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## Using predictive model for strategic control of multi-reservoir system storage capacity

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### Abstract

The paper will describe the algorithm based on adaptive optimization of multi reservoir control, which the medium-term water flow predictions into the reservoirs for several months ahead repeatedly use. Hydrological prediction model was created using ANN method and values of control outflows are searching by optimization based on evolutionary algorithms optimization technique. The objective function was described as the sum of squares deviations between required and actual controlled water outflow from reservoirs where objective function is minimized. The algorithm of adaptive control is applied to the operation storage control of selected reservoir system, which open water reservoirs Vir and Brno are created.

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**Keywords:** Multi-reservoir System, Active Storage Capacity, Strategy Control, Prediction Model, Adaptivity, Optimization, Artificial Neural Network

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### 1. Introduction

The current knowledge in the field of climatology indicates a gradual change in climatic conditions all around the world. Climate changes reflect in changes of the hydrological cycle due to redistribution of precipitation during the year and they contribute to more frequent occurrences of extremes in the form of floods and dry periods. Clear signs of climatic changes have also been occurring in the Czech Republic in the last years. It is worth mentioning, for example, the years 2011 and 2012 which, from the hydrological point of view, were considered extremely dry,

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published Zahradnicek et al. [1]. In extremely dry periods, the storage capacity of surface water resources may be fully threatened by not having the sufficient storage capacity to cover dry periods. One of the possibilities to forestall or fully prevent these problems from occurring is to build water reservoirs or reconsider the storage and protective capacities of the existing reservoirs and to change the method of manipulating the controlled water outflow from the reservoirs.

Classic strategic control of the storage capacity of water reservoirs is based mainly on the rules of control as mentioned Jain [2]. In many cases, the rules of control are derived from historical discharge series, Votruba et al. [3]. However, climatic changes cause that the discharge series curves start to change and it is necessary to seek other methods of control. In the present time we can see an increased social demand as regards an improvement in operative control and also as regards changes in the basic strategic parameters of reservoirs, often with the aim to significantly increase their storage capacity, mentioned Fosumpaur et al. [4]. It is, therefore, possible to respond to hydrological and climatic changes, for example, by intelligent strategic control. Intelligent method of controlling the operation of reservoirs can be achieved using an adaptive approach. Adaptivity is one of the artificial intelligence methods. Adaptive control requires knowledge of hydrological predictions of water inflows into reservoirs. In practice, adaptivity can partly eliminate prediction inaccuracies arising from the experience that the solution is performed in conditions of a significant uncertainty.

Algorithms based on stochastic models of time series are used for creating medium-term to long-term predictions, for example ARMA or ARIMA models are most often used for the stationary stochastic modelling of time series. A large part of forecast models is currently built on neuron network models. Also, the theory of Fuzzy Sets and other methods based on Machine learning can be used to create a predictive model. The Zone Probabilistic Predictive Model, Menšík et al. [5] has been developed as part of the research at the Brno University of Technology (BUT). The paper describes another predictive model developed at BUT based on artificial neural network modelling approach.

In practice, verification of suitability of a predictive model in strategic control of the operation of reservoirs is not possible and, therefore, a simulation model is used to test the operation of a real system of reservoirs. It is a classical simulation model in which the rules of control are replaced with repeated optimization. A new prediction is created for each optimization. Adaptive control is achieved gradually by repeated optimization. The SOMVS program is used for adaptive control of a multi-reservoir system, Menšík et al. [6]. The SOMVS program – a multi-reservoir system simulation and optimization model was created at BUT and has been partly published by Menšík et al. in [7].

## 2. Methods

To simplify it, the methods used in this paper can be divided into two parts. The first part describes a method and procedure for generating predictions of average monthly discharges. The second part describes a mathematical model of the storage capacity of a multi-reservoir system and the algorithm of adaptive strategic control.

