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Medium Term Hydroelectric Production Planning - A Multistage Stochastic Optimization Model

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ABSTRACT: Multistage stochastic programming is a key technology for making decisions over time in an uncertain environment. One of the promising areas in which this technology is implementable, is medium term planning of electricity production and trading where decision makers are typically faced with uncertain parameters (such as future demands and market prices) that can be described by stochastic processes in discrete time. We apply this methodology to hydrosystem operation assuming random electricity prices and random inflows to the reservoir system. After describing the multistage stochastic model a simple case study is presented. In particular we use the model for pricing an electricity delivery contract in the framework of indifference pricing.

Keywords: Hydroelectric Operation, Multistage Stochastic Programming, Risk Management.

INTRODUCTION

In the last decade under a deregulated market framework, in many countries electricity companies are confronted with the need for detailed operation planning tools in which more uncertainties need to be taken into consideration, e.g. because of the rise of renewable energy resources. Among this family, hydroelectricity plays an important role due to its flexibility and complementary use. Hydroelectric operation planning models consider multiple interconnected cascading hydro plants either exclusively or simultaneously with multiple thermal plants, which lead to hydrothermal coordination.

In this study we propose a planning method for hydro unit production under market and weather risks. It is assumed that a production company tries to maximize its risk adjusted expected profit within this environment. The uncertainties considered are the random behaviour of electricity spot prices and of inflows to reservoirs. The company is able to take decisions on the energy production for each hydro unit at discrete points in time $t = 0, \dots, T-1$. Decisions are taken before knowing the prices at which the produced energy can be sold.

Throughout this paper we will use multistage stochastic optimization as the basic method. This approach is applied in

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various fields such as multistage portfolio optimization, energy production models, transportation and telecommunication where decisions must take into account realizations of outcomes that are not known in advance.

To be more precise, in medium term planning (1-3 years) of electricity production and trading, uncertain parameters such as fuel prices, electricity spot prices and demand might be described as stochastic processes in discrete time. In this context information plays a crucial role. When time passes, the initially unknown uncertain parameters can gradually be observed. Stage-by-stage, the amount of information increases and planning decisions have to be made at each time stage based on the information available. This fact is called non-anticipativity (Pflug and Römisch, 2007). The idea of two-stage stochastic programing with recourse dates back to the pioneering work of Beale and Dantzig (1955). In a multi-stage setting decisions are taken at times $t = 0, \dots, T-1$with typically different levels of information. We denote the random process of risk factors by $(\xi_1, \dots, \xi_T)$ and the pertaining multistage decision process by $(x_0, x_1, \dots, x_{T-1})$. The indices of the random process and the decision process differ by one, since at time t, a decision is to be made but the realization of the random process will be observable only at time $t+1$. We should emphasize here, that modelling the scenario process is not within the scope of this research. However, before generating scenario trees, it is necessary to identify a distribution for ξ that can be considered as a highly accurate approximation of the true distribution of the parameters. In energy optimization, such a distribution has to be related to the historical data.

For a broad technical presentation of stochastic programming refer to Ruszczynski and Shapiro (2003) and for applications to the energy market to Eichhorn, et al. (2005). We also mention a state of the art review of optimal operation of multi-reservoir systems by Labadie (2004) in which several solution strategies including implicit and explicit stochastic optimization, real-time optimal control with forecasting and heuristic methods are explored. See also Giacometti et al. (2001) for decision models with deterministic inflows and forward electricity prices.

Compared to Giacometti et al. (2001), we describe a model with stochastic inflows and the possibility to sell electricity at a spot market. This also leads to some effort in estimating suitable econometric models. Moreover, applying this approach for a hydroelectric structure with a cascade topology which consists of several decision possibilities allows us to capture a more extent overview on hydroelectric production portfolios in multistage stochastic optimization framework and observe the correlation between price and production levels in presence of seasonal inflows and price spikes. In addition we apply the overall approach to indifference pricing, i.e. pricing delivery contracts with respect to the possible profit from selling the whole production at the spot market. This valuation approach goes back to insurance mathematics (Bühlmann, 1972) but can be applied to energy production in a natural way.

THE MODEL

Basic Model Structure

A multi reservoir hydro generation system consists of a cascade of interconnected reservoirs along with corresponding turbines, pumps and spillways. Such a system can be represented by a directed graph, as it is shown in Figure 1, where the nodes represent the reservoirs and the arcs represent water flows. Water flows can be either related to power generation by turbines, to pumped water for increasing reservoir storages, or to spillage. Let J denote the set of reservoirs and I denote the set of arcs, then the arc-node incidence matrix, whose ij-entry denoted by $A_{i,j}$ represents the interconnections among reservoirs and arcs as follows:

$$A_{i,j}=\begin{cases}1 & \text{water flows into reservoir} j \text{over arc} i\\ -1 & \text{water flows out of reservoir} j \text{over arc} i\\ 0 & \text{arc} i \text{is not connecte into reservoir} j\end{cases}$$

The potential decisions are given by the water flows over arcs (resulting in electric energy sold at a spot market) and the amount of water stored in reservoirs, in order to maximize risk adjusted expected terminal revenue. This is done by using a mixture of expectation and the conditional value at risk $(AVaR_{\alpha})$ -a risk sensitive acceptability measure- as the objective function.

The average value at risk at level α for a random variable Y is defined as:

$$AVaR_{\alpha}(Y)=\frac{1}{\alpha}\int_{0}^{\alpha} G^{-1}(u)du \qquad (1)$$

where G is the distribution function of Y. This is the simplest version independent acceptability functional and can be accounted as the basis of many other acceptability functions. For further technical details refer to Pflug and Römisch (2007) and also see Eichhorn and Römisch (2005) for an overview on the broader class of polyhedral risk measures in stochastic programming.

