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PEAK HYDROPOWER PLANT OPERATION BASED ON STOCHASTIC DYNAMIC PROGRAMMING ANALYSIS

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This paper describes an explicit stochastic dynamic programming model for long-term optimization of a major reservoir and associated peak hydropower plant, under uncertainty operation conditions. As objective function has been accepted to follow, as much as possible, a monthly energy production schedule. The results of this stochastic dynamic programming analysis were then used to develop a simulation operating model, but which also includes some correction rules (unitary applied in any time-steps) for unwanted situations.

Keywords: optimization, peak hydropower plant, stochastic dynamic programming.

1. Introduction

The management of the major reservoir is designated to respond to various purposes (energy production, water supply, flood control etc.), under uncertainty conditions regarding their inflows and taking into account a lot of constraints of constructive, technological, environmental, economical, legal etc. nature.

For these reasons, the finding of the optimal operating policies becomes a difficult task, which may be only approached using the mathematical optimization models. In Yeh [1], Simonovic [2], Wurbs [3], for example, many similar models are reviewed and properly discussed.

However, it is widely agreed that the dynamic programming (DP) offer some substantial advantages for constrained, nonlinear optimization problems, especially when the system includes one or a small number of reservoirs. Particularly, if random variables are to be included in the analysis, the stochastic dynamic programming (SDP) becomes a more suitable option.

Beside the general books of the subject (as Kall and Wallace [4], Liu [5]), a lot of papers devoted to SDP applications for reservoirs operation are issued during the last 30 years. For example, in Liu et al [6], SDP is used to derive the operating rules for the Three Gorges reservoir as functions of storage levels and inflows. Tejada-Guibert et al [7] presents a comparison between the two manners of implementing in the operating rules of the results obtained by SDP for a multi-

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reservoirs system. In Mujumdar and Nirmala [8], a SDP variant, including the uncertainty of both the previous inflow and that of forecasted ones as well, is described in connection with the operating rules development. As forecasted quantity - an aggregate inflow for the whole system is accepted, and then assigned to each reservoir according with some hydrological criteria. Also, in Archibald et al [9] or Turgeon and Charbonneau [10], various aggregation/disaggregation schemes are proposed in view to simplify the stochastic approach and to obtain some low dimensional sub-problems, but all these methods are rather heuristic based.

Jaafar [11] has limited his SDP analysis to the single reservoir case, but he coupled these results with a simulation model and then the obtained operating policies were verified in real time conditions. In Rashid et al [12] a classical SDP model is presented with application to the Dokan reservoir, Iraq. Some optimal storage guide-curves are illustrated for various levels in storage, at the beginning of the year. Baliarsingh [13] or Alamdarlo et al [14] provides other applications in the field.

In this paper, some results for the Fântânele reservoir/peak HPP Mărișelu are summarized. The objective function used within SDP analysis refers to the minimization of expected sum of squared monthly deviations from the monthly planned energy productions.

A time series of recorded monthly inflows during the 1961-2010 time periods were available. These data were used both to statistically characterize this random variable (required for SDP analysis) and to develop a synthetically generation model for monthly inflows, as well.

It is also proposed a simulation model for the system operation. This model is primarily based on the SDP results, but it includes a set of correction rules for physically impossible or unwanted operational situations which are uniformly applied in all time steps. The simulation model was checked using the 50 years recorded inflow data series, and also with 5 series of synthetically generated inflows, each having a length of 100 years.

In all this verifications, the system performance indices (reliability, resiliency, vulnerability and deficit ratio) were evaluated. Their values confirm the validity of the simulation model. Therefore, this conclusion encourages the inclusion of such model, together with the inflow generation model, within a decision support system to help the management of this hydropower facility.

In a next paper, the same problem will be approached in stochastic context but using as objective function the market value of energy production.

2. Stochastic dynamic programming model

The aim of this section is to develop a SDP model devoted to optimize the long-term (annual horizon) operation of a major reservoir with associated peak HPP, using the month as time step and accepting the monthly inflows as random variable.

In Popa and Popa [15] it was analyzed the case of the greatest Romanian reservoir (Izvorul Muntelui, on Bistrița river) considering two situations: a) with monthly inflow as independent random variable, and b) when the inflow from current month is correlated with the previous month inflow, respectively. Because the simulations over a 60 years period using the recorded monthly inflows have not proved better results in the last variant, and taking into account the similarity of the hydrologic regimes in our geographical area – the monthly inflows are considered as independent random variables in this work.

