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Application of machine learning in management of water resources systems, a case study

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Highlights

- Machine learning is widely applied in science, including civil engineering fields
- Its use in hydrotechnics is limited; this study explores its role in dam engineering
- Focus is on water resources and cascade reservoir systems with real-world cases
- The study applies ML to dam data from Kalimanci, Loshana, Razlovci, and Ratevo
- Tested methods: ANN, SVM/SVR, RF, DT, GPR, and BT using Python implementations
- ANN, SVR, RF, DT, and BT showed the best accuracy; GPR gave poor results overall

Abstract: The use of machine learning (ML) in water resources management has grown due to its ability to process large, nonlinear datasets and generate accurate predictive models. In dam engineering and reservoir operation, where multiple interacting variables influence decision-making, ML provides a powerful alternative to traditional methods. The study in question investigates the application of six ML models – artificial neural networks (ANNs), support vector machines/support vector regression (SVM/SVP), random forest (RF), decision trees (DT), Gaussian process regression (GPR) and boosted regression trees (BT) – to model and predict the inflow into Kalimanci reservoir, the largest and most downstream reservoir in a complex cascade system on the Bregalnica River, North Macedonia.

Using simulated operational data from HEC-ResSim for a 30-year period (2021–2049), the models were trained and tested on multiple input variables, including inflows, water supply, irrigation, water level fluctuations, and hydropower parameters. Model evaluation was based on mean squared error (*MSE*), root mean squared error (*RMSE*), mean absolute error (*MAE*), and the coefficient of determination (R^2).

The RF, DT, and BT models outperformed others, achieving R^2 values of 0.999–1.000 with minimal error rates. In contrast, the GPR model was excluded due to poor accuracy. Feature importance analysis revealed that inflows from upstream reservoirs, particularly Loshana and Razlovci, were the most influential predictors.

The results confirm that ensemble-learning methods offer high accuracy and reliability in modelling complex water resources systems. These models are recommended for integration into real-time operations to improve reservoir management and optimize water allocation decisions.

Keywords: artificial neural networks, boosted regression trees, decision trees, Gaussian process regression, machine learning, random forest, support vector machines/support vector regession, water resources management

INTRODUCTION

Learning from experimental data and transferring human knowledge into analytical models is task that belongs to soft computing, i.e. neural networks, support machines and fuzzy logic (Kecman, 2001). Unlike traditional 'hard' computing, which relies on exact algorithms and precise logic, soft computing allows for more flexible, adaptable, and tolerant models, making it well suited for complex real-world problems where exact solutions are hard or impossible to define. One of the subfields of soft computing is artificial intelligence – a broad field of building systems that mimic human intelligence. The core technology of artificial intelligence – machine learning and its subfields of deep learning, have become quite the interest of people in different spheres ever since the 1940s (Yu *et al*., 2023). Today, modern computer technology with its low-cost and high performance digital processors has played a key role in the rapid growth of the application of artificial intelligence (Ibrahim, 2016).

Machine learning has demonstrated its high efficiency and practicality in many different application, such as pattern recognition, time series forecasting, diagnostics, robotics, process control, optimization, financial forecast and many more (Kecman, 2001). Due to the nature of the problems and processes related to dam engineering and water resources management, it is very interesting to investigate the possible use of machine learning in the respective field. Water is life for animals and plants, and is essential for the modern civilized world we enjoy today. It does, indeed, cover around 71% of the Earth's surface, however, only about 2.5% of it is freshwater (USGS, 2019). Its temporal and spatial distribution does not always coincide with the needs of the ever-growing human population, so the management of this precious resource has become a very complex task.