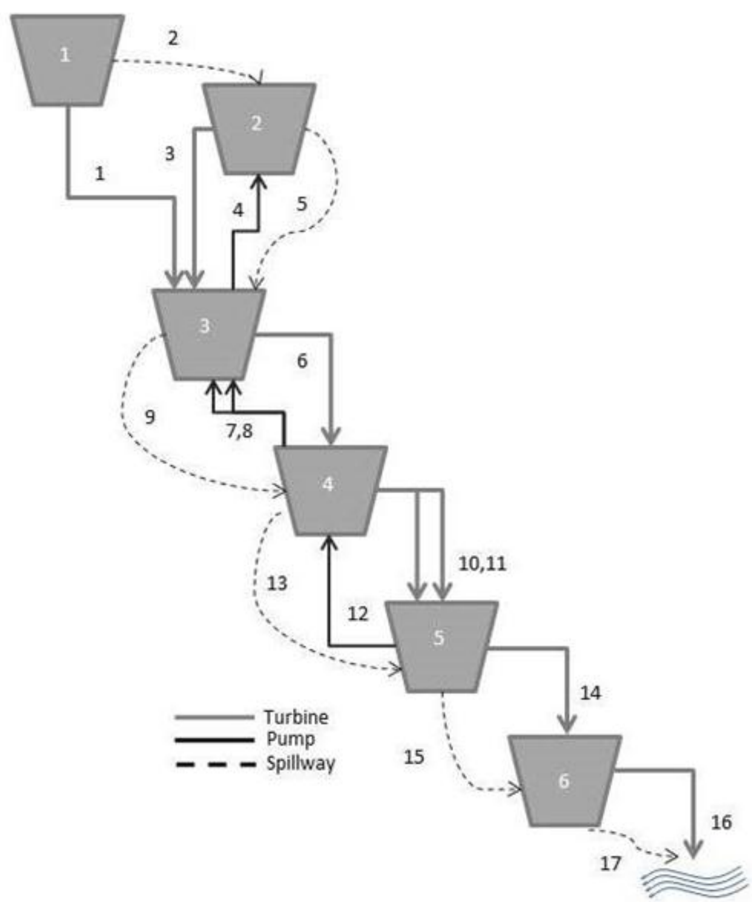

Fig. 1. Hydro system topology.

All decisions on the amount of water flows and related energy production are made at discrete periods in time $t = 0, \dots, T-1$.This leads to a multistage stochastic nonlinear programing problem, where the produced energy within time period of length Δt depends on the elevation difference between headwater and tailwater. For small systems this problem can be solved by dynamic programing, but for large systems with many reservoirs (state variables) dynamic programming is not applicable. Often this problem is simplified by keeping the height (difference between head and tail) constant. This way the model turns to be a large scale but linear multistage stochastic optimization problem. Throughout this paper we will apply this simplification.

Time Based Model Formulation

In this section we aim to formulate the decision problem of a generator using a hydrosystem with prespecified topology in a multistage stochastic optimization setting. Notations are described in (Appendix 5.1). The sources of stochasticity are given by

- The electricity price ξ_t^e at which electricity is sold. In a model with weekly decisions this will usually be an average over hourly spot prices, using a typical production schedule.
- The pumping price ξ_t^p i.e., price it costs to pump up the water into the upper reservoir. With weekly decisions we use an average over off-peak electricity prices.
- Inflows to reservoir f_t^j.

In the stochastic model, f_t^j and prices ξ_t^e, ξ_t^p are random processes while flows through the arcs q_t^i form the decision process. Energy produced x_t^{ei} , accumulated cash x_t^c and reservoir's storage level v_t^j are implied by the decision process and inflows, therefore are named decision expressions.

We assume that the stochastic process $\xi = (\xi_t^e, \xi_t^p, f_t^j)$ describes the observable information at all stages $t = 0, \dots, T$. Hence, the information available at time t is related to the history process $\nu_t = (\xi_1, \dots, \xi_t)$.Notice that, ξ_0 is deterministic and does not contain probabilistic information. F_t is the $\sigma - algebra$ generated by ν_t and the sequence $\boldsymbol{F} = (F_t)_{t=0}^T$ of increasing $\sigma - algebras$ is the corresponding *filtration*. To express that the function ν_t is F_t measurable we shall write $\nu_t \lhd F_t$ for all $t \in T$. The value process $\mathrm{x}_t = (q_t^i,\ x_t^{ei},\ x_t^c, v_t^j)$ which describes the decision variables is also measurable with respect to the filtration $\boldsymbol{F}$ and we write $\mathrm{x} \lhd \boldsymbol{F}$.The objective function is given by a weighted sum of the expected terminal revenue and the end-of-period average value at risk.

For a hydropower producer seeking to maximize the risk adjusted expected terminal revenue, the time-oriented form is formulated as follows, where all the constraints hold for $t = 0, \dots, T$ and all equations and inequalities are considered to hold almost-surely:

Maximize $\lambda \mathbb{E}[x_T^c] + (1-\lambda) AVaR_\alpha [x_T^c]$
Subject to:

$$0 \le q_t^i \le \overline{q}^i \tag{1a}$$

$$\underline{v}^j \le v_t^j \le \overline{v}^j \tag{2a}$$

$$v_{end}^j \le v_T^j \tag{3a}$$

$$v_t^j = v_{t-1}^j + f_t^j + \sum_{\{i \in I : P_{max} > 0\}} A_{i,j} \cdot q_{t-1}^i + \sum_{\{i \in I : P_{max} = 0\}} A_{i,j} \cdot q_t^i \tag{4a}$$

$$x_t^{ei} = q_{t-1}^i \cdot k^i \cdot \Delta t_{(t-1)} \tag{5a}$$

$$x_t^c = x_{t-1}^c \cdot (1+r)^{\Delta t_{(t-1)}} + \sum_{\{i \in I : k^i > 0\}} x_{t-1}^{ei} \cdot \xi_t^e + \sum_{\{i \in I : k^i < 0\}} x_{t-1}^{ei} \cdot \xi_t^p \tag{6a}$$

$$i \in I, j \in J$$

$$\nu_t \lhd F_t$$

$$\mathrm{x} \lhd \boldsymbol{F}$$

Constraints (1a) and (2a) put lower and upper bounds on the flow over arc i and storage level of reservoir j, respectively. In addition, as stated in (3a) a minimum content for each reservoir at the final stage needs to be fulfilled. In (4a) we calculate the water balance for all reservoirs: At each stage the water level at the end of the period depends on the water level at the beginning, and the inflows and discharges during the period based on the system topology. In (5a) the energy produced is calculated, while (6a) is an accounting equation for the cash position over time. It considers the interest rate r, and depends on the gain from selling electricity and the cost of pumping water to the upstream reservoirs. Note that the usage of x_{t-1}^{ei}vs. (ξ_t^e, ξ_t^p) in this equation reflects the fact that decisions have to be made before knowing the actual spot prices, at which electricity is bought and sold.