As a state variable of the system it is accepted the storage volume at the beginning of the month *k*, V_k^i, while the storage volume at the end of the month, V_k^f, was selected as decision variable. Then, the state transformation equation is simply:

$$V_{k+1}^i = V_k^f, \text{ for } k = 1, 2, \ldots \tag{1}$$

The objective function is defined by hydropower reasons as follow:

$$\min\left\{E\left[F = \sum_{k=1}^{K} f_k\left(V_k^i, V_k^f, a_k\right)\right]\right\}, \tag{2}$$

where E is the statistical expectation operator, F denote the global performance over $K = 12$ monthly time-steps, f_k is the performance function in k^{th} month, and a_k is the monthly inflow volume (random variable).

For f_k was adopted the next form:

$$f_k = \left[E_k^* - E_k\left(V_k^i, V_k^f, a_k\right)\right]^2, \tag{3}$$

where E_k^* and E_k are the planned and produced energy in month k.

The planned energy production is defined by:

$$E_k^* = \alpha_k \cdot E_y, \tag{4}$$

with E_y fixed at the average yearly value from the design study, and the monthly energy production coefficients, α_k, are selected so that:

$$\sum_{k=1}^{K} \alpha_k = 1, \tag{5}$$

but according to the month position during the cold or warm seasons (more or less load on the system).

The produced energy is obtained from:

$$E_k = e\left(\overline{V_k}\right) \cdot r_k, \tag{6}$$

where e is the specific production as function of the mean volume in the reservoir, $\overline{V_k} = 0.5 \cdot \left(V_k^i + V_k^f\right)$, and r_k – the released volume through turbines, influenced by the inflow volume a_k.

The operational constraints refer to:

- balance equation (ignoring other losses):

$$V_k^f = V_k^i + a_k - r_k,\ k = 1, 2, ..., K \tag{7}$$

- bordering between the allowed bounds for state/decision variable:

$$V_k^{\min} \le V_k^f \le V_k^{\max},\ \text{for } k = 1, 2, ..., K \text{ and} \tag{8}$$
$$V_K^{\min} \le V_1^i \le V_K^{\max},\ \text{for } k = 1$$

where $V_k^{\max}$ is the maximum accepted value (imposed at normal retention level, NRL, or less – for flood control), and $V_k^{\min}$ – the minimum value (at minimum operation level, MOL, or at safety level, SL, or any other value derived from operational reasons).

- bordering of the released volume by:

$$0 \le r_k \le V_{inst}, \tag{9}$$

with V_{inst} – monthly volume for the installed capacity in HPP.

Recursive functional equation of the SDP model has then the next form:

$$C_k\left(V_k^i\right) = \min_{V_k^f} \left\{ \sum_{j=1}^{J_k} p_{kj}\left(a_{kj}\right)\left[f_{kj}\left(V_k^i, V_k^f, a_{kj}\right) + C_{k+1}\left(V_{k+1}^i\right)\right] \right\}. \tag{10}$$

By J_k is noted the number of classes used to divide the domain of random variable a_k, while a_{kj} and p_{kj} are the representative value for a_k, and the associated probability of occurrence for this value, into the j^{th} class, respectively. Certainly, the stage performance, f_{kj}, will be different for the J_k values of the inflow volume – at any fixed values of the state and decision variables.

Equation (10) is to be solved by using M discrete values for state/decision variables, obtained at a constant step:

$$\Delta V = \left[\max\left(V_k^{\max}\right) - \min\left(V_k^{\min}\right)\right] / (M - 1),$$

and assuming the final condition $C_{K+1}\left(V_{K+1}^i\right) = 0.$

The results of the SDP analysis are finally the follows:

- a matrix of the expected minimum cost function $C_*\left(k, V_k^i\right)$ and

- the corresponding matrix of the optimal decisions in stochastic context, $V_*^f\left(k, V_k^i\right)$, for all stages $k = 1, 2, ..., K$, and all discrete states V_k^{im}, $m = 1, 2, ..., M$, used in computation.

