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Using Predictive Model of Mean Monthly Flows for Large Open Reservoirs Hydropower Control

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Abstract

Conventional hydropower reservoir operations are mostly based on rules or rule curves. The paper describes algorithm which has been created on idea of adaptive control theory. The adaptive control approach uses repeatedly generated medium-term water flow predictions on a several months ahead as inflows into the large open reservoirs. Values of control outflows are searched by evolution algorithm optimization methods. Principle of the predictive model of average monthly flows is introduced in this paper. The algorithm is applied to the operation hydropower control of selected reservoir.

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Keywords: Adaptive; evolution algorithms; hydropower function; large open reservoir; operative control; optimization; predictive model

1. Introduction

The more frequent occurrence of extreme hydrological events points to climate changes in the Czech Republic, as well. The occurrence of extreme flood events and the occurrence of extensive periods of drought are more frequent. The extreme flood events were observed in 1997, 2002, 2006, 2010 and 2013. The years 2000, 2003, 2012 and 2013 were identified as the dry years [1]. From the long-term observations it may be stated that the occurrence of both extremes is more frequent. This may cause danger to the storage function of some large open reservoirs. Most of large open reservoirs are designed for the versatile utilization. Their main purpose consists in the storage and protective function. These functions are often completed with the hydroenergetic function. However, a small change in the active

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storage zone of the reservoir may affect the water power station operation. Then, the decrease of produced energy may be caused.

The conventional operations of hydropower function of reservoirs predominantly comes out from the rules or rule curves [2] that are based on the generalization of historical processes of water inflow into reservoirs represented by historical time series [3]. Nevertheless, in the period of expected climate changes the courses of flow series begin to alter and it is necessary to search for other ways of the control methods. In the following text the means of the intelligent control that enables to react to the topical hydrological situation is described. The intelligent control of the water reservoir operation emanates from the adaptive approach. Adaptability is one of the methods of Artificial Intelligence. The knowledge of hydrological predictions of water inflows into reservoirs is essential for the adaptive control. In practice, by means of adaptability it is partly possible to eliminate an inaccuracy of the prediction emerging from the fact that the solution is carried out in the conditions of considerable uncertainty. In the publication the algorithm of the control is depicted [4] that uses the repeatedly specified predictions of water inflows into reservoirs issued several months in advance.

Different methods for the creation of medium-term to long-term predictions of mean monthly flows have been described abroad. The algorithms based on stochastic modelling of time series are used. The model ARMA (autoregressive moving average) or the model ARIMA (autoregressive integrated moving average) are the most frequently used for the stationary stochastic modelling of time series. For instance in [5] the models ARMA and ARIMA are used for the creation of the long-term prediction of the discharge on the Danube River. A large part of predictive models is built up on the model of neural networks. The application of the model of neural network for the discharge prediction is described, for instance in [6]. In [7] the comparison of the three predictive models of mean monthly inflows into the reservoir Dez based on the model ARMA, the model ARIMA and neural networks is carried out. Next, it is possible to use the theory of Fuzzy Sets for the formation of the predictive model. The combination of fuzzy and neural networks is depicted in [8]. When creating predictive models, a lot of authors mutually combine the mentioned methods. Nowadays, the method of Vector Machines is used for the formation of the prediction. The application of the method of Vector Machines is described into details, for instance in [9] and in [10]. There are many other methods that may be looked up in the scientific literature.

In general, it may be stated that the use of the mentioned approaches is possible in the conditions with the regular hydrological cycle. In the complex hydrological conditions of the Czech Republic the use of these models is complicated and practically hard to be used. In the article the own predictive model is described and it will be possible to be used for the creation of the prediction of the mean monthly flows even in these complicated hydrological conditions. In the following text the model is called the Zone Probabilistic Predictive Model.

2. Methods

2.1. Zone Probabilistic Predictive Model

The predictive model is based on the theory of probability and it enables to predict the sequence of mean monthly water inflows into reservoirs in the specified duration, usually 1 to 12 months. The mean monthly inflows into reservoirs are predicted on the basis of the topical inflow. The knowledge of historical discharge series of mean monthly inflows is necessary when creating the predictive model. Then, the model works with the monthly step. It is suitable to use series of the largest duration for the successful creation of the predictive model. The advantage of the model is the fact that the knowledge of the other hydrological, climatic and meteorological quantities is not essential for the formation of the prediction as it is usual for other types of predictive models.