Tree Based Approximation

In this section, we use finite scenario trees as the basic structure for application of the above model to real world problems. A directed graph $\mathcal{T}$ is called a layered tree of height T, if:

- Its node set N is the disjoint union of $T + 1$ subsets $layer_0$,...,$layer_T$, called layers. The layers are sometimes referred as stages.
- There is exactly one node in $layer_0$, the *root* node.
- Arcs do only exist between nodes of subsequent layers.
- All nodes in layers $0, \ldots T-1$ have at least one direct successor.
- All nodes in layers $1, \ldots, T$ have exactly one direct predecessor.

The node set in layer t is denoted by N_t. The nodes in the last layer T, are called the terminal nodes N_T. A probabilistic tree is a tree of height T for which the terminal node set is a finite probability space. The terminal node set is called the *scenario* set and its probabilities are called the *scenario probabilities*. The nodes of $\mathcal{T}$ are numbered successively beginning with the root node $n = 0$. The predecessor of node $n \neq 0$ is denoted by n_-. Given a tree $\mathcal{T}$, the pertaining tree process ν_t takes the values $n \in N_t$ with probabilities π_n. The node probabilities are calculated from scenario probabilities by coarsening:

$$\pi_n = \sum \{P(k): k \in N_T, k \text{is the successor of} \, n\}$$

There are many ways of representing $AVaR_\alpha$, but (Rockafellar and Uryasev, 2000) showed that $AVaR_\alpha$ can be defined as the solution of the following linear optimization problem:

$$AVaR_\alpha(Y) = \max_{\tau \in R} \{\tau - \frac{1}{\alpha}\, \mathbb{E}[Y - \tau]^-\} \qquad (2)$$

Here τ represents the value at risk. Recall that every real-valued function g can be written as $g = [g]^+ - [g]^-$. We apply this convention for terminal cash $x_n^c - \tau = [x_n^c]^+ - [x_n^c]^-$ and finally replace $AVaR_\alpha$ in (a) by the objective of (2) within our model (b). This leads to the desired linear program as follows:

$$\text{Maximize } \lambda \sum \pi_n \cdot x_n^c + (1-\lambda)\left(\tau - \sum \frac{\pi_n \cdot x_n^{cn}}{\alpha}\right)$$

Subject to:

$$0 \le q_n^i \le \overline{q}^i \qquad (1b)$$

$$\underline{v}^j \le v_n^j \le \overline{v}^j \qquad (2b)$$

$$v_{end}^j \le v_n^j \quad n \in N_T \qquad (3b)$$

$$v_n^j = v_{n_-}^j + f_n^j + \sum_{\{i \in I: P_{max} > 0\}} A_{i,j} \cdot q_{n_-}^i + \sum_{\{i \in I: P_{max} = 0\}} A_{i,j} \cdot q_n^i \qquad (4b)$$

$$x_n^{ei} = q_{n_-}^i \cdot k^i \cdot \Delta t_{n_-} \qquad (5b)$$

$$x_n^c = x_{n_-}^c \cdot (1+r)^{\Delta t_{n_-}} + \sum_{\{i \in I: k^i > 0\}} x_{n_-}^{ei} \cdot \xi_n^e + \sum_{\{i \in I: k^i < 0\}} x_{n_-}^{ei} \cdot \xi_n^p \qquad (6b)$$

$$
\begin{aligned}
& x_n^c - \tau = x_n^{cp} - x_n^{cn} \\
& n \in N_T \\
& i \in I, j \in J \\
& x^{ei}, x^{cp}, x^{cn}, q^i, v^j \in \mathbb{R}_+^m \\
& x^c \in \mathbb{R}^m
\end{aligned}
\tag{7b}
$$

In the tree based formulation non-anticipativity is enforced by the tree structure, which represents the relevant filtration. To summarize, our model is a specification of the medium term hydropower scheduling problem, based on simulated spot price, pumping price and inflow scenarios and leads to a large scale multistage linear stochastic optimization problem, which can be solved by available standard software.

CASE STUDY

We applied our approach to a hypothetical production topology based on a generating system of a European electric utility. The hydro chain is considered to be participating in the market for a midterm period of one year with specification shown in Figure 1. The scenario tree represents the information on weekly spot prices and pumping prices in addition to the weekly inflows to the reservoirs, where each path from the root to the terminal node of the tree corresponds to one scenario. Before setting up the stochastic optimization model, it is necessary to identify the random input data $\xi_1,\ldots,\xi_T$ to represent it by suitable statistical models and to yield a scenario tree using appropriate sampling techniques. In the following sections construction methods of stochastic inflow and price scenarios based on history data is presented.

In the present study, as in (Papamichail and Georgiou, 2001) a SARIMA model is selected to simulate the time series of historical weekly data of natural inflows into a chain of reservoirs over a one year period.

In the model selection stage, both the autocorrelation function and the partial autocorrelation function of the logarithmically transformed time series of inflows are considered. This transformation is done to stabilize the variance, similar to Ledolter (1978) approach. By implementing the “Hyndman-Khandakar” algorithm and by minimizing the AIC (Akaike's Information Criterion (Akaike, 1974), $ARIMA(1,0,2)(2,0,2)_{52}$ seems to be the appropriate candidate model. In Table 2, the details of the model coefficients are shown.

