J. Hydrol. Hydromech., 70, 2022, 2, 213–221
https://doi.org/10.2478/johh-2022-0010

sciendo Journal of Hydrology and Hydromechanics Institute of Hydrology SAS

Adaptive stochastic management of the storage function for a large, open reservoir using learned fuzzy models

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Abstract: The design and evaluation of algorithms for adaptive stochastic control of the reservoir function of a water reservoir using an artificial intelligence method (learned fuzzy model) are described in this article. This procedure was tested on the Vranov reservoir (Czech Republic). Stochastic model results were compared with the results of deterministic management obtained using the method of classical optimisation (differential evolution). The models used for controlling of reservoir outflow used single quantile from flow duration curve values or combinations of quantile values from flow duration curve for determination of controlled outflow. Both methods were also tested on forecast data from real series (100% forecast). Finally, the results of the dispatcher graph, adaptive deterministic control and adaptive stochastic control were compared. Achieved results of adaptive stochastic management were better than results provided by dispatcher graph and provide inspiration for continuing research in the field.

Keywords: Stochastic; Artificial intelligence; Storage function; Optimisation.

INTRODUCTION

At present, most of the territory of the Czech Republic is facing a long-term occurrence of drought and its effects. The significant dry season was in 2016, at the end of 2017 and in 2018. In 2019, the drought period was interrupted only in the winter, and the rest of the year was again very dry (Crhova et al., 2019). From the point of view of the groundwater level and the number of occurrences of river profiles below the drought level, this is the worst historically recorded drought in the Czech Republic. The occurrence of drought itself has a significant impact not only on the amount of groundwater and surface water in selected areas but also on the quality of surface water in general.

The very low groundwater levels affect not only the possibilities of its abstraction but also the overall water content of the river network, especially during long rainless periods (droughts). Such greatly reduced water flows in river networks have an impact on the management of storage functions of reservoirs, which face long-term very low values of water inflows into the reservoir and relatively high demands on outflows. The most significant exacerbation of the conflict between the target outflows and the controlled (provided) outflow occurred in 2018, when some smaller reservoirs were not able to further improve the flows in the profiles below them, because the storage volume of these reservoirs was completely emptied (inflow = outflow). In the spring of 2018, extraordinary manipulations were introduced for selected large reservoirs as part of a strategy to avoid completely emptying the storage volume of the reservoirs and the consequent loss of the ability to control the storage functions of reservoirs. These measures were revoked in January 2019 and reintroduced on selected reservoirs in February 2020.

From the point of view of climate scenarios, droughts should occur more frequently. The drought periods themselves are expected to lengthen and deepen. These expectations are associated with the expected reduction of the values of the long-term average flow (Qa) up to the values of 80% of its value (0.8 * Qa) (Kasparek, 2005).

For the above reasons, an increase in the tension between the supply and demand for water can be expected, which will lead to need for the optimization of the control of the storage function of the tanks. The actual control of the storage function of the reservoirs is currently carried out using the method of dispatching graphs (DG), which is based on historical records. However, DGs compiled in this way are not able to respond correctly to the expected changes. It would therefore be appropriate to use control of the storage by optimization based on the prediction of water inflows into the reservoir. However, deterministic prediction alone appears to be insufficient because average monthly flow values are random processes (Hirsh, 1979; Svanidze, 1961). To use only one value for water inflow predictions is an oversimplification, which can cause significant errors in the reservoir control itself.

For these reasons, stochastic predictions and subsequent stochastic procedures should be used. The procedure proposed in this paper uses the predictive stochastic model. The stochastic model is based on deterministic adaptive learned fuzzy model (ALFM) (Kozel and Stary, 2021). For stochastic generation of predicted inflows model ALFM extends it to a stochastic model using the Monte Carlo method. Randomly generated variances (rndi) are added to the inflow predictions created by the ALFM model. The ALFM model itself is based on a learned fuzzy model (Sugeno, 1977; Tagaki and Sugeno, 1985). The principle of reservoir storage is based on the method described in Kozel and Stary (2019) but extends and improve it in some aspects. Unlike the original application, which was tested on a fictitious reservoir, the control methodology is applied to a real reservoir. Furthermore, not only one average value of the targeted outflow is used, but a separate targeted outflow value can be assigned to each month. Management itself is extended by the possibility of simplified use of water reserves in the snow cover. For stochastic control, a combination of different probabilities procedures based on the current filling of the reservoir is used.

