The ex ante/ex post problem. The OR is calculated ex ante, while the AR is calculated ex post. Normal operating procedure is to benchmark ex ante decisions against realized outcomes.
- It is difficult to compare years, since the benchmark depends on factors characteristic for the actual year.
- The hydropower scheduling model may model reality inaccurately and be a poor indicator of the optimal revenue because it ignores the decisions made by the generation planners after running the model. It also fails to consider whether the planners adhere to the decisions made by the model.

3.2 Criteria for Benchmarks

In this section we establish some criteria for benchmarks, and discuss their relevance. In general, benchmarks should:

- Give relevant/fair measures of management optimality
- Support comparisons over time for a single system
- Support comparisons across systems
- Support comparisons among companies on an aggregated level.

The term “system” refers to the actual power system or company whose profitability we seek to measure. Its management should not be penalized for factors that are beyond its control. For instance, the benchmark should account for the inflows and prices that will vary from year to year. A good benchmark should also contain “global” properties that make it possible to compare the same system over time, across systems, or between companies on an aggregated level. These are desirable, and useful measures

3.3 General Features of the Benchmark and Reference Plan

As mentioned earlier revenue will depend on price and inflows. In a planning setting we use the expected values of inflows and price, while the known values are used after the evaluation of the planning process. An index for the quality and profitability of the generation scheduling process could consist of the ratio between the actual generation revenue and the revenue from a reference plan.

At year end, all relevant information is known and it is possible to calculate a reference plan. One of the problems of finding a reference plan consists of an accurate and good modeling of the spot price.

A systematical use of an index will improve the generation scheduling process and the profitability. In the modeling of this index there is a trade-off between an accurate modeling and user-friendly properties.

4 MANAGEMENT'S OBJECTIVE

In many companies compensation schemes are typically based on management's performance above some target or minimum level. Here we describe some possible results of these constraints on the performance of the company. A stochastic model could be used to incorporate the effects on the revenues of the uncertain inflows and correlations between inflows and prices.

The total revenue is often an important indicator of the competitive position of a firm within the industry. Moreover, increased in sales revenues are often regarded as a sign of managerial success. It is even conceivable that the remuneration of the management depends on this particular performance index. Thus revenue maximization appears to be a plausible alternative objective in the corporate set-up, provided that the management always sees that the profit level does not fall below a certain prescribed minimum, π_0 . The objective of the management is then stated as:

$$\begin{aligned} & \text{Max } R(Q) \\ & \text{st.} \\ & C(Q) - R(Q) \leq -\pi_0 \\ & Q \geq 0 \end{aligned} \tag{1}$$

where Q is the output. We assume a concave revenue function $R(Q)$ and a convex cost function $C(Q)$ and that both functions are differentiable so that the Kuhn-Tucker theorem can be applied. The associated Lagrangian is:

$$L = R(Q) + \lambda [-\pi_0 - C(Q) + R(Q)] \tag{2}$$

The Kuhn-Tucker conditions are:

$$\begin{aligned} \frac{\partial L}{\partial Q} &= R'(Q) + \lambda [-C'(Q) + R'(Q)] \leq 0 \\ \frac{\partial L}{\partial \lambda} &= [-\pi_0 - C(Q) + R(Q)] \geq 0 \\ Q \geq 0, \quad Q \cdot \frac{\partial L}{\partial Q} &= 0, \quad \lambda \cdot \frac{\partial L}{\partial \lambda} = 0 \end{aligned} \tag{3}$$

By complementary slackness, the first condition must be satisfied as equality. We obtain the revenue-maximizing output rule as:

$$R'(Q) = \frac{\lambda}{1 + \lambda} C'(Q) \tag{4}$$

If $\lambda > 0$ the profit constraint is binding and $\frac{\partial L}{\partial \lambda} = 0$ by complementary slackness conditions. The company is only earning π_0 , the minimum profit required. The revenue-maximizing rule then indicates that $R'(Q) < C'(Q)$ (be-

cause $\frac{\lambda}{\lambda+1} < 1$) which would generally yield a higher output level than the profit-maximizing output rule $R'(Q^*)=C'(Q^*)$. The output rule is illustrated in Figure 1, where P is the price.