So far, successful attempts have been made to make use of machine learning in water-related problems such as forecasting water demand, determination of flood probability in arid regions, analyses of data on dam behaviour, groundwater level forecasting, and many more (Ahmed, 2024). Shahra *et al*. (2019) have analysed historical usage data of water distribution system and resulted with answers concerning optimum water allocation, predict future demand and help detect system leaks. Bui *et al*. (2020) introduced a novel approach using deep learning neural networks to aid in forecasting the likelihood of flash floods. Hosseiny's (2021) study utilised U-net, to predict river flood depth and extent. Huang *et al*. (2003) used convolutional artificial neural networks for coastal water level predictions. Ren *et al*. (2021) implemented an interpretable mixed attention mechanism long short-term memory model to predict displacement associated with concrete dams. Salazar, Irazabal and Conde (2024) have constructed a web application based on Boosted Regression Trees, developed for dam monitoring data analysis with possibility of application in other settings. Hosseini *et al*. (2016) have applied adaptive neural fuzzy interface system to determine the discharge coefficient of a labyrinth spillway. Snousy *et al*. (2025) has used a novel ANN-based hybrid arctic puffin-hippopotamus optimization model to enhance prediction of groundwater quality index in semi-arid regions achieving $R^2 = 0.99$ for irrigation water quality index (*IWQI*) prediction during testing. A recent study applied an artificial neural network (ANN) model to predict the water quality index (*WQI*) in two Himalayan wetlands – Alital and Bandatal Lakes in Nepal (Dahal *et al*., 2025). Using 40 water samples and 16 physicochemical parameters, including total dissolved solids (TDS) and turbidity, the ANN achieved excellent predictive accuracy ($R^2 = 0.99$). The model effectively distinguished between minimally impacted and heavily degraded sites, demonstrating its potential for supporting sustainable wetland management under the pressures of climate change and human activity. In the Ergene River Basin, Türkiye, a novel ensemble machine learning (En) model – combining shallow and deep learning methods optimized with the coronavirus herd immunity optimizer (CHIO) – was developed for groundwater level forecasting (Saqr *et al*., 2025). Trained on weekly data from 1966 to 2023, the model achieved excellent performance ($R^2 \approx 0.99$; $RMSE \approx 0.5$ m) and outperformed all individual machine learning (ML) models. This integrated approach offers a robust, transferable tool for sustainable aquifer management under increasing environmental and anthropogenic stress.

In respect of dam reservoir operation, few articles have been published with outstanding results of application of ML. ML models including random forest (RF), support vector machine (SVM), and artificial neural networks (ANN) were applied to forecast daily outflows from eight reservoirs in Galicia, Spain (Soria-Lopez *et al*., 2023. The models showed high accuracy, especially under normal operating conditions. In the Zhoushan Islands, China, deep learning models like long short-term memory, gated recurrent unit, and least squares support vector machine were used for streamflow forecasting (Guo *et al*., 2021). These predictions were integrated into a multi-objective reservoir operation framework, improving water supply reliability and cost-effectiveness. A study by Chen *et al*. (2022) presents a generic data-driven reservoir operation model (GDROM) with hidden Markov-decision tree applied to deriving representative operation modules for reservoir. A classification and regression tree algorithm is used to identify the application and transition conditions for the operation modules. Another study applies reinforcement learning methods, specifically Deep Deterministic Policy Gradient, Twin Delayed Deep Deterministic Policy Gradient, and Soft Actor-Critic, to develop improved dam operation policies by using offline simulators built with real data and mathematical models of upstream inflow, demonstrating that when the inflow dynamics are modelled with a Dynamic Linear Model, the resulting reinforcement learning-based policies significantly outperform traditional human-generated operating policies (Wang *et al*., 2020).

This paper focuses on research of the possibility of using different machine learning methods in overseeing the operational parameters resulted from management of a complex water resources system in dam design phase versus operational phase. The case study is a cascade reservoir system formed with Ratevo dam, Loshana dam, Kalimanci dam and Razlovci dam on Bregalnica River, in the east of Republic of North Macedonia. This system is not fully operational yet since dam Razlovci is in the design phase, however, all the others are in function. The combined work of all four reservoirs is analysed through simulation model in HEC ResSim (USACE, 2013). Results from the simulation model are used as input data for the machine learning models.

METHODS

Six machine learning methods are applied for analyses of the operational capacity of the proposed water resources system: Artificial neural networks (ANNs), support vector machines/

support vector regression (SVM/SVR), random forest (RF), decision trees (DT), Gaussian process regression (GPR) and boosted regression trees (BT). The algorithm of the calculations is a code in Python, constructed during the research. For the models training and testing process, input data is created for the proposed case study. As follows, details on the input data are elaborated.

The case study is located in the upper catchment area of Bregalnica River, located in eastern North Macedonia (Fig. 1). The water resources system is consisted of the following four dams with reservoirs: Ratevo, Razlovci, Loshana and Kalimanci. Details on the capacity of the reservoirs, characteristic water levels and water allocation for each reservoir, are given in Table 1. Out of all four reservoirs, Ratevo, Kalimanci and Loshana are in operation, while Razlovci is in design phase.

The catchment area borders with Republic of Bulgaria on the east, and is part of Vardar River basin. With analyses on the available data on registered flows in the Bregalnica River basin, the unit flow from the furthest downstream point (measurement station 'Shtip' with total catchment area of 2940 km^2) is 3.82 dm^3·s^{-1}·km^2 with average annual flow at this point of 11.24 m^3·s^{-1}. The hydraulic correlation between all four analysed reservoirs is given in Figure 2. Namely, Kalimanci reservoir is the most downstream reservoir with largest active volume capacity. In cascade row, upriver from Kalimanci reservoir is the planned Razlovci reservoir. Loshana reservoir is located on Loshana stream – a tributary to Bregalnica River. Ratevo reservoir is the oldest existing reservoir in the analysed water resources system and it is located upriver from Razlovci reservoir.