CONTROL MODEL

Solving the problem of controlling the storage function of the reservoir in an adaptive way (one of the methods of artificial intelligence AI) allows of controlling the storage function of the reservoir with consideration of stochastic inflow predictions. The use of the Monte Carlo method is proposed for the stochastic adaptive control. The principle of the Monte Carlo method is applied in the set of predictions, generated which are modifications of historically measured flow series, to which the random component is added. In this way, a set of possible future combinations of water inflows into the reservoir is created. However, such a water management solution for reservoirs often encounters limitations in terms of computer technology (high demands on the computing time required). At least 300 repetitions of the calculation are required for a reasonable evaluation of repeated random states (Kozel and Stary, 2019). Stochastic adaptive control will be understood in the following text as such a control of the storage function of the reservoir, in which in each step of the calculation, for a given filling of the storage volume of the reservoir, future controlled outflows are calculated based on a randomly generated set of predicted inflows. That is, for each inflow prediction, the optimal controlled outflow is sought. The values of the controlled outflows are then processed into Flow duration curves. For the control of the storage function of the water reservoir, it is possible to use deterministic (direct) optimization methods or artificial intelligence (AI) methods. AI methods approximate the methods of direct optimization based on the I/O matrix (target behaviour matrix). Direct optimization methods, such as genetic algorithms (GA) or the method of differential evolution (DE) (method of evolutionary algorithms), offer the possibility of obtaining the result without significant loss of accuracy (AI methods are approximating the target behaviour matrix) but at the cost of increased computational demands. The DE method was chosen for this task (Deb, 2001; Price et al., 2006), which uses real coding and unlike GA allows the use of more than 2 parents.

The direct optimization method searches the area of acceptable solutions Ω, with a number of dimensions equal to the number of predicted months of the flow series forecast. The methods quantify water outflows (controlled outflow) from the reservoir for the specified initial volume of water in the reservoir and the predicted inflows of water into the reservoir in the current period. The optimization criterion is the sum of the differences of the squares between the targeted average monthly outflow of water from the reservoir O_P and a series of controlled (computed) average monthly outflows of water from the reservoir O, which is minimized

$$\pi = \left[\sum_{j=1}^{N} \left(O_P - O_j \right)^2 \right] \rightarrow MIN. \tag{1}$$

where O_p denotes targeted outflow, O_j is the value of the calculated controlled average outflow, N is the total number of months, j is the number of the month and π is the value of the criterion function.

If the values of the reservoir storage volume are considered according to the currently measured values, and the inflow forecasts are based on the measured data, it is possible to use the control algorithms described for operative control of the reservoir storage function in real time. The simulation of the reservoir behaviour during control in one time step Δt is described in relation (2), which is the basic equation of the reservoir in differential form. At each time step, the current member of the series Q (boundary conditions) is replaced by the current prediction, and adaptive control is performed, the result of which is the determination of O^τ. The mentioned procedure is recurrently applied to all time steps Δt, the order of which is given by $\tau = 1, 2,\ldots, N$. The initial volume of water in the reservoir V^0 is replaced by the volume obtained by measurement during control in real operation. In the control simulation, V^0 for the recalculation is replaced by V^1 from the previous calculation.

$$Q^\tau - O^\tau = \frac{V^\tau - V^{\tau-1}}{\Delta t}. \tag{2}$$

In relation (2), $V^{\tau-1}$ is the volume of water in the reservoir at the beginning of the respective time step. For the time step $\tau = 1$, the initial condition is V^0 (measured value). The members of the series O^τ for $\tau = 1, 2, .., N$ can take an infinite number of values, which depend on the filling of the reservoir and the means of controlling the outflow of water from the reservoir. If the value of $\tau > 1$, the initial condition $V^{\tau-1}$ for each further time step τ is calculated according to Equation (2), in which the predicted value is used instead of the real value of the inflow, which is considered the real value in the calculation, and the outflow value, which is the calculated value from the previous control time step, is used. Before starting the next calculation step, it is necessary to calculate the actual value of the storage volume according to Equation (2). The outflow of water from the reservoir, which is controlled to the value O_P (targeted outflow), can take values from the interval (0, O_P >). In this case, the forced outflow for evaluation is considered to be the value of O_P.

FORECASTING MODEL

The forecast model of water inflows into the reservoir itself is stochastic. It is based on a deterministic forecast model, based on a learned fuzzy model using the similarity of average monthly flows (Kozel and Stary, 2021). A simplified scheme of the deterministic forecasting model ALFM is shown in Figure 1.

For the construction of stochastic forecasts (predictions) alone, it is assumed that the prediction distribution is subject to the Rayleigh distribution (Evans et al., 2000; Papoulis, 1984). For the purpose of creating a stochastic prediction, the deterministic value (forecast) Q^τ_j of the deterministic model described above is used as the mean value of the prediction distribution $u(Q^\tau_j)$. If the predicted value is lower than the historical minimum $MIN(Q^\tau_j)$, the new historical minimum is set to 0.9 * $u(Q^\tau_j)$. According to Equation (3), the scale factor λ Rayleigh distribution is calculated:

$$\lambda\left(Q_j^\tau\right) = \frac{u\left(Q_j^\tau\right) - MIN\left(Q_j^\tau\right)}{\sqrt{\frac{\pi}{2}}}. \tag{3}$$