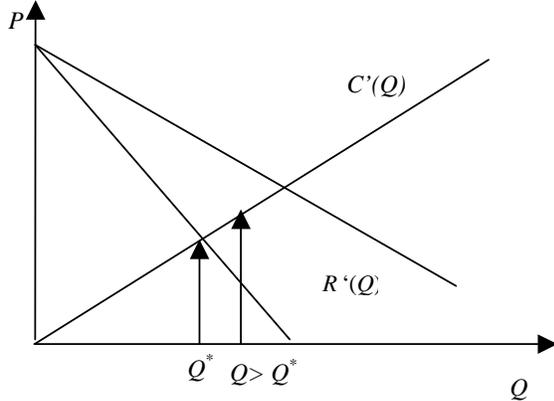


Figure 1: The revenue-maximizing output rule.

In the case of a multi-period model, the result above may be modified depending on whether the profit requirement is separate for each period or throughout the entire multi-period. The optimization problem for a two-period separate profit requirement is:

$$\begin{aligned} \text{Max } R_1(Q_1) + R_2(Q - Q_1) & \quad (5) \\ \text{s.t.} & \\ C_1(Q_1) - R_1(Q_1) & \leq -\pi_{01} | \lambda_1 \\ C_2(Q - Q_1) - R_2(Q - Q_1) & \leq -\pi_{02} | \lambda_2 \\ Q_1, Q_2 & \geq 0 \end{aligned}$$

where we assume that $Q_1 + Q_2 = Q$ and the dual variables of the respective constraints are indicated. For hydropower generation, there would be reservoir storage constraints for each period but we have omitted these for simplicity. The company then studies the opportunity costs of stored water, which itself is a function of electricity generated. The cost of an additional unit produced today equals the marginal loss of tomorrow's revenues calculated today. There are three possible outcomes of the problem in Equation (5): 1) no constraints bind, 2) one of the constraints bind, and 3) both constraints bind. If no profit constraints are binding:

$$R_1'(Q_1) = R_2'(Q - Q_1)$$

shows that management seeks to equalize marginal revenues in both periods. The situation is illustrated in Figure 2.

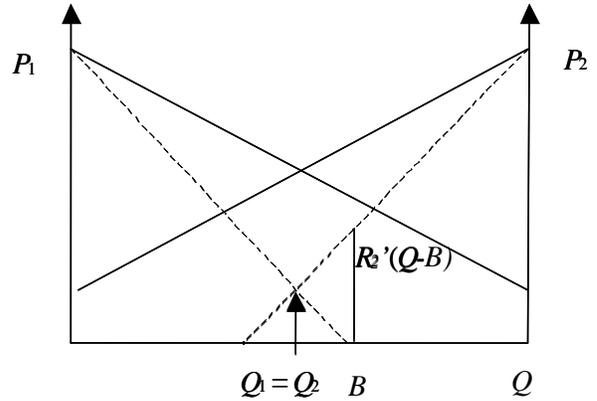


Figure 2: Illustration of marginal revenue equalization.

Here, P_1 and P_2 are the prices in the two periods and the demand curves are identical. The dotted lines represent the marginal revenues. If no constraints are binding, the company produces the same quantity in both periods, $Q_1 = Q_2$. However, assume that the reservoir storage constraint is such that at most BQ^4 can be produced in period two. Then the output in period one would be increased to B and the marginal revenue in period one would equal zero. Likewise, the marginal revenue in period two would be larger as indicated in Figure 2.

If reservoir storage constraints are binding, the marginal revenues net of the water values in each period are equal. The revenue-maximizing output rule in case of binding profit constraints is defined as:

$$\begin{aligned} -R_1'(Q_1)(1 + \lambda_1) + R_2'(Q - Q_1)(1 + \lambda_2) & \quad (6) \\ = -\lambda_1 C_1'(Q_1) + \lambda_2 C_2'(Q - Q_1) \end{aligned}$$

Management then looks at the opportunity costs of meeting the profit constraint in the future. The marginal value of meeting the profit constraint today is equal to the marginal value of meeting the constraint in the future calculated today. Assuming $\lambda_1 > \lambda_2$, then it is more important to meet the profit constraint in period one. Furthermore assume that the marginal costs in each period are zero. We then have:

$$R_1'(Q_1) = \frac{(1 + \lambda_2)}{(1 + \lambda_1)} R_2'(Q - Q_1) \quad (7)$$

which implies that the marginal revenue in period one is greater than in period two. Therefore management would allocate more of its output in period one to meet the profit constraint.