2.2. Algorithm of Predictive Model Formation and Creation of Prediction

From the perennial discharge series the particular years $y = 1, 2, \dots \dots, Y$ are allocated, where Y is the number of years. From the whole number of years Y for each month of the year $m = 1, 2, \dots \dots, 12$ is allocated the set of Q_m inflow. The set Q_m is thus created by mean monthly water inflows into the reservoir $q_{m,y}$ of all Y years of corresponding inflows in the month m. For each calendar month in the year the set of mean monthly inflows is allocated. In the set Q_m is found the maximum $maxQ_m$ and minimum $minQ_m$ historical value of the inflow. The

interval between values $< minQ_m, maxQ_m >$ is divided into the selected number of zones. In general, it is possible to mark the zone sequence by means of the letter z and it applies $z = 1, 2, \dots \dots, Z$, where Z is the number of zones. The number of zones Z is for each month m equal but the zone interval $< minQ_m^z, maxQ_m^z >$ may be different. The size of each zone z is for the month m determined on the basis of the requirement so that each zone contains approximately the equal number $q_{m,y}$. The elements $q_{m,y}$ ranked to the particular zone z create the subset Q_m^z.

Based on the initial mean value of the water inflow Q_m^c in the month m, in which the decision on the control is made, the zone z is selected, for which it is $Q_m^c \in < minQ_m^z, maxQ_m^z >$. Through the zone z the selected set of the historical series $s = 1, 2, \dots \dots, S$ goes, where S is the total number of series going through the zone z. For each historical series s in the set S applies that $q_{m,s} \in Q_m^z$. The following members of the historical series s of the set S represented by mean monthly inflows $q_{m+t,s}$ in the months $m + t$, where t is the sequence of the month of the prediction, are subsequently used to determine the interval of the prediction zone zp. For t is applied $t = 1, 2, \dots \dots, TP$, where TP is the number of predicted steps (months) and $q_{m+t,s} \in Q_{m+t}^{zp}$. For the sequence of the months $m + t > 12$ applies $m + t - 12$. For each month of the prediction $m + t$ only one zone of the prediction zp is determined. The predicted value of the mean monthly water inflow into the reservoir Q_{m+t}^p in the month $m + t$ equals the value occurring in the interval of the prediction zone zp with the highest probability (modus). The average monthly inflow is predicted as follows. For all the elements $q_{m+t,s} \in Q_{m+t}^{zp}$ the density of the probability division $f(q_{m+t,s})$ is created. The form of the continuous function $f(q_{m+t,s})$ is for simplification triangle (small number of elements in). The base of the triangle is formed by the interval $< minQ_{m+t}^{zp}, maxQ_{m+t}^{zp} >$ and the vertex of the triangle corresponds with the presupposed position of the modus $Mod(q_{m+t,s})$ of the quantity $q_{m+t,s} \in Q_m^{zp}$. For the estimation of the modus position the assumption is used that applies:

$$\int_{\min Q_{m+t}^{zp}}^{\max Q_{m+t}^{zp}} f\left(q_{m+t,s}\right) dq_{m+t,s} = 1, \tag{1}$$

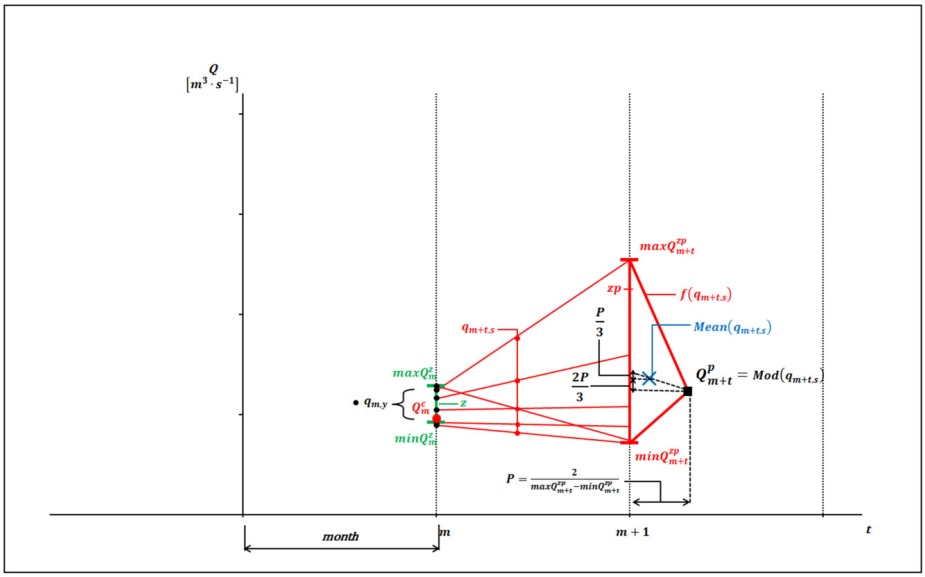

Fig. 1. The procedure of the location of the modus position.