After calculation of the scale factor λ_j, the neighbourhood of the mean value is calculated using Equation (4):

$$Q_{i,j}^\tau = \lambda_j \sqrt{-2\ln\left(\mathrm{rnd}_{i,j}^\tau\right)} + MIN\left(Q_j^\tau\right), \tag{4}$$

where $rnd^\tau_{i,j}$ is a random number from a Rayleigh distribution from the interval 0 to 1, i is the prediction order from 1 to 1000 and j is the prediction month from 1 to 12. Using the above procedure, a prediction matrix Ap of 1000 rows and with the number of columns corresponding to the length of the forecast (number of predicted months) is created for each forecast month. The stochastic prediction model itself will be further

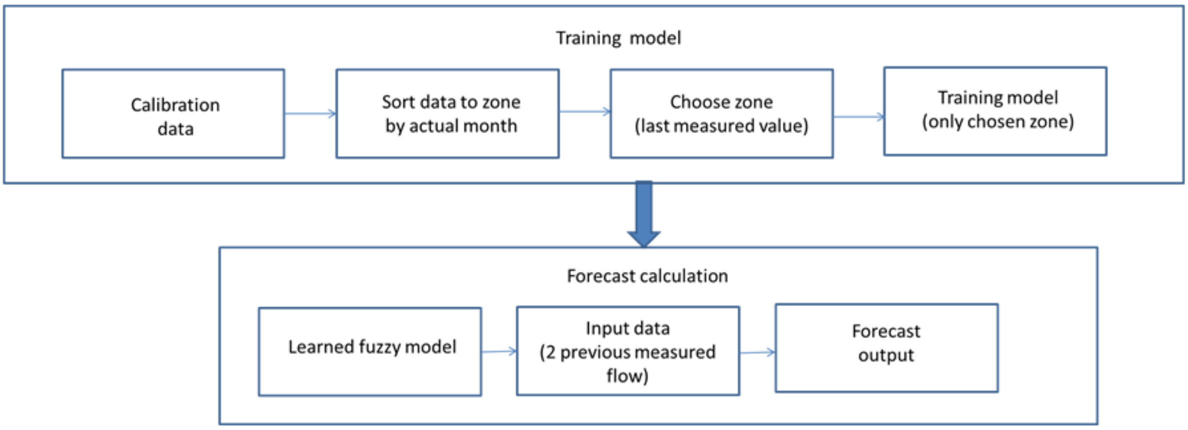

Fig. 1. Simplified schema of AFLM model.

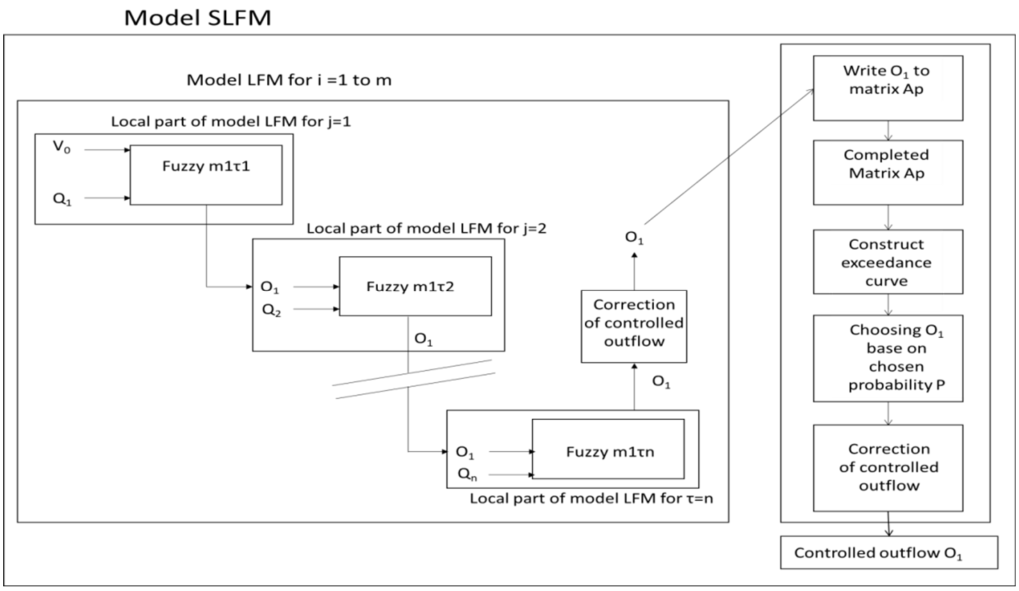

Fig. 2. Schema of SLFM model.

labelled SALFM. The use of the above procedure was chosen due to the very problematic transformation between the distribution with non-zero asymmetry (distribution of average monthly flows for the selected month) and the normal distribution (zero asymmetry).