3. Simulation operating model

Based on the matrix of stochastic optimal decisions obtained by SDP, a simulation model for reservoir operation is proposed. This model respects, as much as possible, the stochastic optimal decisions, but also includes a set of correction rules. These corrections will be unitary applied, in any time step when necessary, and are related to the energy production, water supply for downstream users, flood control and other purposes. Literally speaking, these rules provide:

1. Optional selection of the minimum accepted level at MOL or SL.
2. The maximum imposed level will not, in any circumstances, exceed the NRL value.
3. The minimum monthly energy production in the warm season (April-September) is assigned to a value $E_{\min}^*$, able to ensure the required flow for downstream users.
4. For the months in the cold season, the planned energy production, E_k^*, is desired, and this value is obtained if:
   - it does not descend below the minimum accepted level;
   - it does not exceed an imposed emptying gradient, Δz (m/month).
5. In any other month of the year, if the energy production obtained with stochastic optimal decision is greater than E_k^*, the E_k value is limited at E_k^*, but without overtaking the maximum imposed level.
6. If by one of the previous changes the $V_*^f\left(k\right)$ value – placed on the highest optimal trajectory (which corresponds to initial state $V_1^i = V_1^{\max}$) - is exceeded, then V_k^f is limited to this value, but without exceeding the turbines capacity V_{inst}.
7. If the released volume exceeds the V_{inst} value, the release is limited to V_{inst}, but without overtaking the maximum imposed level.

The simulation model algorithm is as follows:

1. From the previous month operation (or simulation), the initial volume for current month *k*, V_k^i, is known, together with the forecasted (or recorded, or synthetic generated) inflow, a_k.

2. From the stochastic optimal decisions matrix, $V_*^f\left(k, V_k^i\right)$ one obtains the decision V_k^f and the released volume results as:

$$r_k = V_k^i - V_k^f + a_k . \tag{11}$$

3. This stochastic optimal release, r_k, is corrected in the order and situations below:

3.1 If $r_k < r_{\min}$, where $r_{\min} = E_{\min}^* / e\left(\overline{V}\right)$ and $\overline{V} = 0.5 \cdot \left(V_k^i + V_k^f\right)$ in warm season, then $r_k = r_{\min}$ and the final volume is corrected with eq. (11) to the $\left(V_k^f\right)_c$ value. If this value is so that $\left(V_k^f\right)_c < V_k^{\min}$, then $V_k^f = V_k^{\min}$, r_k becomes smaller than $r_{\min}$, and for this month it results that $E_k < E_{\min}^*$.

3.2 If $E_k > E_k^*$, the released volume is corrected by:

$$\left(r_k\right)_c = r_k \frac{E_k^*}{E_k}, \tag{12}$$

and the final volume V_k^f will be ajusted by eq. (11), using $\left(r_k\right)_c$.

3.3 If in the cold season it results $E_k < E_k^*$, the released volume is increased with a relation like (12), and the corrected final volume, $\left(V_k^f\right)_c$, is computed with $\left(r_k\right)_c$ value. If $\left(V_k^f\right)_c < V_k^{\min}$, then $V_k^f = V_k^{\min}$, the new r_k is computed, and for this month will result that $E_k < E_k^*$.

Also, if $z_k^i - z_k^f > \Delta z$, then $\left(z_k^f\right)_c = z_k^i - \Delta z$, and the values of V_k^f, r_k and E_k (which will be smaller than E_k^*) are recomputed.

3.4 If by one of the above corrections the monthly final level, z_k^f, is that $z_k^f > z_k^{\sup}$ (where $z_k^{\sup}$ is the level on the highest optimal stochastic trajectory), then it is imposed $z_k^f = z_k^{\sup}$, and the new values V_k^f, r_k, E_k are recomputed.

3.5 If $r_k > V_{inst}$ and $V_k^f < V\left(NRL\right)$, then $r_k = V_{inst}$ and the new values for V_k^f and E_k are obtained.

3.6 If by one of the above changes, the final volume exceeds the $V\left(NRL\right)$ value, then $V_k^f = V\left(NRL\right)$ and the new values r_k and E_k are computed.

4. With operating solution for the current month – directly computed or corrected as above – one passes to the operation (simulation) for the next month using the same algorithm.

4. Input data for case study

There were selected, as a case study for validation of the above described models, the major reservoir Fântânele and associated peak HPP Mărișelu. However, the simulation operating model also includes, in a simplified manner, the reservoir and HPP Tarnița which are downstream placed on the same Someșul Cald river.