The procedure of the location of the modus position on the interval $< minQ_{m+t}^{zp}, maxQ_{m+t}^{zp} >$ is graphically displayed in the Fig. 1. For the predicted value of water inflow into the reservoir in the month $m + t$ is applied:

$$Q_{m+t}^{p} = Mod\left(q_{m+t,s}\right) \tag{2}$$

The algorithm of the prediction creation Q_{m+t}^{p} for more steps (months) is shown in the Fig. 2.

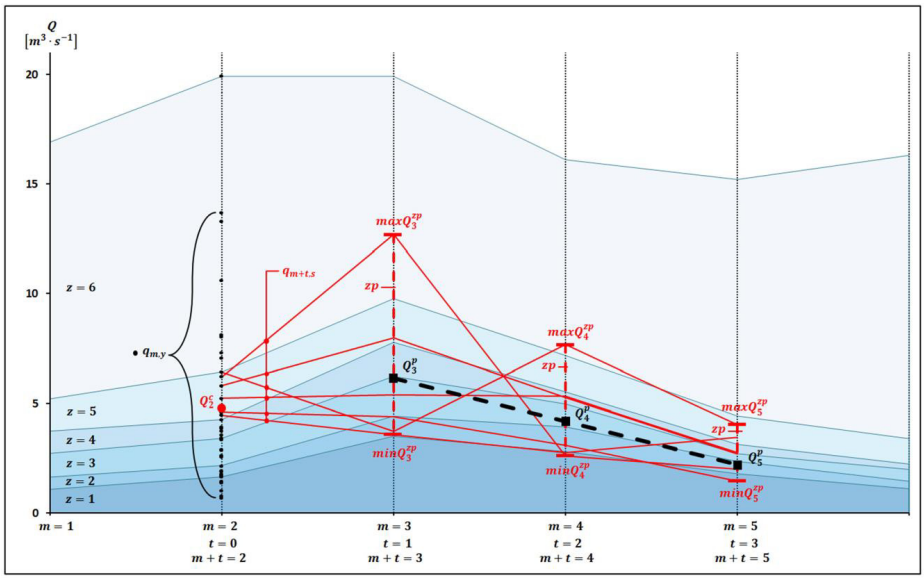

Fig. 2. The algorithm of the prediction creation.

2.3. Adaptive Control Algorithm

The verification of the suitability of the predicative model on the existing reservoir would be practically impossible and that is why a simulation model (global model) is used for its testing. It is the classic simulation model in which the rules of control are replaced by optimization. The step of the simulation model is $T = 1, 2, \dots\dots, M$, where M is the total number of steps (months). It is possible to describe the algorithm of control in the three steps that gradually repeats. In the first step on the basis of the topical flow Q_m^c in the month m the prediction of the mean monthly water inflow into the reservoir on the selected number of the predicted months TP is created. In the second step the optimization model of the reservoir control is compiled. By means of optimization in each time step of the local model $\tau = 1, 2, \dots\dots, N$, where N is the total number of steps, turbine discharges Q_T^τ on the controlled period are looked for. The method of differential evolution [11] is used for the finding of Q_T^τ. Maximum possible value of the discharge in the hydropower plant Q_T^τ is generally determined by the absorption capacity of turbine. The higher flow is distributed, so called flow above the maximum possible value is released directly into the watercourse under the reservoir. The number of steps N is equal with the number of the predicted months TP. Marginal conditions of the solution are then created by the predicted water inflows into the reservoir. The initial condition of the solution is the volume in the reservoir at the end of the time step $\tau = 0$. In reality it corresponds with the measured value of the volume in the reservoir. The criterion of optimization is the sum of squared deviations between the required electric power P_W^τ and the actual controlled electric power P_P^τ of the hydropower plant, which minimizes (3).