We used hourly spot prices from EEX (European Energy Exchange) as the basis for the models weekly electricity and pumping prices. In particular we used an estimation approach described in (Kovacevic and Paraschiv, 2013). Both the estimated inflow and price models were used to simulate price and inflow scenario paths. However, such bunch of sample paths (scenario fan) does not reflect the information structure in multistage stochastic optimization and neglects the fact that information is revealed gradually over time. For this reason various scenario tree generation algorithms for multistage stochastic programs have been developed. We used an algorithm described in (Heitsch and Römisch, 2005) which consists of recursive scenario reduction and bundling steps. The study horizon was split into 52 stages, each representing one week, and for the following numerical example we considered 152 scenarios.

Finally we used AIMMS 3.12 for formulating and solving the linear multistage stochastic problem (b) for a chain of 6 reservoirs with 17 arcs. In the following we discuss the numerical results obtained.

Numerical Results: The Basic Model

In Figures 2-4 the scenario trees of stochastic inflows are depicted for three corresponding reservoirs. Clearly, reservoirs 3, 4 and 5 are downstream reservoirs i.e.

there are no natural inflows. Also it can be seen from the graph that the inflows follow a pattern, which depends on the seasons of the year.

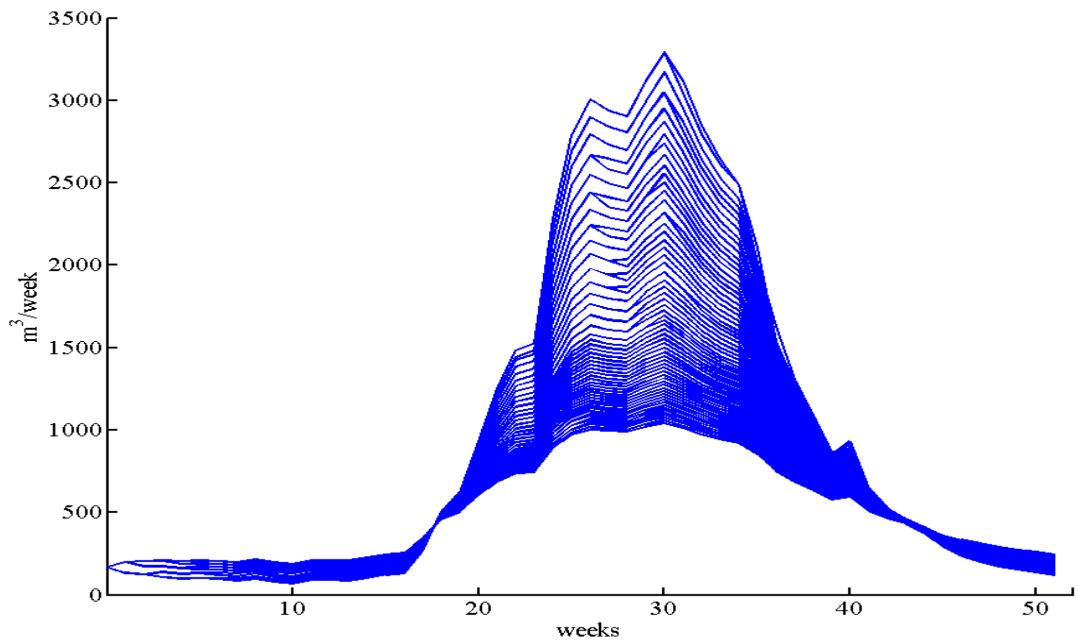

Fig. 2. Scenario tree of annual stochastic inflows to reservoir 1.

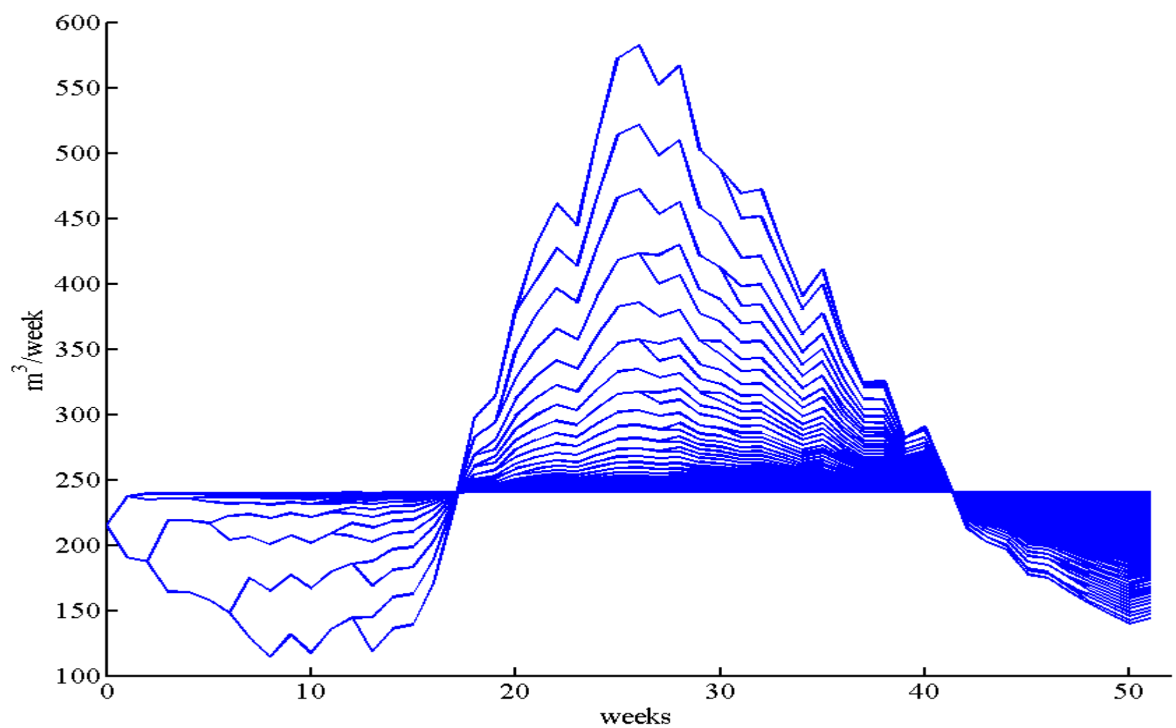

Fig. 3. Scenario tree of annual stochastic inflows to reservoir 2.