The Fântânele reservoir has an active storage volume of $200 \cdot 10^6\,\text{m}^3$ (200 Mcm) and an average annual inflow of 12 m^3/s, from which about a half is collected by secondary conveyance tunnels. The peak HPP Mărișelu has an installed capacity of 220 MW and an average yearly production of $E_y = 390$ GWh (at design stage), for the installed discharge $Q_{inst} = 60\,\text{m}^3$/s.

The downstream reservoir Tarnița has a total volume of 74 Mcm at NRL, but only 15 Mcm is accepted as active storage (from efficiency reasons). The average inflow from his catchement is about 2.45 m^3/s. The project data for HPP Tarnița are as follows: installed capacity 45 MW, average yearly energy 80 GWh, and installed discharge 65.4 m^3/s.

The first two lines in Table 1 include the level – storage curve for the Fântânele reservoir, defined by some pairs of values *z*(mASL) – *V*(Mcm).

One notices that the NRL = 991 mASL, $V(NRL) = 220\,\text{Mcm}$, while the MOL is accepted as MOL = 946.6 mASL and $V(MOL) = 20\,\text{Mcm}$.

Within SDP analysis, the boundary values $V_k^{\max} = 220$ Mcm, $k = \overline{1,12}$; $V_k^{\min} = 20$ Mcm, $k = \overline{1,11}$ and $V_{12}^{\min} = 112$ Mcm are accepted. Meantime, a discretization step $\Delta V = 1$ Mcm is adopted, so it results a number of $M = 201$ discrete values for the possible state/decisions.

Line 4 of the Table 1 contains the monthly values of safety level, z_k^{SL}, and the next one includes the $z_k^{\sup}$ values, obtained by SDP analysis for the highest optimal stochastic trajectory. The last two lines of this Table contain the monthly production coefficients, α_k (applied to the E_y value), and the mean values of the prices on the DAM (Day-Ahead Market) for the peak hours interval, w_k, (the 2008 year data), respectively.

Table 1

Some input data used in analyses

z (mASL)	945	946.6	950	955	960	965
V (Mcm)	17.5	20	25.7	36.6	50.5	67.6
Month k	1	2	3	4	5	6

z_k^{SL} (mASL)	970.3	966.5	951.7	958.1	967.0	970.5
$z_k^{\sup}$ (mASL)	987.7	984.41	982.8	986.1	989.3	990.5
α_k (-)	0.095	0.09	0.095	0.075	0.075	0.075
w_k (RON/MWh)	261	229	204	169	147	189
z (mASL)	970	975	980	985	990	991
V (Mcm)	87.8	112	141	175	212	220
Month k	7	8	9	10	11	12
z_k^{SL} (mASL)	973.7	976.6	978.6	976.1	976.1	975
$z_k^{\sup}$ (mASL)	991	991	990.3	988.5	986.6	985
α_k (-)	0.07	0.07	0.075	0.09	0.095	0.095
w_k (RON/MWh)	205	220	245	279	308	253

The specific production, e, was obtained by recorded data processing and this is as:

$$e(z) = 0.94996 + 0.11387(z - 947)/44 \text{ GWh/Mcm},$$

where the connection between V and z is derived by linear interpolation within first two lines from Table 1. The maximum emptying gradient in the cold season, Δz, was imposed as 8 m/month, while the minimum accepted monthly energy production for the warm season is fixed at $E_{\min}^* = 10$ GWh.

In simulation model, for Tarnița reservoir/HPP it was admitted: $z_{NRL} = 521.5$ mASL, $z_{MOL} = 514$ mASL, $\Delta z = 1.5$ m/month, planned yearly production of 80 GWh, with the same α_k coefficients as above, a minimum monthly production of 2 GWh in warm season. Two alternatives are available for operation: with constant level during the year or with variable level, between the allowed boundaries. Details on the level-storage curve and specific energy production are not presented here.

Regarding the hydrological data, two time-series of mean monthly inflows, during the 1961-2010 interval, were available – for Fântânele reservoir and as catchment difference flow for Tarnița reservoir, respectively.

The mean multiannual inflow for Fântânele is 12.28 m^3/s, with mean monthly values between 6.35 m^3/s (February) and 26.86 m^3/s (April). The minimum monthly values are between 1.87 m^3/s (January) and 9.46 m^3/s (May), while the maximum ones are placed between 14.44 m^3/s (February) and 57.61 m^3/s (April). In the SDP analysis, a number of $J_k = 5$ classes for inflow in every month were accepted, and the representative values, Q_{kj}, together with the associated probabilities, p_{kj}, are included in Table 2 for months 1, 4, 8 and 12 – as illustration.