If one of the profit constraints is non-binding we obtain the following result:

$$R_i'(Q_i) = \frac{\lambda_i}{\lambda_i + 1} C_i'(Q_i), \quad i \text{ binding} \quad (8)$$

The result is the same as for the one-period problem. If the dual variables are identical in both periods such that the profit requirement is emphasized equally, we obtain:

⁴ The unit of BQ is typically MWh.

$$\left(-R_1'(Q_1) + R_2'(Q - Q_1)\right) = \frac{\lambda}{\lambda + 1} \left(-C_1'(Q_1) + C_2'(Q - Q_1)\right) \quad (9)$$

Likewise, if there is a combined profit constraint for periods one and two, it can be shown that we would obtain the same result as in Equation (6).

The results demonstrate that the allocation of output depends on the marginal revenues, marginal costs, the reservoir storage constraints, and the profit constraints. Likewise, management may operate differently whether or not it experiences a profit constraint.

To illustrate the use of a large-scale stochastic model including a contract portfolio and a penalty function⁵ for not fulfilling a certain revenue, we refer the reader to [4]. The general observations made from that model include the following:

- An increased penalty function gives a more risk-averse operation of the reservoir
- In general it was found that the expected income decreased with increasing penalty
- The minimum income scenarios in the closest income periods were reduced when risk aversion was introduced
- When no hedging in the futures market is allowed, the water was moved between the different time periods (seasons) to meet the income targets.

5 USING SCHEDULING MODELS

We describe finding a reference plan by using hydropower scheduling model outputs.

We assume a linear relationship between the annual revenue, annual average spot prices, total annual inflows and annual change in reservoir level. Therefore we assume that the annual revenue R is a function of the annual average spot price p , the total annual inflow i and the change in the reservoir level Δr throughout the year.

$$R(p, i, \Delta r) = a + b \cdot p + c \cdot i + d \cdot \Delta r + e \quad (10)$$

where b , c and d are constants and e is a residual term. The intuition behind the model is that a higher price (for example in a dry year) results in higher revenue. Likewise a higher inflow would result in more generation and possibly higher revenue. If the change is positive we would expect that the hydropower generator is reserving water for the future and therefore “moves” the revenue from one period to another. This would result in a lower revenue in the current period; the coefficient d would be negative. There may be problems with this relationship if there is a very high correlation between the price and inflow because the linear regression breaks down.

The model can be tested on outputs from hydropower scheduling models. Then a linear regression is run on simulated inflows and changes in reservoir levels as well as price forecasts for a specific period (e.g. one year). The constants a , b , c and d can then be read straight (for example, a linear regression in Excel). The intercept is b when all variables are zero. Likewise a regression program calcu-

⁵ The penalty function models the risk attitude of the hydropower company.

lates the R-squared value, which is the square of the correlation coefficient. It gives us a measure of the reliability of the linear relationship between p , i , Δr and R values.⁶

It is possible to use historical data from a real power system to test this formula, but because the data is limited it may be insufficient to validate the formula. Bear in mind that years have different characteristics. 1996 and 2002/2003 were dry years with low inflows and high prices, while 2000 was a wet year with high inflows and low prices. In one Norwegian power company the total income was highest for 2001 and lowest for 1998. We found that the general opinion among managers is that 1996 was a poor year, while 1998 was a medium year. These historic results show that the absolute value of the income is a poor indicator for the success of the generation plan.

Another problem is that actual annual income is calculated on an hourly basis, but annual model income is calculated based on a weekly time resolution. Therefore some of the optimization within the week will not be captured.

6 USING MARKET INFORMATION

An alternative approach is to use forward or futures prices as a guide for generation scheduling. This approach is appropriate when there is fixed volume consideration, but it may fail when there are strong price/volume correlations. It also requires a forward/futures market such that market prices can be observed and a forward price function can be constructed.

In this approach all decisions are made today based on current forward or futures prices. The planner can assume a certain revenue today by selling generation in the forward or futures market. Deviations from the generation sold in the forward or futures market will be exposed to the real-time market prices.

It is questionable how far ahead the planner should allocate generation. Usually, a water value simulation is done on a weekly basis and the planner might allocate generation on a weekly basis, while accounting for generation capacity constraints or other plant constraints.

It might be possible to characterize the forward price curve with a greater time resolution. This forward price function which gives us today's price of a unit of electricity delivered at a specific future moment, is not directly observable in the marketplace. The power contracts trading on Nord Pool are all written on a future average which is the delivery period of the contracts. We must establish the relationship between the forward price function and the average price based contracts.