CONTROL LEARNED FUZZY MODEL (LFM)

The control model itself contains learned local fuzzy models (each month has its own fuzzy model assigned). The first local model has two inputs, the volume of water in the reservoir at the beginning of step V^0 and the inflow of water into the reservoir (real values for calibration, prediction for validation). If the length of the prediction vector (number of predicted months) Q is greater than one when applying the control, local LFM models are used repeatedly until all members of the prediction vector are exhausted. Other local models (second to N) also have two inputs, where one input is the relevant member of the prediction vector, and the other input is the output from the previous local LFM model. The resulting output from the model is a controlled outflow of water from the O^1 reservoir. The LFM model uses the principle of gradual aggregation of inputs (Janal and Stary, 2012), which reduces the difficulty of compiling a matrix of rules. In stochastic control, the LFM model works with the prediction matrix *Ap*, where the model performs controls for individual rows of the matrix (prediction vector), and the individual controlled outflows are stored in the matrix of controlled outflows. The LFM model performs control for all rows of the matrix *Ap*. The probabilities of exceeding individually controlled outflow are calculated according to Chegodayev (the relationship was taken from Kozel and Stary, 2019):

$$P = \frac{i - 0.3}{n + 0.4}, \tag{5}$$

where i is the order of the elements in the file sorted from maximum to minimum, and n is the total number of elements in the file. The plotted empirical line of crossing into a rectangular coordinate system is interpolated using a theoretical line of crossing using Chebyshev polynomials (Hochstrasser, 1972). From the theoretical line of exceedance constructed in this way, any probability of exceeding the controlled outflow (quantile P) can be deducted. Figure 2 shows the global SLFM model, which includes individual local LFM models. Local LFM models are learned on a matrix of target behaviour and thus approximate its behaviour.

The use of snow cover is incorporated into the calculation using a simple algorithm that works with the current value (known value of water reserves in the snow in the basin above the reservoir). The water supply in the snow can be added to the inflow of water into the reservoir for the selected month. Flow from snow cover was calculated by the method degree/day in this study (Bras, 1990). For whole of March only one temperature value was used, which was the average temperature for this month. If all snow was depleted, the outflow value was set to be zero. In the next step values were averaged. This method is simplifying the whole process, but for the purpose of this study it is satisfying the control of storage function. The main reason for using this method was the in March of high values of snow cover. In the case of the procedure described in the article, these values were added to the inflow values for March (climatic conditions of the Czech Republic). In the case of real control, the month can be changed or, in the case of favourable values of reserves in the snow, a lower quantile of controlled runoff can be selected than would otherwise be applied.

APPLICATION

The overall control was applied to the Vranov reservoir, the position of which is shown in Fig. 3. The reservoir itself is located on the river Dyje. The total water storage volume of the reservoir V_{max} is 87,000,000 m^3. The targeted outflows were taken from the handling rules of the reservoir and are contained in Table 1. The targeted outflows themselves have built-in average evaporation values.

The Vranov reservoir itself has two tributaries. The first is the river Dyje with a measuring profile Podhradí, for which the value of the long-term average flow is 8 m^3/s. The second tributary is the river Želetavka with a measuring profile Vysočany and a value of long-term average flow of 0.6 m^3/s. The reservoir itself was chosen because of a long series of measurements and because there is no larger reservoir higher in the basin. The reservoir itself struggled during the drought in 2018 and again in the spring of 2020 with reduced control water outflows from the reservoir to 2 m^3/s due to low storage volume values as part of the strategy for ongoing drought. The measures were repealed in the summer of 2020.

DATA

There was an 84-year-long flow series (1934–2018), which was created by summing the values of average monthly flows in the Podhradí and Vysočany profiles. The data were divided into two parts for calibration and validation purposes. The calibration part for the control model was in the years 1934 to 2002, and the last 15 years were left for validation. Data from 1934 to 2002 were used for the prediction model, but the calibration period was gradually extended to previous years. The above extension of the calibration data is common practice to ensure greater representativeness of the data.

CALIBRATION

For the purpose of SLFM control model calibration, the period 1934–2002 was chosen, where the data for the construction of the target behaviour matrix were obtained using the DE method. During the calibration period, however, there were no faults on which the SLFM model could learn. For the above reason, the individual water inflows were reduced by 10% (0.9 * Q). To rebuild the target behaviour matrix, the DE method was used. For both models (SLFM and SALFM), the Fuzzy C-means method was used for the learning process itself (Bezdec, 1981).

VALIDATION

The next step in the SLFM control model was to test its limits. The limits of the SLFM model were tested using real inflows (100% forecast). The limits themselves are shown in Figure 4, where the limits for the DE method obtained in the same way are plotted. The length of the forecast was 12 months to determine the limits. Figure 4a) shows the inflows in the validation period. Figure 4b) shows the resulting controlled outflows obtained by the DE method, the learned fuzzy model and targeted outflows. Figure 4c then shows the course of volumes in the validation period for the DE method and the learned fuzzy model.

Fig. 3. Location of the Vranov reservoir.

Table 1. Values of targeted outflow from the Vranov Reservoir (Handling order for VD Vranov, 2011).