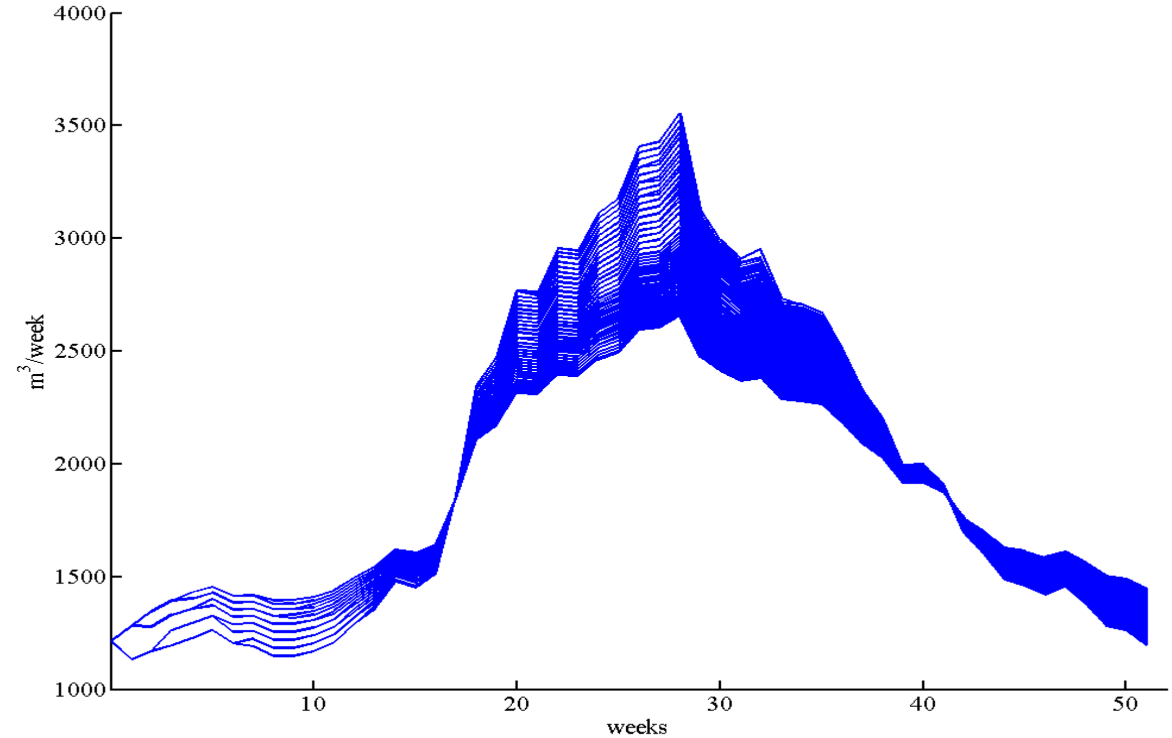

Fig. 4. Scenario tree of annual stochastic inflows to reservoir 6.

In addition the spot price scenario tree is depicted in Figure 5. As it was mentioned, weekly spot prices are calculated as an average over hourly spot prices, using a typical production schedule.

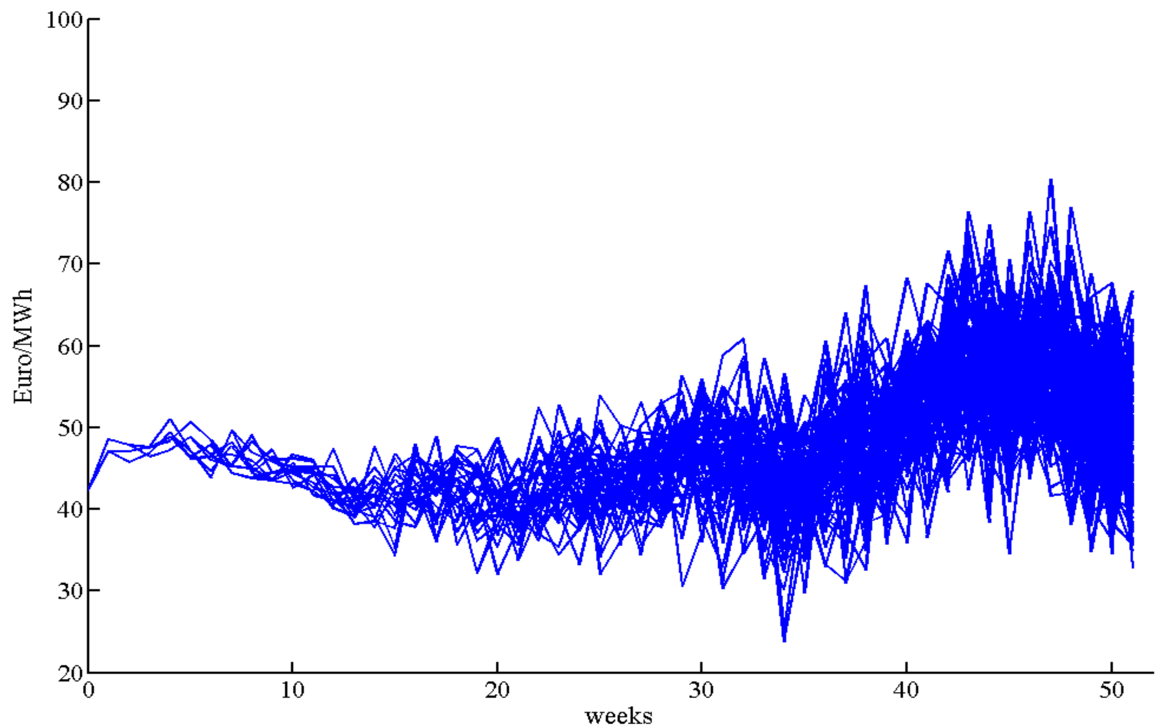

Fig. 5. Scenario tree of electricity spot prices.