### 2.1. Predictive model

The conventional multilayer feed-forward backpropagation neural network was used in this paper. The feed-forward neural network is one of the most frequently used networks. The backpropagation algorithm, which is widely used along with the feed-forward network, is known too. The algorithm is based mainly on the work by Rimelhart et al. [8]. The network training process is as follows. When training the feed-forward backpropagation model, the values of synoptic weights are changed in the network. The process of synoptic weights correction used in this method runs forwards and at the same time backwards from the output layer to the input layer. When training the network, deviations are calculated between set output signals and calculated signals. The total error difference is obtained by deducting the sum of squares of model errors from the sum of squares of calculated errors. The repeated correction of weights during training is ended by achieving the optimum total error.

## 2.2. Mathematic model of the storage capacity of a multi-reservoir system

A system of water supply is defined by the construction of weighted directed graph  $G(V,E)$ .  $G(V,E)$  is formed by the set of graph vertices  $V(v_i \in V)$  and graph edges  $E(e_{i,j} \in E)$ . The set of vertices  $V$  is made up by the vertices of water resources, distribution vertices, reservoirs, and water customers. The set of graph edges  $E$  is made up of watercourses.

In the strategic control of water flow through a system, the length of time step  $\tau$  is most often one month. The time at which water flows through an entire system is usually much shorter than the length of a selected time step. The above mentioned assumption allows neglecting transition phenomena in graph edges. In the solution period, continuous discharges are replaced with average monthly discharges. The calculation of water flow through graph edges is solved in a simplified manner by simple balancing.

Two basic types of tasks are defined for a water supply system (strategic control) – a task of optimum system control and a task of optimum system development. Both tasks can be formulated as finding the vector of unknown  $X$ , which contains all unknown quantities. The mathematical model is elaborated in details, for example, in [7].

The formulated tasks represent an optimization problem in which limiting conditions are linear and criteria functions nonlinear. An optimization method (optimization model) can be used to find an optimum solution. Using the optimization model, the vector of unknown  $X$  is quantified in summary as a whole. From the view of the sequence of time steps  $\tau$ , the sequence of fulfilling the limiting conditions is not decisive. This solution does not require specification of the system control method.

A simulation (global) model is used for adaptive control. The global model step is  $T = 1, 2, \dots, M$ , where  $M$  is the total number of steps (months). Then average monthly inflows into the system (predictions) are created for  $T = 1$  and for the selected number of months ahead. Then an optimization (local) model is created. The total number of steps  $N$  of the local model is always the same as the number of prediction months. The boundary conditions of the model are prediction inflows into the system. The initial condition is the volumes of water in reservoirs at the end of time step  $\tau = 0$ . The found solution of the optimization model is controlled water outflows from the reservoirs. In the next step, correction is always made on the basis of the initial volumes of water in the reservoirs, prediction and actual inflows of water into the system and the actual volumes of water in the reservoirs at the end of the solved step of global model  $T$  is found. Correction allows taking prediction inaccuracy into account as in real operation. After the correction is made, the actual volumes are the initial condition for the next local model step. By successively repeating the local model steps, the model is adapted and the process ends by reaching the total number of global model steps ( $T = M$ ).

## 3. Case study

A practical application is performed on a selected water management system of the Vir, Brno. Water reservoirs system is situated in the eastern part of the Czech Republic. The technical parameters of the reservoirs are based on real values. The considered subsystem of reservoirs has two major tributaries (sources), the river Svratka and the river Bobruvka ( $Q_1^\tau$  and  $Q_3^\tau$ ) – see Fig. 1. The real discharge series of average monthly discharges were provided by the Czech Hydrometeorological Institute. The discharge series are 56 years long and they are from the years 1953 to 2009. Verification of suitability of the predictive model is performed by using adaptive control. Adaptive control is applied on three periods (selected hydrological years). The first period represents the extreme dry year, the second period represents an average year and the third period represents the extreme wet year.