$$\left[\pi = \sum_{\tau=1}^{N=TP}\left(P_W^\tau - P_P^\tau\right)^2\right] \rightarrow MIN. \tag{3}$$

Actual controlled electric power P_P^τ in each time step τ is calculated according to:

$$P_P^\tau = g \cdot \rho \cdot Q_T^\tau \cdot H^\tau \cdot \eta, \tag{4}$$

where g is gravitational acceleration, ρ is density of water, H^τ is head the turbine in the time step τ and η is coefficient of hydraulic losses which is equal to 0.9. In the third step on the basis of the actual inflow and found controlled outflow which corresponds with the first step of the local model $\tau = 1$ the simulation of the reservoir behaviour is carried out in time step $T = 1$ by means of the simulation model. The resulting size of the volume of water in the reservoir at the end of the first time is the initial condition for the solution of another optimization of the control on the next local model that is shifted by one time step. The model gradually adapts to the new conditions by means of the repetition of the steps 1 to 3, for each step of the global model T – newly created predictions of water inflows. The process of adaptation is terminated when reaching the time step $T = M$. The software SOMVS (Simulation and Optimization Model of Multi-reservoir Systems) is used for the adaptive control [12]. The software has been created at Brno University of Technology (BUT), Faculty of Civil Engineering, Institute of Landscape Water Management. In general, the software enables to create the simulation and optimization model of the multi-reservoir systems. Models may be used for the solution of tasks of optimal development and tasks of optimal control of the system of water supply. The mathematical model is written in the programming language FORTRAN and the graphical user interface in the language C#.

3. Application

The evaluation of the results of the application of the predictive model to simulate the control of the operation of the specific hydropower function of the reservoir is used for the assessment of the predictive model quality. Control is applied to the hydro energetic function of the water reservoir Mostiště. The reservoir Mostiště is situated in the Czech Republic in the catchment area of the Svratka River. The reservoir lies on the watercourse Oslava and serves for the production of electric energy, for the decrease of flood discharges, water withdrawal and for ensuring of the minimum discharge. The volume of the dead storage zone equals 1.045 million m^3 and the active storage zone volume equals 9.339 million m^3. The maximum turbine absorption capacity equals the value 1.5 $m^3.s^{-1}$. Historical flow series of mean monthly water inflows into the reservoir has the duration of 86 years. The first 76 years are used for the formation (calibration) of Zone Probabilistic Predictive Model ($Y = 76$). The number of the zones of the model z equals 5. The predictive model is validated on the remaining 10 years. The control is applied to the period of the duration 10 years, where the number of steps of the simulation model M equals 120. The number of the predicted months is chosen gradually $TP = 1, 2, \dots\dots, 12$. The objective function is expressed in the additive form by means of the technical indicators (3). The effort is always to approximate the actual controlled electric power to the required electric power $P_W^\tau = 200\ kW$ for the whole solved period N. The size of the value of the required electric power is determined so as not to be possible to achieve the value at least in one time step T. The adaptive control is performed for twelve variants. The individual variants differ in the number of the predicted months $TP = 1, 2, \dots\dots, 12$. The twelve variants are completed with the other two variants for the comparison of the success of the procedure for the predicted values (variants 13 and 14). In the thirteenth variant the control is solved from month to month based on the current water inflow into the reservoir. It is the simulation model, where the discharges through the hydropower plant are determined gradually in the individual months so as to be ensured the production of the required electric power. This way of control does not use the prediction and it currently corresponds to the most frequent means of the control. In the fourteenth variant the adaptive control is performed in the historical flow series. From the perspective of the predicted values we work with the prediction that has 100% accuracy – corresponds to reality. The number of the predicted months is $TP = 12$. Control success in each time step T can be expressed using:

$$\Delta P^T = P_W^T - P_P^T. \tag{5}$$

Control success over the whole period M can then be expressed by:

$$\sum P = \sum_{T=1}^{M} \Delta P^T . \tag{6}$$

In the case of the sufficient size of the mean monthly inflows the value ΔP^T and $\sum P$ would be equal to the value 0. This case would be ideal. The resulting control success over the whole period M for the variants 1 to 12 is stated in the Table 1. The resulting control over the whole period M for the variant 13 is $\sum P = 365\ 442\ W$ and for the variant 14 is $\sum P = 74\ 617\ W$. The graphic comparison of control success for each time step T for variants 4, 13 and 14 can be seen in the Fig. 3.