The following results were calculated with a parameter value $\alpha = 0.05$ and a mixing factor of $\lambda = 0.5$. In Figure 6, the stage-wise cash gain and loss scenarios (gray shade) are shown, moreover the mean of all scenarios (black line) is also added to the figure.

Figure 7, depicts the probability density of accumulated cash over time for the last 10 weeks of the decision horizon i.e. weeks 42-52. The density plot exhibits a clearly increasing trend over time.

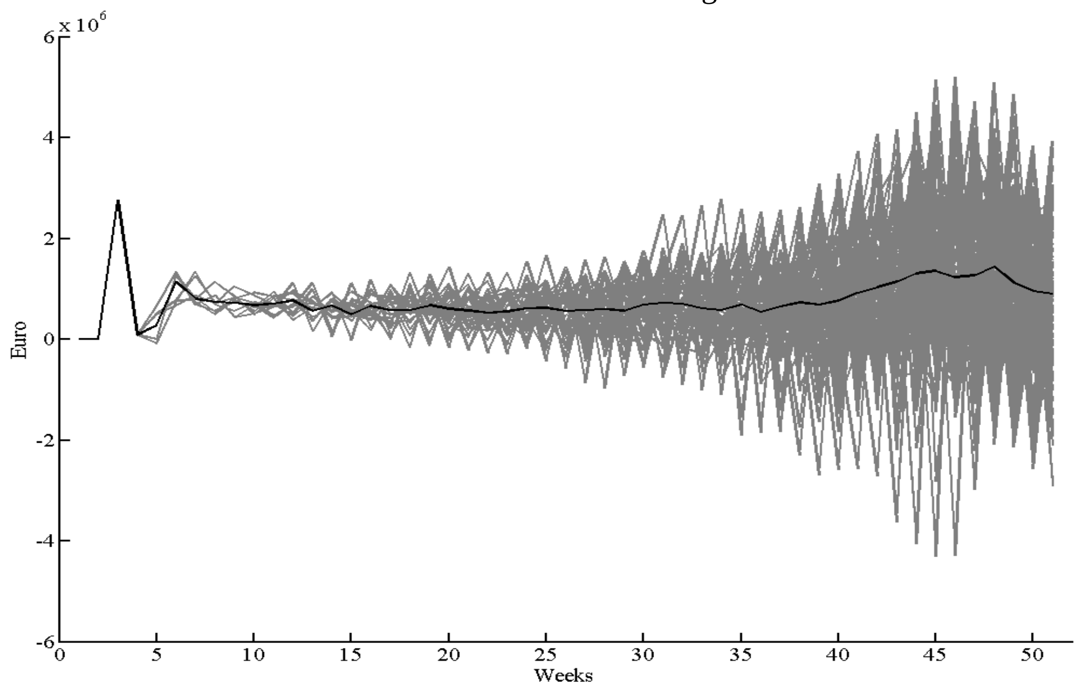

Fig. 6. Cash gain and loss scenarios.

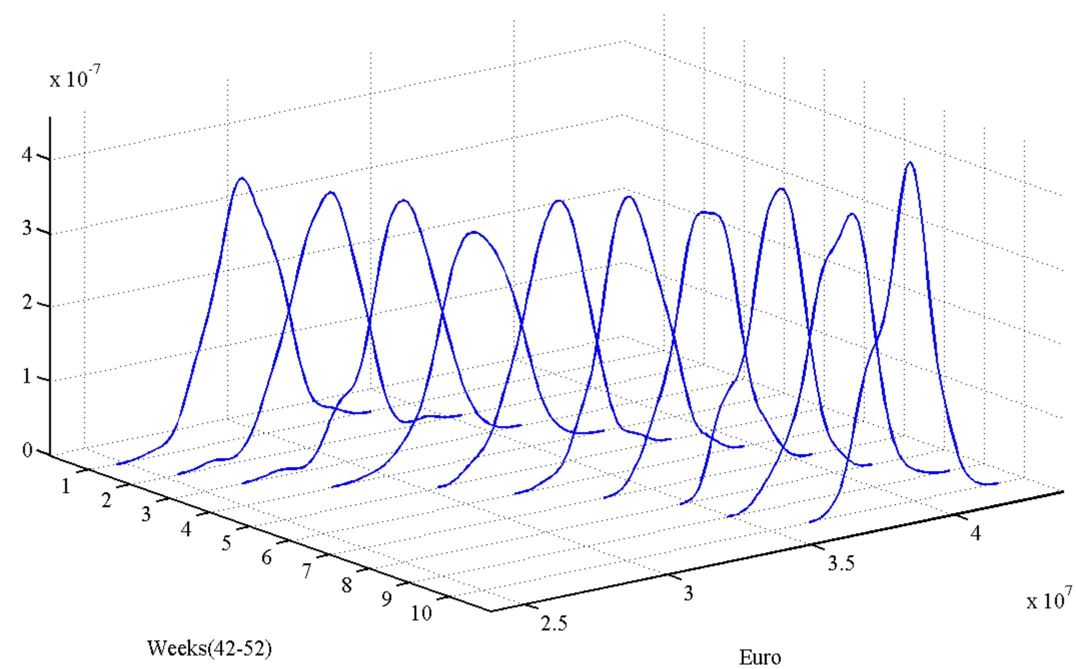

Fig. 7. Accumulated cash density (weeks 42-52).

Finally, in Figure 8 the reservoir storage level scenarios for reservoirs1, 2 and 3 are shown. Thicker lines depict the means of storage levels in the corresponding reservoirs. It should be noted that the storage levels are in m^3 per week. The interconnection of reservoirs 2 and 3 can be observed from the storage level patterns, when e.g. pumping up decisions show a decrease in storage level of lower reservoir, simultaneously the storage level in the upper reservoir is showing an increase.