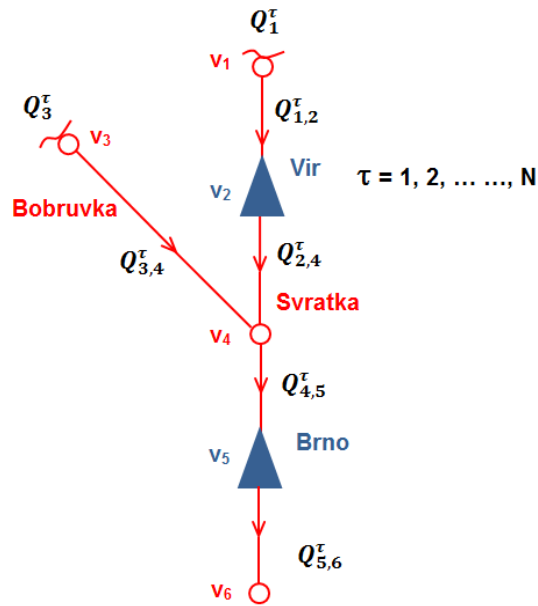


Fig. 1. Subsystem of water reservoirs (Vir, Brno).

The basic idea of using ANN hydrological prediction was taken from paper published by Cheng et al. [9]. The paper was a guideline for drawing up a prediction model which was further extended and adjusted for the purposes mentioned in this paper. The prediction using the neural network model was drawn up for hydrometric profiles which are built and operated on the Bobruvka and Svratka rivers. As above mentioned the prediction was made for three selected periods called – extreme dry year, average year and extreme wet year. For these periods, predictions of average monthly discharges were drawn up according to the selected prediction length corresponding to lengths  $N = 1, 2, 3, 4, 6, 8, 12$  months ahead. The set of input data was divided into training and validation sets. The validation set contained the last 10 years of the discharge row including three selected periods. The process of drawing up the prediction was as follows.

Input data conditioning was performed in the first step. Data normalization was performed to accelerate and specify the neural network training. Using the equation (1), the discharge values were adjusted in such a way that the normalized values range in an interval  $<-1.1>$ .

$$x_{m,i} = \frac{\left( Q_{m,i} - \left( \frac{Q_{m,\min} + Q_{m,\max}}{2} \right) \right)}{\left( \frac{Q_{m,\max} - Q_{m,\min}}{2} \right)} \tag{1}$$

Where  $Q_{m,i}$  is discharge value over time,  $Q_{m,\min}$  is minimum discharge value in that column (month  $m$ ),  $Q_{m,\max}$  is maximum discharge value in that column (month  $m$ ).

The neural network setting was obtained by setting up the network topology, training elements, coefficients and by selecting suitable functions for training. The neural network was selected as a two-layer network where the ratio of neurons in the hidden layer was set to five. The LOGSIG function was set in the hidden layer while the PURELIN function was set in the output layer.

The set of predicted discharge values was compared using determination coefficient between validation data and predicted data. At first, determination coefficient  $R^2$  was used to find the optimum length of input months  $M$

required for training the network and drawing up the most suitable prediction. The procedure for finding the length of input months is based on a suitable set-up of the neural network described above, and also on the shift (rotation) of months over time or from month to month during a hydrological year. The optimum length of input months  $M$  of the training matrix was determined by evaluating the determination coefficients for the selected predicted period of 12 months. The most suitable length  $M$  of input months was finding the maximum value  $\Sigma R^2$  for the rotation period of 12 months. In this way, the best length was set to be  $M = 9$  input months for the training matrix. To draw up the final prediction, the above mentioned training matrices with the length of input months  $M$  and the corresponding length of prediction  $N$  were trained and used to draw up the required prediction of average monthly discharges with prediction lengths  $N$ . This means that a total of 7 prediction sets were drawn up for 3 selected hydrological periods for 2 hydrometric profiles which were then used as input hydrological data for the purpose of managing the reservoir systems of Brno and Vír I. Samples of prediction results are illustrated in graphs for profiles 1 and 2 for an average water year for  $M = 9$  and prediction length  $N = 12$ .