Month	Jan.	Feb.	March	April	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
O_p [m^3/s]	4.813	4.960	4.981	6.744	8.051	9.489	8.412	8.010	7.026	5.794	4.87	4.727

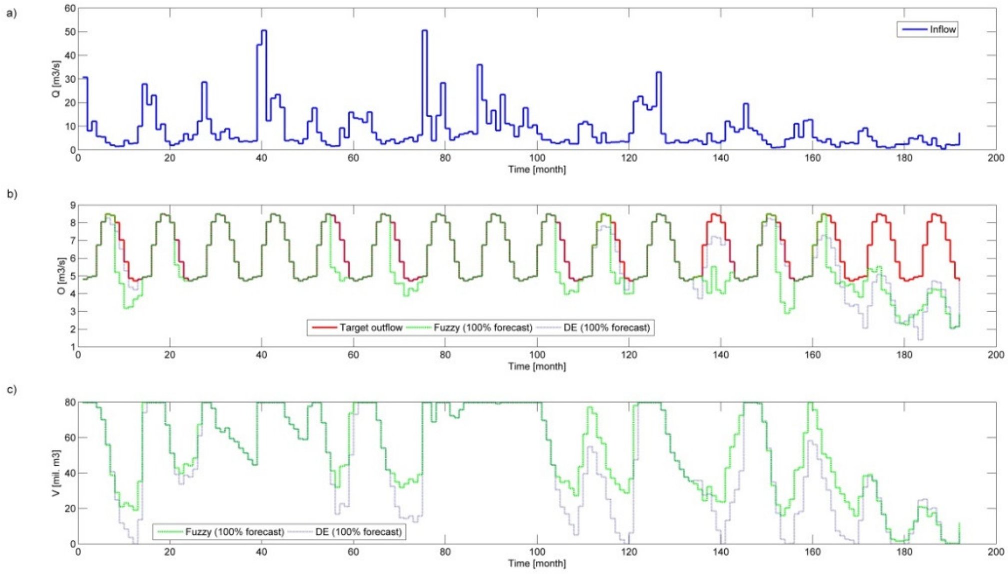

Fig. 4. Results for the calibration period: a) Inflow into the reservoir, b) controlled outflows of the fuzzy model and DE method and c) course of volume for control of the reservoir for the fuzzy model and DE method.

Table 2. Controlling quantiles values.

Interval of use	<0 ; 0.5*V_{max})	<0.5 ; 0.8* V_{max})	<0.8* V_{max} ; V_{max} >
Quantile	0.95	0.6	0.4

The evaluation of the quality of the control described above was performed on the basis of the sum of the square of the difference between the targeted and controlled outflow. In the following text, this criterion will be marked π1 (relation 1, applied to the validation period). For the management process itself, the predictions of the SAFLM model were used by the learned fuzzy model and the DE method. During the validation, different prediction lengths, outflow quantiles (single quantiles during whole validation period was used) and combinations of different outflow quantiles were tested. The values of quantiles from the interval 0.3 to 0.95 (after the value of 0.05) and the quantile 0.97 were used for control. The results of a procedure that used only one quantile proved to be insufficient. Using high quantile values, the SLFM + SAFLM and DE + SAFLM methods were able to transform deep and short disturbances into long and shallow (desirable) ones. The disadvantage of all the models was that the failures occurred even in periods when the reservoir was relatively full. The rate of this phenomenon increased with the length of the forecast. Using low and medium quantile values (higher inflows), very good results were obtained in periods with sufficient water, but the results in long dry periods did not differ much from those provided by the DG method. For the above reasons, a combination of quantiles (controlling quantiles) was used. The resulting control can therefore be considered as a form of decision tree, where based on the current volume of water in the reservoir, the appropriate quantile is used for control, based on which the controlled outflow is read from the empirical line of exceeding the controlled outflow. To find a suitable control, the results of control with individual quantiles and findings obtained on the basis of the above evaluation were used. To simplify the search for a suitable quantile combination, three control stages were introduced (three control quantiles, which corresponded to a preselected value of the water volume at the beginning of the solved step). The results of the course of volumes (Figure 4) and the distribution of individual zones in DG showed that the key values are around the values 0.8 and 0.5 * V_{max}. For the above reason, the values of 0.8 and 0.5 * V_{max} were taken as the values delimiting the individual validity of the control quantiles. Table 2 lists the resulting control quantiles for which the best results were generally obtained.

Figure 5 shows the courses of controlled outflows for individual quantiles and the results obtained using a combination of control quantiles for the DE + ALFM method.

Figure 6 shows the results of the control quantile combination for the fuzzy SLFM + SALFM model. The best results were achieved for a forecast length of 7 months according to the selected criterion. Using the same prediction length, the DE model also achieved the best results. For the sake of clarity, Figures 5 to 6 do not show the course of the targeted outflows. The targeted outflows themselves are plotted from Figure 7.

In the next step, the best results of the fuzzy model and the DE method using prediction (length 7 months) were compared. The aim of this comparison was to evaluate the extent to which the results of the fuzzy model differ from the results of direct optimization provided by the DE method. It can be seen from Figure 7 that the generally controlled outflows provided by the fuzzy model reached higher values in the area of the lowest flows than the DE method results. With the exception of a very similar course between the results of the fuzzy model and the DE method in the period around 140 months, where the DE method achieved better results. During the main disorder (160–192 months), the results of both methods are comparable. Furthermore, Figure 7 shows the controlled outflows and the resulting course of controlled outflows provided by the DG method. It is clear from the figure that the DGs themselves could not cope with the main disorder, and subsequently, the storage volume was completely emptied, and the uncontrolled disorder occurred.