Table 2

Examples of monthly inflows, Q [m^3/s], and associated probabilities, p [%], by classes

Month *k* / Class *j*	1		4		8		12	
	Q	***p***	***Q***	***p***	***Q***	***p***	***Q***	***p***
1	2.934	0.1	8.89	0.06	4.95	0.24	2.413	0.06
2	5.132	0.58	17.976	0.34	7.397	0.24	5.301	0.40
3	8.073	0.18	26.994	0.32	9.34	0.08	8.486	0.32
4	11.17	0.06	34.167	0.14	12.035	0.26	13.516	0.10
5	17.113	0.08	48.537	0.14	16.249	0.18	21.67	0.12

The time–series modeling for Fântânele inflow followed the procedure described by Yevjevich [16] and: 1) it was identified a trend of mean; 2) there were quantified the parameters of six harmonics for each of the periodical mean and standard deviation respectively; 3) the dependent stochastic component was expressed by an AR(2) model, and 4) the remainder independent stochastic variable was identified by a log-normal distribution.

Using this model, there were generated five sets of 100 years monthly inflows, in view to validate the simulation model from Section 3. In table 3 are listed only the means and standard deviations of the 12 x 100 = 1200 data from each set, along with the same data of the recorded inflows.

Table 3

Means and standard deviation for generated and recorded inflows

Data set	1	2	3	4	5	Rec. data
$\overline{Q}$ (m^3/s)	12.28	12.30	12.34	12.35	12.38	12.28
σ (m^3/s)	8.075	8.303	8.545	8.827	8.711	8.88

One observes that the generated mean values differ by less than 1% comparing with the recorded value.

The inflow from catchment between Fântânele and Tarnița has a mean recorded value of 2.49 m^3/s, with standard deviation of 1.993 m^3/s. Mean monthly values are placed between 1.25 and 5.24 m^3/s, the minimum values in range 0.1 – 0.5 m^3/s, and the maximum ones between 3.5 and 18.19 m^3/s. The model of this temporal series contains only: the period components, an AR(2) model, and a normal distribution for stochastic, independent component. The five sets of 100 years generated for this variable have the mean values between 2.47 and 2.52 m^3/s, the standard deviations in the range 1.973 – 2.07 m^3/s, therefore acceptable comparing with the recorded data.

5. Results of SDP analysis

The two matrices with SDP results – the expected minimum cost $C_*\left(k, V_k^i\right)$, and optimal decisions $V_*^f\left(k, V_k^i\right)$ – cannot be included here, each having 13 columns and 201 rows of data.

As regarding the minimum expected cost, it is noted here only that, for discrete values of initial volume at the beginning of the year (placed between 112 and 220 Mcm), the performance function differs from 3509 to 4105. Given the definition of *F* from eq. (2) and f_k from eq. (3), it is noted that 3509 corresponds to an expected mean monthly deviation of $|\Delta E| = \sqrt{3509/12} = 17.1$ GWh, and 4105 to $|\Delta E| = 18.5$ GWh comparing with the planned monthly energy.

However, the second result of SDP, i.e. the matrix of optimal stochastic decisions, $V_*^f\left(k, V_k^i\right)$, is really used in the simulation model. From such a table, there can be drawn some storage (or level) guide-curves, during the year, in stochastic conditions, each one corresponding to a certain storage/level at 1st of January. For illustration, in Figure 1, there are shown five optimal stochastic trajectories, corresponding to $V_1^i =$ 112, 139, 166, 193 and 220 Mcm. The levels denoted as $z_k^{\sup}$ in Table 1 are the ones placed on the trajectory for $V_1^i = 220$ Mcm.

Certainly, it is possible to drawn: $220 - 112 + 1 = 109$ such guide-curves, but their usefulness is not justified in real operation. In fact, such a trajectory may be or may not be followed during a current year of operation, depending on the real values of monthly inflows. This dilemma is solved by the algorithm described in Section 3.