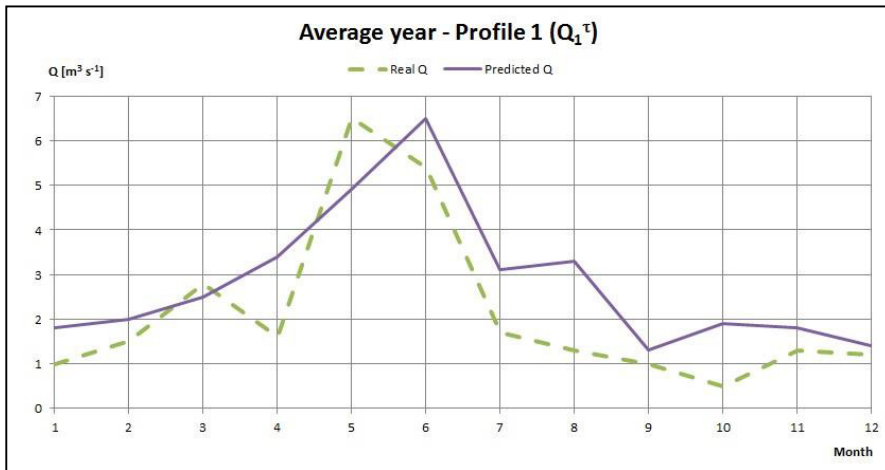


Fig. 2. Results of prediction in profile 1, prediction length  $N = 12$ .

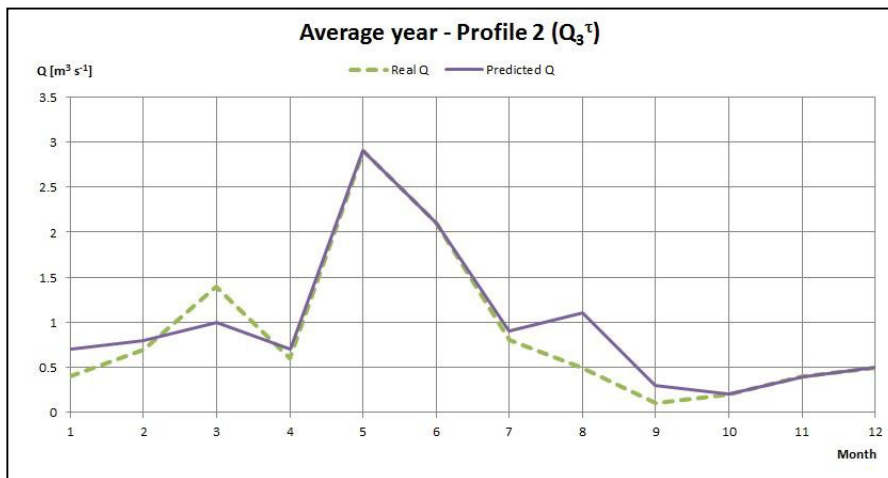


Fig. 3. Results of prediction in profile 2, prediction length  $N = 12$ .

Adaptive control is used for more detailed evaluation of the success rate of prediction. Adaptive control takes place at two levels. The first level is created by a local model. In the local (optimization) model, outflows from reservoirs are sought by the optimization method of differential evolution. The form of the local model objective function is:

$$\left[ \pi = \sum_{t=1}^N \left( (Q_{2,4}^t - W_{2,4}^t)^2 + (Q_{5,6}^t - W_{5,6}^t)^2 \right) \rightarrow \text{MIN} \right] \quad (2)$$