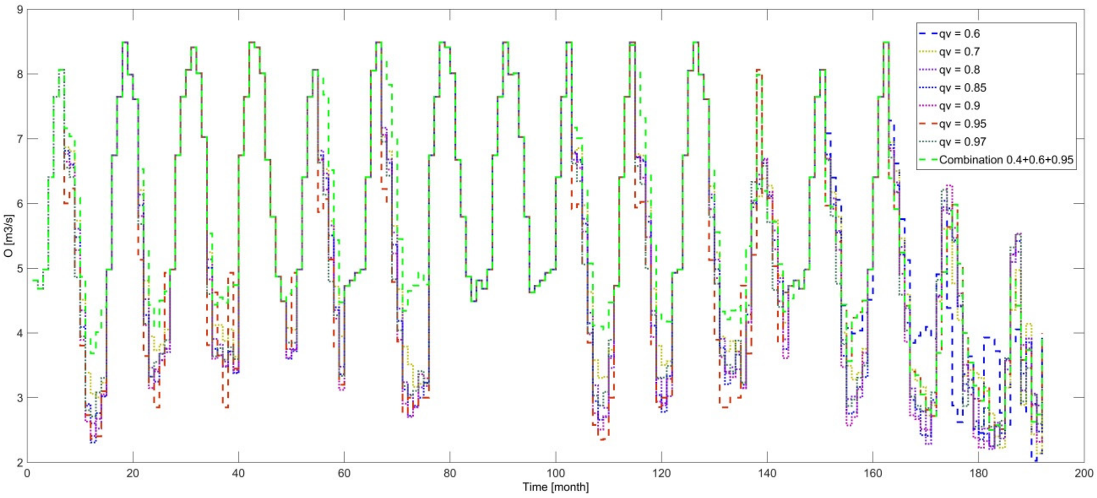

Fig. 5. Results for the DE method choosing a single quartile and a combination of control quantiles.

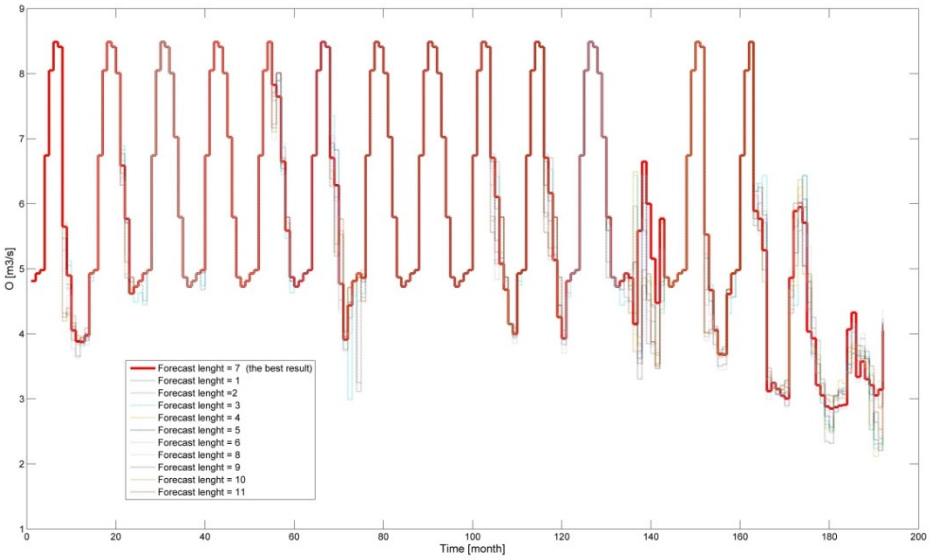

Fig. 6. Influence of the forecast length on the result (fuzzy model).

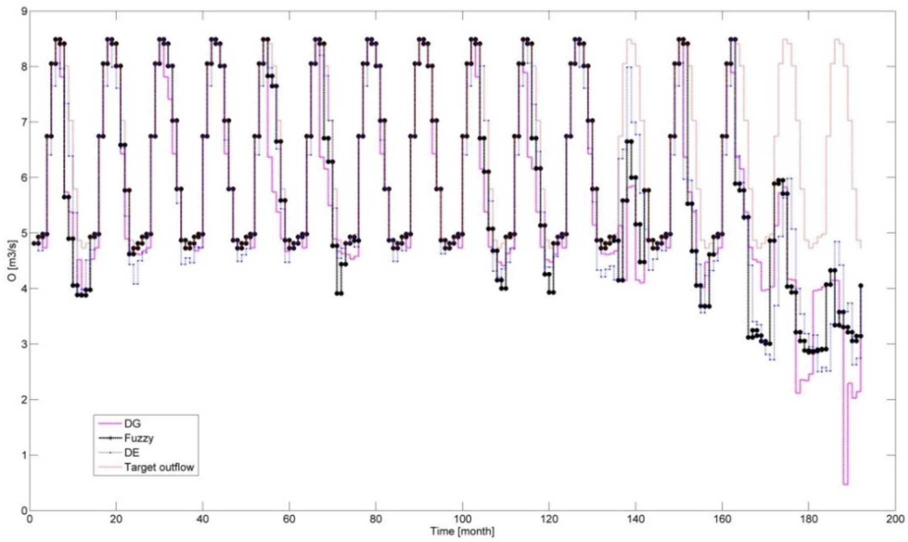

Fig. 7. Results of selected methods (DG, DE, fuzzy) and targeted outflow.