Following [5] we can establish a forward price function $F(\cdot)$ based on seasonal or monthly Nord Pool contract with delivery from T_1 to T_2 as:

$$F(t, T_1, T_2) \approx \int_{T_1}^{T_2} \frac{1}{T_2 - T_1} f(t, s) ds \quad (11)$$

where $f(t, s) = V_t[\tilde{S}_t] e^{r(s-t)}$ is the forward price at a given time t and \tilde{S}_t is the uncertain future spot price and $V_t[\cdot]$ is

⁶ Values close to 1 indicate excellent linear reliability.

a valuation operator at time t . By using observed forward prices and requiring that the theoretical forward price is higher or equal to the bid price as well as lower or equal to the ask price, we can construct a theoretical forward price function. Assuming that today is August 31, 2004, observe the monthly forward prices as shown in Table 1.

Forward contract	Price (NOK/MWh)	Time for end of delivery (year)
ENOMOCT-04	278.25	0.082
ENOMNOV-04	293.50	0.17
ENOMDEC-04	302.00	0.25

Table 1: Observed forward prices on August 31, 2004.

Assume a spline function for each forward contract:

$$f(t) = a_i + b_i t + c_i t^4, \quad i = 0, 1, 2 \quad (12)$$

and that the function in each period is continuously connected to the next one so that the aggregate function is smooth. By integrating each function and calculating the forward price according to Equation (11) and then evaluating the functions and their derivative at the point where delivery ends for one contract and starts for the next (for example at $t=0.082$ and $t=0.25$ in the above example), a set of equations can be constructed and solved. Solving these equations yields a forward price function as shown in Figure 3 based on the contract prices in Table 1. The parameters of the different spline functions are shown in Table 2.

Function	a_i	b_i	c_i
0	71808.09	92.58	273.79
1	-11883.96	278.46	262.33
2	0.00	56.57	290.14

Table 2: Spline function parameters.

This function can be used to calculate the fair price of a forward contract starting delivery at time 0.17 and ending at time 0.25 by using Equation (11):

$$F(0,0.17,0.25) \approx \int_{0.17}^{0.25} \frac{1}{0.08} (290.14 + 56.57s) ds$$

$$= \frac{1}{0.08} \left[290.14s + 0.5 \cdot 56.57s^2 \right]_{0.17}^{0.25} = 302.00$$

which is exactly the forward price observed for the monthly December forward contract.

The potential problems associated with constructing such a forward price function may be that:

- Real-time input prices are bid/ask prices
- The calculations are more complicated with overlapping periods in the forward/futures market
- The method ignores market information not present in prices
- The curve gives less information for shorter periods of time such as days and hours; however, this may be improved using weekly or daily futures prices to construct a futures market price function with a daily or hourly time resolution, respectively
- The long end of the forward curve may be unrealistic and therefore more seasonal contracts or fake prices might be employed

- The method makes sense for fixed volume only and might fail if there is price and volume correlation.

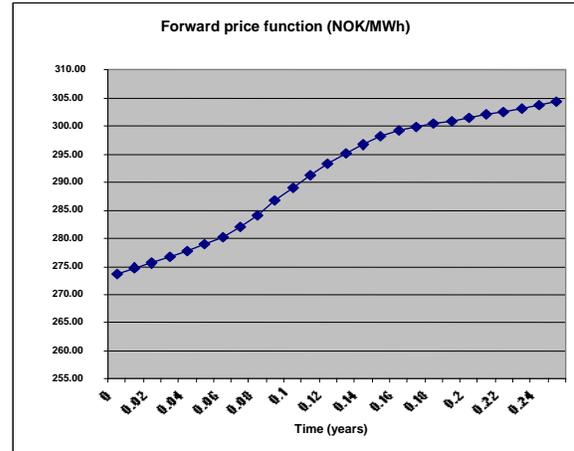


Figure 3: Forward price function.

When the forward price curve is established, decisions regarding allocation generation output can be made. Then the generation planner decides to allocate generation to the hours and days with the highest prices. The generation company must also consider the price area in which it is located and may hedge itself with Nordic contracts for differences (CfDs) against the risk that the area price and the system price may differ. Currently, only the area Norway 1 (Oslo area) has CfDs. If the generation company sells all its generation in the forward or futures market, then it will have no uncertainty (ignoring deviations in the real-time market) with its future income because it has fixed it to the current forward and futures prices. In this case the benchmark will be the forward and futures prices.

Market players in the Nordic region find on average a negative risk premium (the forward price being higher than the spot price) in the short end of the forward curve. Conversely, there is a positive risk premium in the long end (the forward price being lower than the spot price). Distribution companies selling to end-users want to purchase short-term contracts and therefore increase the price and demand of these contracts, while generators want to sell their generation on long-term contracts and therefore decrease price and demand. On average, generators would expect to make money on selling short-term contracts because of the risk premium. However, they might prefer to sell power on long-term contracts to receive stable future revenue. In the Nordic region some generators report increased revenues by hedging a smaller part of their generation [6].