where  $Q_{2,4}^t$  and  $Q_{5,6}^t$  are the found optimum controlled water outflows from reservoirs during individual time steps  $N$ .  $W_{2,4}^t$  and  $W_{5,6}^t$  are prescribed required water outflows from the reservoirs. The purpose of such selected objective function (2) is to distribute the possible non-supply of water, if possible, uniformly to individual months.  $W_{2,4}^t = 3.37 \text{ m}^3 \cdot \text{s}^{-1}$  is for the Vir reservoir and  $W_{5,6}^t = 2.4 \text{ m}^3 \cdot \text{s}^{-1}$  is for the Brno reservoir. The selected required outflows will cause a tense hydrological situation. The tense hydrological situation will cause an occurrence of failure periods. The second level is formed by a global model. The global model simulates the operation of a real system of water reservoirs. The simulation of operation takes place in three periods. The number of global model steps for each period is  $M = 12$ .

Adaptive control (AC – P) is repeatedly performed by using several predictions which differ from one another by the number of prediction steps (months). To compare the success rate of adaptive control to prescribed values, the solution is performed similarly in the historical discharge series (AC – H). From the view of prediction values, we then work with the prediction with 100% accuracy – corresponding to reality. Control of water reservoirs system is also solved from month to month on the basis of the required outflows, control for improved outflow (CIO). It is a simulation model where, in the case of a sufficient inflow and sufficient water volume in the reservoirs, outflows from the reservoirs are always equal to required outflows. If the water inflow into the reservoir or the water volume in the reservoir is not sufficient, the water outflows from the reservoir is equal to the outflows which corresponds to the size of water inflow and the remaining volume of water in the reservoir. This method of control does not use predictions and is currently one of the most frequent and simplest methods of control.

The total amount of non-supplied water  $D$  for the number of global model steps  $M$  is used to evaluate the success rate of adaptive control and to interpret the results. The total amount of non-supplied water  $D$  is expressed by the equation:

$$D = \sum_{T=1}^M \left( (Q_{2,4}^T - W_{2,4}^T)^2 + (Q_{5,6}^T - W_{5,6}^T)^2 \right) \quad (3)$$

Where  $Q_{2,4}^1$  and  $Q_{5,6}^1$  are found water outflows from reservoirs corresponding to the first step of local model  $\tau = 1$ . If  $(W_{2,4}^1 - Q_{2,4}^1) < 0$  or  $(W_{5,6}^1 - Q_{5,6}^1) < 0$ , then water outflow from the reservoir is larger than the required outflow and  $(W_{2,4}^1 - Q_{2,4}^1) = 0$  or  $(W_{5,6}^1 - Q_{5,6}^1) = 0$ . The expression form (3) can be designated as a penalty form, when penalties for not supplied amount of water in each step (month) grow progressively with the square of not supplied amount of water. The penalty form used is based on an assumption that from the view of the operation of water reservoirs, introduction of shallow and long failures in advance is much more suitable than to only have one very deep failure (critical failure) [5].

Table 1 shows the total amount of not supplied water  $D$ . The total amount of not supplied water is shown control for improved outflow and adaptive control. In adaptive control, the total amount of not supplied water is determined separately for each period and for various lengths of predictions. The values shown in Table 1 indicate that the suitability of adaptive control of the storage capacity of a multi-reservoir system is directly dependant on the water quantity of discharge series. This can be observed straight on the total amount of not supplied water. The more water quantity of period is the lower amount of the not supplied water. From the view of prediction length (the number of prediction months), control to shorter predictions is more suitable for the dry year. Control for longer predictions is more suitable for an average year. In a dry year, dependence on the success rate of predictions is greater; therefore control to shorter predictions is more suitable. In an average year, the success rate of prediction does not take effect

so much, therefore, in control; better results are shown than for longer predictions. Adaptive control for the wet year for shorter predictions is identical to control for improved outflow. In adaptive control to longer predictions, the total amount of not supplied water is larger than in control for improved outflow. A larger amount of not supplied water is caused by the prediction inaccuracy. The prediction inaccuracy grows with the prediction length.

Table 1. The total amount of not supplied water for the total steps of the global model.