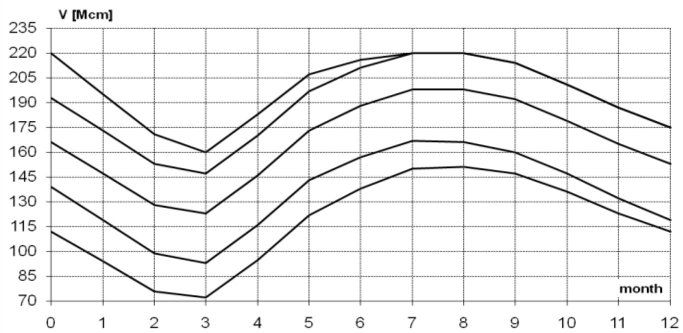

Fig. 1: Optimal stochastic time – variation of storage level for some initial values at the beginning of the year.

6. Main results of simulation operating model

To evaluate the quality of this operating model results, the computer program has been run on the 50 years with recorded inflows, and also for each set of 100 years with monthly generated inflows.

Besides the global performance parameters (as: average yearly energy production, average yearly energy production in the cold season, statistics of the monthly levels placed in various strips between MOL and NRL etc.), the mean annual market value of energy (computed with the prices from Table 1) is included – in order to perform a comparison with the results of a next study having as objective function the market value of the energy production.

Also, the four performance indices (relevant for operation under risk conditions) – defined in Mujumdar and Nirmala [8] and inspired from Hashimoto et al [17] – are evaluated. Under a given policy:

reliability = the probability that the system output is satisfactory;

resiliency = the probability that the system output in the time-step $k+1$ is satisfactory, if it is unsatisfactory in time-step k;

vulnerability = the ratio of the average of the largest annual deficits to the planned energy; and

deficit ratio = the ratio of the total deficit to the total planned energy during the operation period.

For a good performance of the system it is desirable to obtain high values for reliability and resiliency, and low values for vulnerability and deficit ratio.

It must be underlined that, in any analysis/discussion about the system performance under risk conditions, it is necessary to define what means a satisfactory/unsatisfactory state. Because the objective function is of energy nature, in this work it was considered as unsatisfactory state the case when, in any month, the planned energy, E_k^*, was not produced.

However, the simulation model ensures that, in the warm season months, a minimum production of $E_{\min}^* = 10$ GWh/month is obtained and this condition is achieved in all simulations. On the other hand, in Raje and Mujumdar [18] is defined as full failure state for hydropower reliability, the one when at most 25% of demands are met. No matter such interpretations, any month with $E_k < E_k^*$ was accepted to be in unsatisfactory state.

Obviously, related to the resiliency and vulnerability, there are also different definitions and interpretations within the recent references.

To clarify the vulnerability definition adopted here, for each year it was considered the largest monthly deficit, $\max\limits_{k=\overline{1,12}} \left\{E_k^* - E_k\right\}$, and an average value of these data over the number of years from the simulation period, $\overline{\Delta E}$, was computed. The monthly mean planned energy production, $\overline{E^*} = E_y/12$, has then been used to obtain the relative vulnerability as $Vul = \overline{\Delta E} / \overline{E^*}$.

In some papers (for example Ajami et al [19]), the three performance indices are combined to define an overall performance of the system – the sustainability – by:

$$\text{Sustainability} = \text{Reliability} \cdot \text{Resilience} \cdot (1\text{-Relative Vulnerability}), \quad (13)$$

In addition to the above performance indices, it was also evaluated the system reliability for annual planned energy, and for the annual planned energy in cold season, respectively. Any situations with energy in surplus to E_k^* were ignored, at monthly and also yearly level.

Table 4 includes these results, namely: E_{an} – average yearly energy production of HPP Mărișelu/and Tarnița; E_{cs} – average energy production in cold season; E_{cs}/E_{an} for HPP Mărișelu; *Rel* – reliability; *Res* – resiliency; *Vul* – vulnerability; *Dr* – deficit ratio; R_y – reliability for yearly planned energy and R_{cs} – reliability for cold season planned energy – all these for HPP Mărișelu. In the last column, the average yearly value of energy production at the two HPP is presented.