Subsequently, the results were compared between the best results achieved on the basis of model control + stochastic prediction and model results where, instead of the prediction, sections from the real series were used (100% accurate forecast).

Figure 8 shows a comparison between the results of the stochastic control of both methods and the results of the methods used, for which real series sections were used (100% accurate prediction). Figure 8 therefore shows the control limits for both methods.

Finally, the very benefit of stochastic control was evaluated (Figure 9), comparing the results obtained by the fuzzy LFM model + deterministic prediction (ALFM model; Kozel and Stary, 2021) and the results of stochastic control provided by the learned fuzzy model and the DE method.

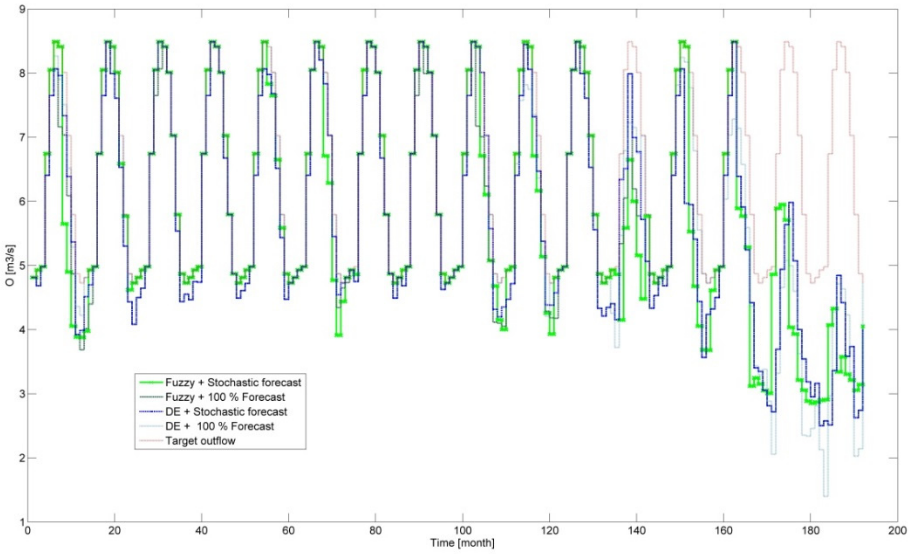

Fig. 8. Results for the fuzzy model and DE method using the 100% accurate forecast and the same models using the best predicted forecast.

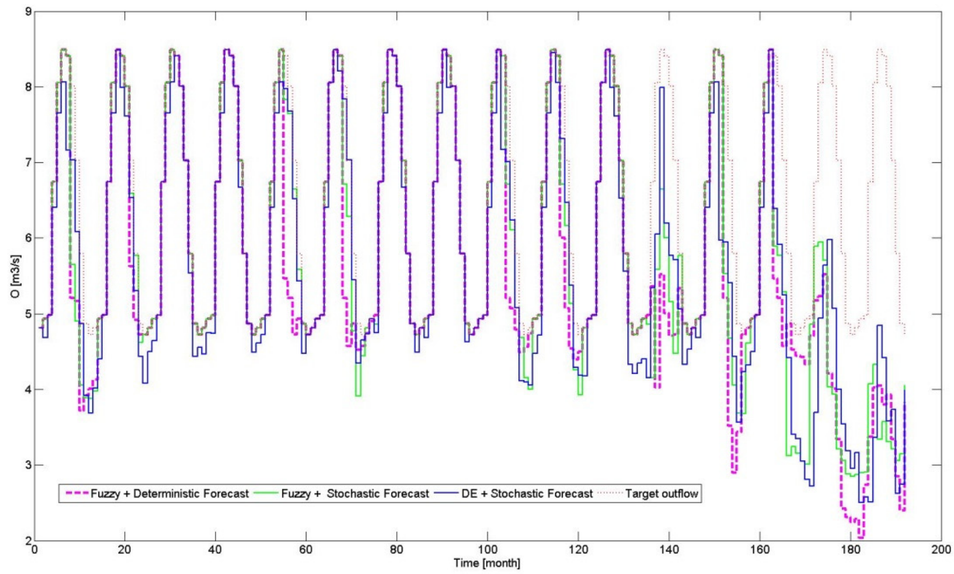

Fig. 9. Results for the fuzzy model and DE method using the stochastic forecast and the fuzzy model using the deterministic forecast (ALFM).

Table 3. Values of selected criteria for individual models. The π1, mean square error (MSE) and residual mean square error (RMSE) values are given.