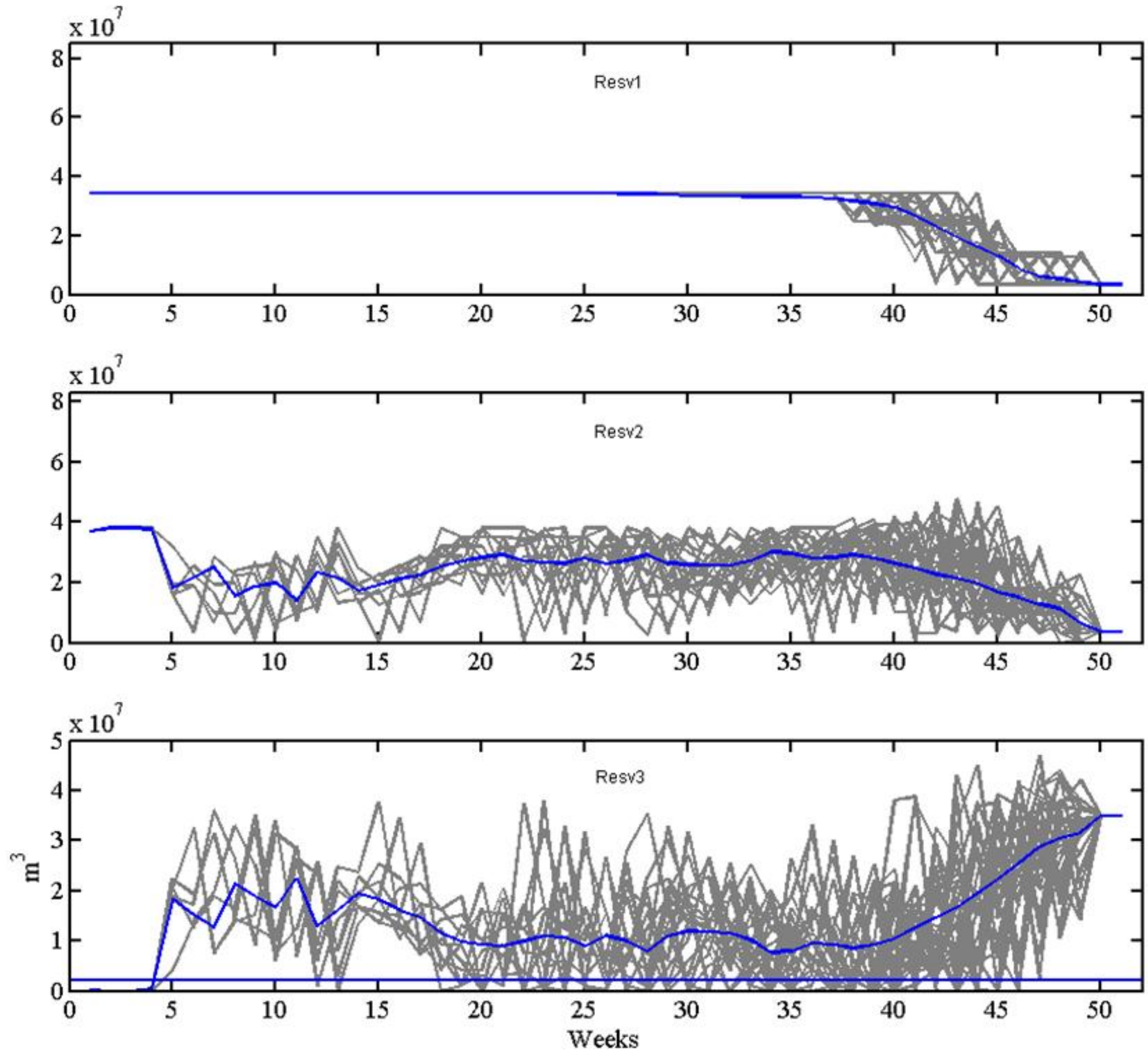

Fig. 8. Reservoir storage level scenarios and decision sensitivity.

Indifference Pricing

Consider now electricity delivery contracts with given contract size $E(MWh)$, deliverable at a constant load during the whole planning horizon at a fixed price $K\left(\frac{Euro}{MWh}\right)$. The contracted energy has to be delivered regardless of the actual inflows and electricity prices. Only excess production capacity can be traded at the spot market, whereas shortage in production (denoted by $y_t \geq 0$) can be compensated at the market. We use indifference pricing as an approach to find a price at which the producer will sell the contract: According to the indifference principle, the seller of a product compares his optimal value with and without the contract and requests a price such that he is at least not worse off after closing the contract. This idea goes back to insurance mathematics (Bühlmann, 1972) and has been used for pricing financial contracts later on. See (Carmona, 2009) for an overview. Further applications in energy can be found e.g. in (Kovacevic and Paraschiv, 2013), (Kovacevic and Pflug, 2013). Within this framework and choosing value $\alpha = 0.05$ and $\lambda = 0.5$ as above, we solve the original planning problem in order to find the optimal value v^* without the delivery contract i.e. selling all produced electricity on the market. Then a modified optimization problem, searching for the minimum bid price is formulated. The producer should be indifferent between closing the contract and refusing the contract, hence the most important constraint is given by $\lambda \mathbb{E}[x_T^c] + (1-\lambda) AVaR_\alpha [x_T^c] \geq v^*$. In addition the contract has to be fulfilled. i.e. $\sum_{i \in I} x_t^{ei} + y_t \geq E$. Finally, the cash position has to be corrected because parts of the electricity are sold at the contracted price K. The minimum bid price for contract sizes between 1000 and 28000 MWh is shown in Figure 9. Small contract sizes are comparably expensive, but due to economy of scales the indifference price decreases fast. While the mean electricity price lies at $\sim 49.73 Euro/MWh$ the indifference price goes down to $\sim 47.56\ Euro/MWh$, which reflects the efficiencies of the turbines in the system. Note also that the calculated indifference price does not reflect fixed operating costs. For large contract sizes, starting near the maximum weekly production of $\sim 72\,000\ MWh$ (not shown in Figure 9), more and more electricity has to be bought at the spot market, which results in a slight increase of the indifference price, tending more and more to the mean spot price.

CONCLUSIONS

In this paper we have presented a medium term multistage stochastic optimization model for multi-reservoir hydroelectric systems. In particular we considered the stochasticity of electricity prices and natural inflows. A case study for a cascading system with a one year planning horizon and weekly decisions has been implemented, and the results were presented and discussed. In particular we applied indifference pricing to a delivery contract and obtained minimal production prices for different contract sizes.