Table 4

Main results of simulation operating model

R_{nns}	E_{an}	E_{cs}	$\frac{E_{cs}}{E_{an}}$	*Rel*	*Res*	*Vul*	*Dr*	R_y	R_{cs}	Energy value
	[GWh]	[GWh]	[%]	[%]	[%]	[%]	[%]	[%]	[%]	[mil.RON]
Rec. inflow	405.25/ 96.09	230.06/ 50.87	56.8	76	40.28	36.6	7.73	56	98	114.74
Set 1	405.84/ 96.17	233.38/ 51.16	57.51	74.25	45.31	41.7	7.64	53	100	115.27
Set 2	406.82/ 96.14	232.44/ 50.98	57.14	76.08	49.13	40.7	7.14	50	99	115.53
Set 3	407.38/ 96.71	228.01/ 50.45	55.97	75.25	43.43	38.9	7.61	49	98	114.89
Set 4	407.92/ 96.53	230.28/ 50.71	56.45	73.92	47.28	39.1	7.49	52	97	115.26
Set 5	409.27/ 96.94	230.03/ 50.6	56.20	76.83	51.08	36.6	6.72	53	100	115.61

The runs started with initial levels in reservoirs: at 985 mASL (Fântânele) and 521 mASL (Tarnița), by imposing $z^{\min} = z_{MOL} = 946.6$ mASL for Fântânele reservoir, and with Tarnița reservoir operated at variable levels (between the accepted bounds).

One observes that all the performance indicators have very closed values, for the run with recorded inflows (50 years) as well as for the five runs with generated inflows (each on 100 years). The average yearly energy productions exceed the data from design stage (390 GWh – HPP Mărișelu, 80 GWh – HPP Tarnița).

Percentage of the cold season production is greater than 55% from annual production at peak HPP Mărișelu. A reliability of about 75% is reasonably good, especially when the full failure is avoided by limiting at $E^*_{\min} = 10$ GWh the monthly energy production in warm season. The transition from an unsatisfactory state to a satisfactory one appears in about 40 – 51% of situations, and a vulnerability of 38%, or a deficit ratio of 7% seems to prove an acceptable performance. Even if $E_y = 390$ GWh was obtained in a few over 50% of the years, the cold season planned energy is satisfied in more than 97% of the years.

It has to be underlined that, in the simulation with 50 years of recorded inflows, from the all 600 months of operating period, in only 30 months were obtained the minimum imposed production of 10 GWh/month (that is 5% of total period). Also, in 31 years of the considered period there is no month with such a low energy production and the maximum annual number of months having only 10 GWh energy production was only 3 months a year.

Table 5 includes the statistics of final monthly levels from Fântânele reservoir over $50 \cdot 12 = 600$ month (with recorded inflows) and over 1200 months (with generated inflows).

Table 5

Statistics of final monthly levels from Fântânele reservoir

R_{nns}		Recorded inflow	Set 1	Set 2	Set 3	Set 4	Set 5
z_k^f [mASL]	$= z_{MOL}$	1	0	0	2	2	0
	≥ 955	595	1198	1199	1193	1191	1199
	≥ 965	578	1183	1187	1170	1165	1188
	≥ 975	529	1094	1079	1074	1042	1083
	≥ 985	290	602	611	588	571	630
	$= z_{NRL}$	64	125	116	122	116	129

One observers that the proposed operating policy leads to situations when, more than 90% of the months, the levels in storage are placed in the upper third of the active volume, and in more than 10% of the months the levels are at NRL – that is, also, a satisfactory performance.

A different run with the recorded inflows and in the same conditions – excepting the minimum accepted level which was now imposed at z_k^{SL}(safety level, as in Table 1) – leads to the following results: $E_{an} = 406.23/95.95$ GWh; $E_{cs} = 229.15/50.50$ GWh; $E_{cs}/E_{an} = 56.41\%$; *Rel* = 74.17%; *Res* = 41.94%; *Vul*=37.1%; *Dr* = 8.09%; $R_y = 58\,\%$ and $R_{cs} = 86\%$; energy value = 114.779 mil.RON. For levels statistics resulted 0, 600, 596, 547, 307 and 67 monthly data. Obviously, in this situation the Fântânele reservoir was operated with greater levels and a bigger mean annual production has been obtained in respect to the first alternative.

For comparison, in Fig. 2.a it is shown the level variation in Fântânele reservoir during the first 10 years of operating simulation period, with $z_k^{\min} = 946.6$ mASL (MOL) and in Fig. 2.b – the same variation when $z_k^{\min} = z_k^{SL}$ (SL). Both figures include the minimum accepted level variations. One notices that this simulation period contains the only situation when the level is at MOL.