Model	Criterion π1 [$m^6 s^{-2}$]	MSE [$m^6 s^{-2}$]	RMSE [$m^3 s^{-1}$]
DG	418	2.18	1.48
DE + deterministic forecast	341	1.78	1.33
Fuzzy + deterministic forecast	383	1.99	1.41
DE + stochastic forecast	285	1.43	1.20
Fuzzy + stochastic forecast	315	1.64	1.28
DE + 100% accurate forecast	266	1.39	1.18
Fuzzy +100% accurate forecast	287	1.45	1.21

From the results shown in Table 3, it is clear that the worst results were provided by the DG method. Deterministic control achieved better results but failed to overcome the results of stochastic control. The results of the fuzzy + stochastic forecast reached very good values and came very close to the results of the criteria for Fuzzy + 100% accurate forecast. The best values for the criteria were achieved by the DE + stochastic forecast method, the results of which exceeded those of the fuzzy model for 100% accurate forecast and were very close to the results of the DE + 100% accurate forecast method. The fuzzy model alone in combination with stochastic prediction achieved very good results and, in terms of computational time, the whole calculation for the combination of control quantiles took approximately 35 minutes (medium-power desktop PC). The DE + combination of control quantiles method (stochastic forecast) achieved excellent results, but a computational cluster (12 PCs; 48 cores) was required for the calculation, which took approximately 55 minutes.

DISCUSSION AND CONCLUSION

From the above results, it is clear that the storage function of a real reservoir can be effectively controlled using a stochastic approach. By using one quantile, better results can be achieved than by using a deterministic model, but the results obtained are only slightly better. When performing control using only one quantile, the full potential of the stochastic control approach offered by a fan of possible outflows cannot be exploited. For this reason, the possibility of using a combination of different quantiles to control the storage function of the reservoir was explored. When switching control quantiles based on the current reservoir filling, the control aggressiveness is adjusted and thus adequate responses for current situations (drought x normal period) are achieved. The high quantiles (0.75 to 0.99) correspond to a very aggressive control, where low inflows of water into the reservoir are expected.

From the above results it is clear that the stochastic control formed by a combination of the SAFLM prediction model and the methods of direct DE optimization or learned fuzzy models was able to very effectively control the storage function of a real reservoir. Using a combination of quantiles (P40, P60 and P95), the best results were obtained for the selected criteria. The resulting control quantiles correspond to the capabilities of a deterministic prediction model, which tends to underestimate higher and average flow values. The AI methods themselves were able to significantly reduce the computational time required to calculate the stochastic control of the real reservoir (35 minutes), when the computational time for the DE method was, on average, 38 hours (on the same PC). When using a computing cluster, the computing time was significantly reduced to around 55 minutes.

The lowest achieved values of the criterion $\pi 1$ show that the control using the combination of stochastic prediction and fuzzy learned model $\pi 1 = 315$ m^6 s^{-2} reached worse values than when using the methods of direct optimization and stochastic prediction $\pi 1 = 285$ m^6 s^{-2}. Both variants of the calculation achieved the best results for a forecast length of 7 months. When using a longer prediction, worse values of the criterion $\pi 1$ were achieved, because the error of the prediction model increased above the allowable limit. When using shorter forecast values, worse results were achieved due to the shorter time for the introduction of a timely reduction of controlled water outflows from the reservoir.

The results of the stochastic control themselves were compared with the results of the deterministic control using the DE +ALFM method. Further the previous results were compared with results of DG method. The results of the above methods showed a similar course of the final procedure up to the vicinity of 140 months. The management using the DG method failed to cope with a very long period of drought, when the storage volume was emptied during this period. Subsequently, a short but deep uncontrolled fault occurred. The results of the DG method alone achieved the worst results for the criterion $\pi 1 = 418$ m^6 s^{-2}. Compared to the results of the DG method, the deterministic control performed significantly better (DE $\pi 1 = 348$ m^6 s^{-2}; Fuzzy $\pi 1 = 383$ m^6 s^{-2}), but the deterministic forecast alone could not fully capture the future values of water inflows into the reservoir. This led to an underestimation or overestimation of the water inflows into the reservoir and to a subsequent erroneous determination of the controlled outflow. The above shortcomings arose to a much lesser extent using stochastic control, which used a combination of quantiles.

The use of stochastic control itself places significantly higher demands on computer technology compared with that of commonly used DGs, which are a very suitable tool for control during a regular cycle of water inflows into the reservoir. Due to the global change in weather, which is associated with a more frequent occurrence of long and deep periods of drought (disruption of the regular hydrological cycle), the DGs used so far may very quickly prove to be an ineffective tool. The DG method alone is not able to capture significantly irregular cycles of water inflows into the reservoir. Stochastic control, with regular expansion of training matrices and re-teaching (AI methods), is able to capture very well even a very irregular cycle of water inflows into the reservoir and is a very suitable tool for crisis management of the storage function of the reservoir.

Acknowledgements. The article was supported by grant FAST-S-22.

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Received 23 July 2021
Accepted 10 February 2022