APPENDIX

Nomenclature

Let J denote the set of reservoirs (nodes) and I denote the set of water flows (arcs). In the following, in Table 1, list of symbols and the corresponding units used to represent the data, random processes, decision and expression variables are presented.

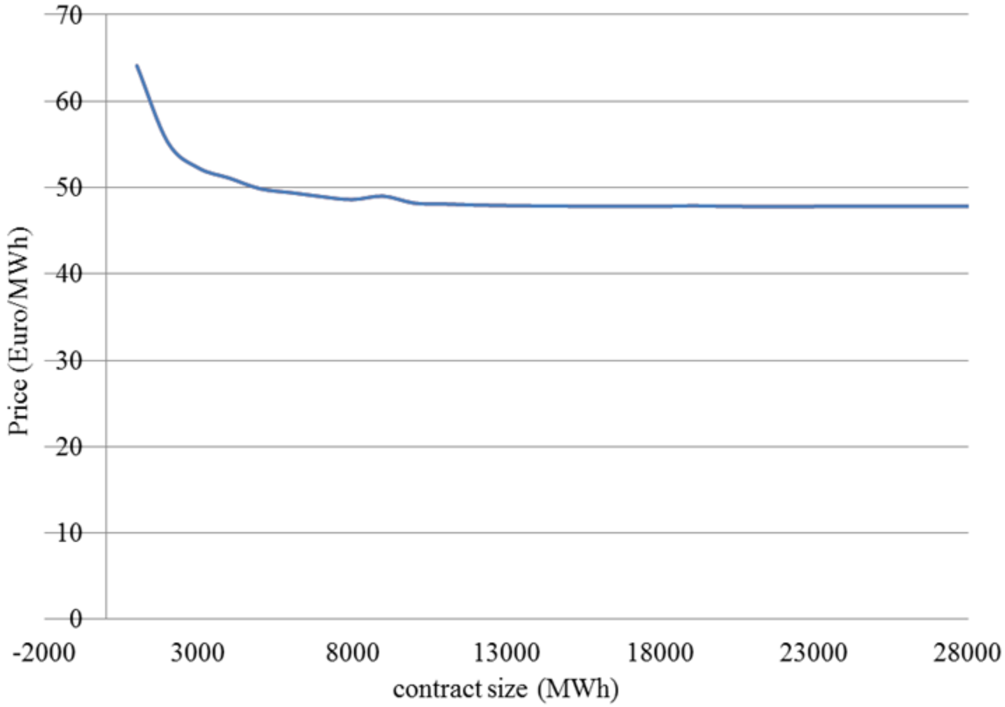

Fig. 9. Indifference prices for different contract sizes.

Table 1. Nomenclature.

Data	
$k^i[MWh/10^3m^3]$	Energy coefficient
$k^i > 0$	- arc i represents generation;
$k^i < 0$	- arc i represents pumping;
$k^i = 0$	- arc i represents spillage.
$\bar{q}^i[10^3m^3/\Delta t]$	Maximum water flow in arc i.
$\bar{v}^j[10^3m^3]$	Maximum storage volume in reservoir j.
$\bar{v}^j_{end}[10^3m^3]$	Minimum storage volume required in reservoir j at the end of panning horizon.
$\underline{v}^j[10^3m^3]$	Minimum storage volume in reservoir j.
Random Process	
$f^j_t[10^3m^3/\Delta t]$	Natural inflow into reservoir j.
$\xi^e_t[Euro/MWh]$	Electricity spot price.
$\xi^p_t[Euro/MWh]$	Electricity pumping price.
Decision Variables	
$q^i_t[10^3m^3/\Delta t]$	The water flow in arc i - turbined volume if arc i represents generation; - pumped volume if arc i represents pumping; - spilled volume if arc i represents spillage.
Decision Expressions	
$v^j_t[10^3m^3]$	Storage volume in reservoir j.
$x^{ei}_t[MWh]$	Energy produced during the next stage for each arc i.
$x^c_t[Euro]$	Cash
$\tau[Euro]$	Value at risk

Incidence Matrix

Below the incidence matrix of the implemented topology is shown. Rows represent the arcs and columns the reservoirs.

-1	0	1	0	0	0
-1	1	0	0	0	0
0	-1	1	0	0	0
0	1	-1	0	0	0
0	-1	1	0	0	0
0	0	-1	1	0	0
0	0	1	-1	0	0
0	0	1	-1	0	0
0	0	-1	1	0	0
0	0	0	-1	1	0
0	0	0	-1	1	0
0	0	0	1	-1	0
0	0	0	-1	1	0
0	0	0	0	-1	1
0	0	0	0	-1	1
0	0	0	0	0	-1
0	0	0	0	0	-1

Parameter Estimates

Table 2. Parameter Estimates.

Parameter	Estimate	Standard Error
ϕ_1	0.8521	0.0386
Φ_1	0.1701	0.1824
Φ_2	0.8296	0.1827
θ_1	-0.2893	0.0561
θ_2	-0.2478	0.0432
Θ_1	-0.1608	0.1693
Θ_2	-0.8074	-0.8074

Seasonal ARIMA model is formed by including additional seasonal terms in the ARIMA models and is written as follows:

$$ARIMA \quad \underbrace{(p,d,q)}_{non-seasonal} \quad \underbrace{(P,D,Q)}_{seasonal}$$

where m is the number of periods per season. The seasonal part of the model consists of terms that are very similar to the non-seasonal components of the model, but they involve backshifts of the seasonal period. Denoting the backshift operator with B, the corresponding $ARIMA(1,0,2)(2,0,2)_{52}$ which is without the constant terms is written in the following closed form:

$$(1-\phi_1 B)(1-\Phi_1 B^m - \Phi_2 B^{2m})y_t = (1+\theta_1 B+\theta_2 B^2)(1 + \Theta_1 B^m + \Theta_2 B^{2m})e_t$$

Parameters' estimates are shown inTable 2.

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