	D (m <sup>6</sup> .s <sup>-2</sup> )								
	Extreme dry year			Average year			Extreme wet year		
	CIO	AC – P	AC – H	CIO	AC – P	AC – H	CIO	AC – P	AC – H
No predictions	35.42	–	–	28.01	–	–	0.00	–	–
N = 1	–	30.11	30.93	–	23.86	23.17	–	0.00	0.00
N = 2	–	28.60	24.19	–	24.70	19.97	–	0.00	0.00
N = 4	–	31.05	16.28	–	15.19	15.11	–	0.01	0.00
N = 6	–	32.79	17.78	–	13.34	11.03	–	0.65	0.00
N = 8	–	32.20	17.28	–	14.53	7.23	–	1.81	0.00
N = 12	–	34.42	17.91	–	22.32	6.76	–	6.58	0.00

The curves of control in the dry year for prediction length N = 2 are shown in Fig. 2 and the curves of control in an average year for prediction length N = 6 are shown in Fig. 3. A line graph is used for better visualization.

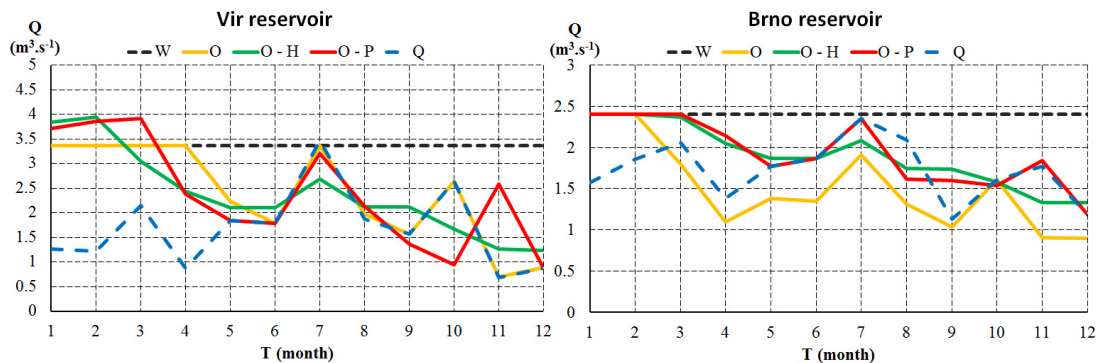


Fig. 4. The resulting courses of the control in the extreme dry year.

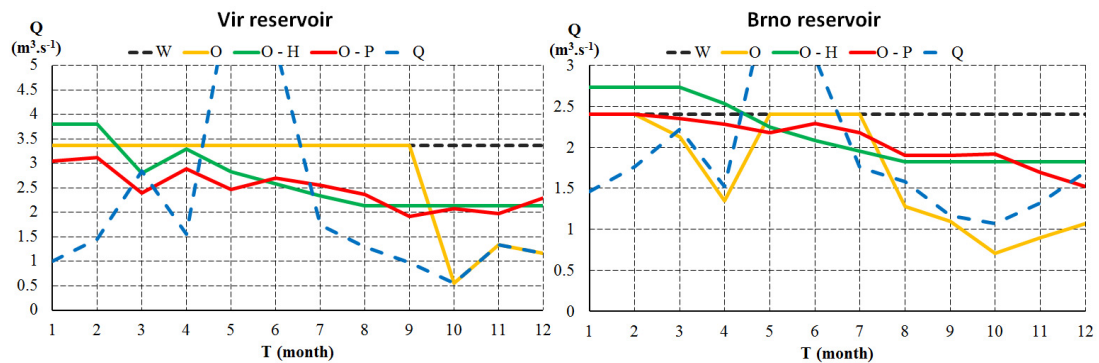


Fig. 5. The resulting courses of the control in the average year.