Another possible benchmark is to use the relationship between the forward price, the spot price and the risk premium. Knowing the realized spot prices, the basis can be established. (The basis is the spot price of the asset to be hedged minus the futures or forward price of the contract used to hedge.) A non-zero basis implies that there is a risk premium. The risk premium relationship can then be used to establish a benchmark that varies with the part of the forward curve where the market players sell their generation.

Mathematically we can state the relationship between the forward price, spot price and the risk premium. Let (E) be the expected future spot price discounted at the risk premium v defined as the difference between the investor's discount rate f and the risk-free interest rate r at the time s . The forward price can now be expressed as:

$$F(t, s) = E(\tilde{S}_s) \cdot e^{(r-f)(s-t)} = E(\tilde{S}_s) \cdot e^{-v(s-t)} \quad (13)$$

where the life of the forward position is $s-t$. The forward-spot price relationship can be analyzed depending on the sign of v . A positive risk premium for a generator implies that the forward prices are lower than the expected future spot price. A negative risk premium for a consumer implies that the forward prices are greater than the expected future spot price. Several implications can be drawn, depending on the roles of the players (i.e. generators or consumers) and the dominance of each in the market. If the market player is a risk-averse generator it may want to hedge its production in the forward market. A market with dominant risk-averse generators will involve a forward market in backwardation. If the risk-averse consumers are the dominant players, this would imply a market in contango.

We can express the ratio between the forward price and the expected spot price as:

$$\frac{F(t, s)}{E(\tilde{S}_s)} = e^{-v(s-t)} \quad (14)$$

and taking the natural logarithm:

$$v = \frac{1}{(s-t)} \ln \left[\frac{E(\tilde{S}_s)}{F(t, s)} \right] \quad (s-t) \geq 0 \quad (15)$$

The risk premium v is then negative when the forward price is higher than the expected spot price (long end) and positive when the forward price is less than the expected spot price (short end). By using historical price information, it might be possible to estimate the risk premium by using forward prices and realized spot prices as an approximation for expected spot prices. This benchmark is more qualitative than quantitative but does provide information about how the forward market expectations differ from the spot market expectations. An approximation for this a benchmark could be to take

$\min\left(\frac{\text{forward price}}{\text{expected spot price}}, 1\right)$ in the short end of the forward curve and the $\min\left(\frac{\text{expected spot price}}{\text{forward price}}, 1\right)$ in the

long end of the forward curve. The min operator is used to ensure that if the forward or spot prices turn out to be higher than the spot and forward prices, respectively, the benchmark at most will equal one.

7 CONCLUSIONS

This paper has described benchmarks currently in use for hydropower generation scheduling. Furthermore, we discussed some possible management objectives and how

revenue requirement constraints determine a company's strategy.

Next we presented two possible approaches for benchmarking of hydropower generation scheduling. One is a regression model where generation scheduling model outputs are used as inputs to calculate theoretical revenues. The advantage of this approach is that it is on a "global" level and it is easy to implement. The disadvantage is that it does not capture all of the hourly hydropower generation decisions within a week because the outputs from the scheduling models are calculated on a weekly basis.

The second approach uses market information such as forward or futures prices as a guide to decision making. The advantage of this approach is that all decisions can be made today to fix the future revenues. The disadvantage is that it only makes sense for fixed volumes. It may also fail when there are price and volume correlations.

8 REFERENCES

- [1] A. Haugstad and O. Rismark, "Price Forecasting in an Open Market based on System Simulation", in *Proc. EPSOM'98*, Zurich, Switzerland, 1998.
- [2] Ivar Wangensteen, *Generation Planning in an Open Market*. Lecture Notes, Norwegian University of Science and Technology, 2004.
- [3] M. V. F. Peireira, "Optimal Stochastic Operations Scheduling of Large Hydroelectric Systems", *Electrical Power & Energy Systems*, Vol. 11, No. 3, July 1989, pp. 161-169.
- [4] B. Mo, A. Gjelsvik, and A. Grundt, "Integrated risk management of hydro power scheduling and contract management", *IEEE Transactions on Power Systems*, Vol. 16, May 2001, pp. 216-221.
- [5] G. Stensland, *Energy forward markets*, lecture notes, Norwegian School of Economics and Business Administration, 2004.
- [6] Montel homepage, August 31, 2004, available: <http://www.montelpowernews.com/>.