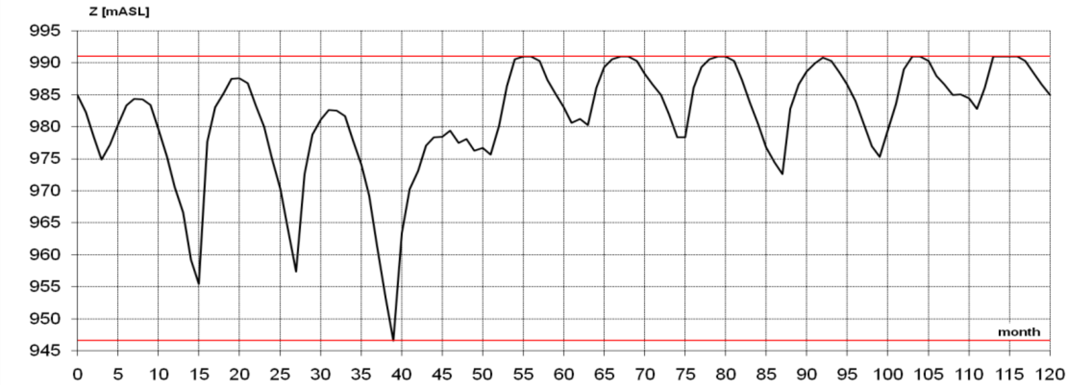

Fig. 2a: Level variation in Fântânele reservoir when $z_k^{\min} = 946.6$ mASL (MOL).

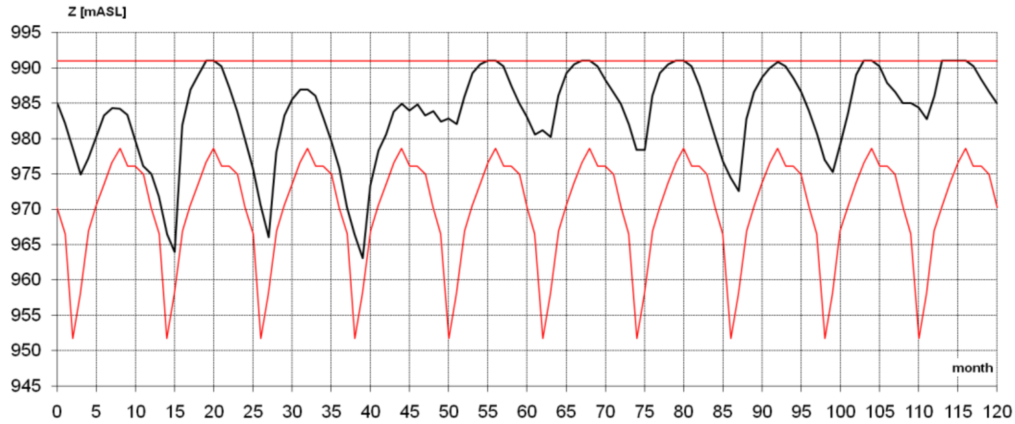

Fig. 2b: Level variation in Fântânele reservoir when $z_k^{\min} = z_k^{SL}$ (SL).

7. Conclusions

The subject and results presented in this paper are parts of a more extended research devoted to the hydropower system including the Fântânele reservoir / HPP Mărișelu and Tarnița reservoir / HPP. Because of the possible addition to this system of the pumped storage plant (PSP) Tarnița – Lăpuștești, the management of such a complex water power development must be assured by a decision support system, able to conduct the long-term (monthly time-steps) but as well the medium-weekly term (length of filling-empting cycle for upper reservoir of the proposed PSP), and short-term (daily-hourly) operation, respectively.

This paper proposes a long-term simulation operating model for the two existing reservoirs and HPPs. The operating simulation is based on the results of a SDP analysis, having a performance function that follows an imposed monthly production plan, under uncertainty conditions about the monthly inflows. A next paper will be devoted to the same problem, but with a different objective, namely the market value of energy production.

By analysing the results of the performance indices and general energetic data for the two alternatives, it is possible to adopt the better solution (or a combination), in view to be included in the decision support system for long-term operation.

At least in this analysis, all simulations have demonstrated that the proposed operating policy seems to offer some reasonable values of the system performance indices. Combining this simulation model with the forecasting/generation inflow model and with the current forecast of the specialized institutions and with the effective possibility of updating for the monthly operation decision after each week (or decade) – may be a good chance to obtain a such valuable decision support program.

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