Fig. 4 and Fig. 5 show the curves of average monthly water inflows into the reservoir (Q). The required outflow from the reservoir is shown by the curve (W). Also, the figure shows two curves of adaptive control. The curve of controlled outflows (O – H) corresponds to control performed on the basis of knowledge of 100% prediction accuracy. The curve of controlled outflows (O – P) corresponds to control that uses predictions. The curve of controlled outflows (O) shows control for improved outflow.

#### 4. Conclusion

The case study indicates that in the control for improved outflow the total amount of not supplied water is larger than in adaptive control. This fact confirms the assumption that control for improved outflow is one of the simplest methods of control and thus it reaches worse (corresponding) results. Better results are achieved by adaptive control to historical discharges (100% prediction), and also by control to prediction discharges. Adaptive control is suitable for both dry years and average years. In control in dry years, the prediction inaccuracy takes larger effect than in control in average years. The suitability of control in average years is also confirmed by the assumption that control using a historical (real) discharge series reaches a higher success rate also in average years than in dry years.

If there is enough water in the system (an extreme wet year), adaptive control within the case study has no significance. If longer predictions are used, adaptive control may be even worse than in control for improved outflow. In practice, it will be complicated to estimate a significantly extreme wet year in advance and when adaptive control is used, it will be necessary to be careful or to change over to a simpler form of control. On the other hand, if adaptive control is used also during an extreme wet year and with longer predictions, the results are only slightly worse than in control for improved outflow.

It can be expected that the application of adaptive control will be more suitable also in a different multi-reservoir system than common control for improved outflow or control using simplified rules which are expressed, for example, by control curves. It can also be expected from the results reached and on the basis of the complexity of the solved problem that before any trial introduction of this type of control into practice, it will be necessary to carry out an analysis for each multi-reservoir system individually. It will be necessary to test various predictive models for each multi-reservoir system, in combination with various lengths of predictions and in various hydrological situations. It will also be necessary to adapt the correction process which is applied at the global model level and in practice it represents a process running at the water management central control level.

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#### References

- [1] Zahradnick P., Trnka M., Brazdil R., Mozny M., Stepanek P., Hlavinka P., Zalud Z., Maly A., Semeradova D., Dobrovolny P., Dubrovsky M. and Reznickova L., The extreme drought episode of August 2011–May 2012 in the Czech Republic, *International Journal of Climatology*, 2014, pp 1-18.
- [2] Jain S. K., *Reservoirs-Multipurpose*, Water Encyclopedia, 2005, pp 382–387.
- [3] Votruba L., Broza V., *Water Management in Reservoirs*, New York: Elsevier Science Ltd, 1989.
- [4] Fosumpaur P., Kendik T., Brezina K., *Zodpovedny pristup pri rezeni moznych zmen strategickeho rizeni nadrzi, Priehradne dni 2014*, Slovenska republika, pp 89-90, 2014.
- [5] Mensik P., Stary M., Marton D., *Using Predictive Model of Mean Monthly Flows for Large Open Reservoirs Hydropower Control*, *Procedia Engineering*, vol. 89, no. 12, 2014, pp 1486-1492.
- [6] Mensik P., Stary M., *SOMVS – Simulation and Optimization Model of Multi-reservoir Systems*, url: <http://uvhk.fce.vutbr.cz/somvs.php>.



- [7] Mensik P., Stary M., Marton D., Water Management Software for Controlling the Water Supply Function of Many Reservoirs in a Watershed, *Water Resources*, vol. 42, no. 1, 2015, pp 133-145.
- [8] Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986b). "Learning Internal Representations by Error Propagation," in *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, vol. I, D. E. Rumelhart, J. L. McClelland, and the PDP Research Group. MIT Press, Cambridge (1986).
- [9] Cheng CH., Chau K, Sun Y, Lin J., Long-Term Prediction of Discharges in Manwan Reservoir Using Artificial Neural Network Models, *Advances in neural networks, Second International Symposium on Neural Networks, Chongqing, China, May 30-June 1, 2005 : proceedings*. New York: Springer, 2005. ISBN 35402591473 pp 1040-1045.