Table 1. The resulting control success over the whole period *M* for the variants 1 to 12.

Variant	*TP*	$\sum P$ [W]	Variant	*TP*	$\sum P$ [W]
1	1	148 848	7	7	117 456
2	2	117 174	8	8	119 862
3	3	116 586	9	9	119 510
4	4	116 437	10	10	121 533
5	5	116 618	11	11	126 802
6	6	117 148	12	12	124 247

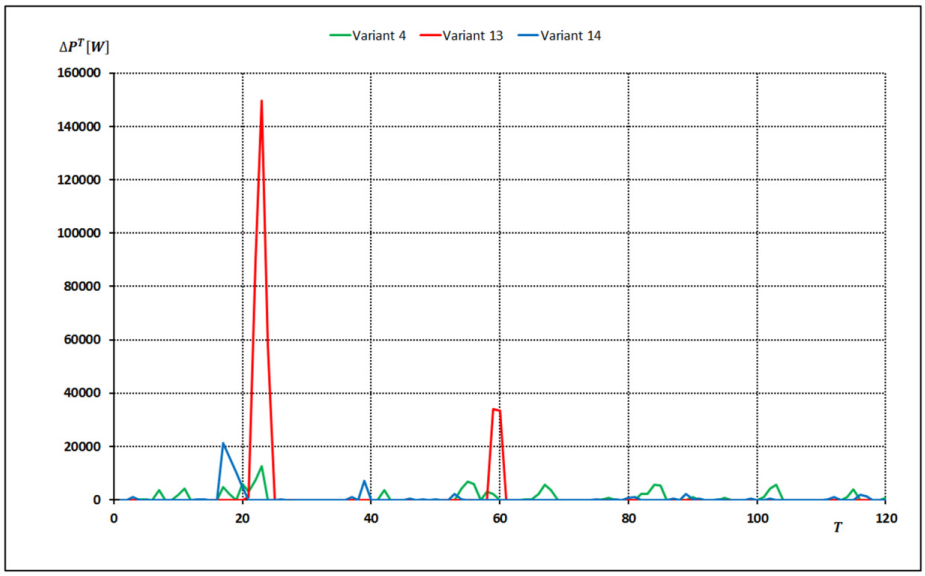

Fig. 3. The graphic comparison of control success for each time step *T* for variants 4, 13 and 14.

4. Conclusion

When compiling the predictive model, the part of the historical series of mean monthly inflows of water into the reservoir with the duration of 76 years was only used to build the model. The remaining part of the series (10 years) was used for the own application of the operation control of the hydropower function of the reservoir – for the validation of the model. The objective control of the predictive model quality was ensured by this procedure. Within the mutual comparison of the control success of all the investigated variants it is possible to notice that control success of the variants 1 to 12 is better than the variant 13. These results could be expected. The variant 13 does not consider the prediction and corresponds to the simplest way of control. There is an effort to achieve the required electric power

in each time step of the global model T for this variant. The effort to achieve the required electric power may lead to the emptying of the significant portion of the active storage zone resulting in a significant increase in the value ΔP^T. The above-mentioned fact is seen in the shape of ΔP^T in the Fig. 3. The control of the reservoir operation is performed in the historical flow series for the variant 14 (100% accuracy of prediction). The results of this variant are only theoretical and in practice they will never be achievable. The variant serves only for the determination of the theoretical control success and corresponds to the best possible way of the control. Based on the fact that the control success of the variants 1 to 12 is better than the variant 13 and slightly worse than the variant 14, it can be concluded that the adaptive control in the combination with the predictive model of inflows of water into the reservoir makes sense. The described prediction model allows creating sufficiently successful predictions. From the results of the control it is obvious that the number of predicted steps (months) has a significant impact on the overall control success. It is evident from Table 1. In the used application of control the biggest control success is achieved in the variant 4. The variant considers the prediction for four months in advance. For simplification it can be concluded that the less regular the hydrological cycle is, the shorter prediction is suitable for the adaptive control. It can be assumed on the basis of the fact that the reservoir Mostiště is situated in the upper part of the catchment area. In the future it will be appropriate to examine the influence of the number of steps of the prediction on the quality of the resulting control in details. It will also be appropriate to carry out the analysis of the impact of the number of zones on the control quality. It will be advisable to verify the predictive model within the control of the storage function of the reservoir as well as the control of multi-reservoir systems.

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