The input data for the models consists of five different time series: (1) hydrographs on inflow in each reservoir, (2) hydrographs on delivered water for water supply, (3) hydrographs on

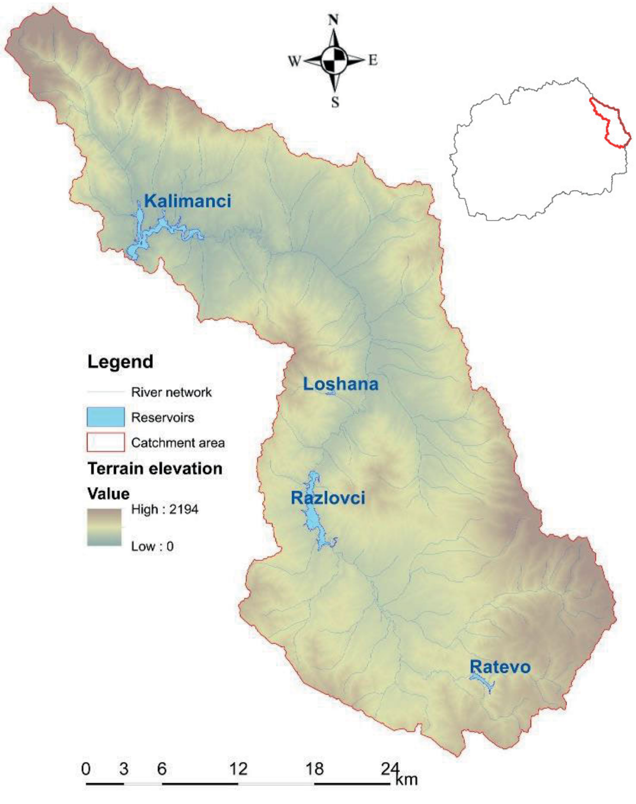

Fig. 1. Location of the case study area; source: own elaboration

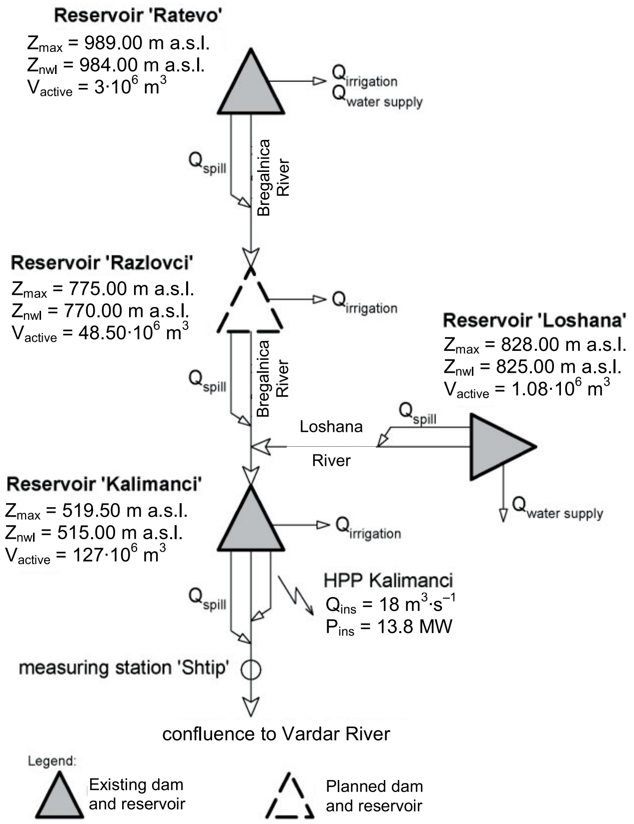

Fig. 2. Hydraulic correlation of the analysed water resources system; Z_{max} = maximum operational level of the reservoir, Z_{nwl} = normal operation level of the reservoir, V_{active} = active volume of the reservoir, $Q_{irrigation}$ = demand of water for irrigation, $Q_{water\ supply}$ = demand of water for water supply, Q_{spill} = spillway flow, Q_{ins} = installed flow capacity of the penstock, P_{ins} = installed power of the units in the power house, source: own elaboration

Table 1. Physical characteristics of the reservoirs analysed in the case study, with details on water allocation for each and one of them

Dam and reservoir	Status	Active volume of reservoir (10^6·m^3)	Water level (m a.s.l.)			Water allocation
			normal	maximal	minimal	
Ratevo	in operation	3.00	984	986	947	water supply, irrigation
Razlovci	planned	48.50	770	775	750	irrigation
Loshana	in operation	1.08	825	828	805	water supply
Kalimanci	in operation	127.00	515	519.5	460	irrigation, electricity production

Source: own elaboration acc. to MoEPP (2016).

delivered water for irrigation, (4) hydrographs on fluctuation of water level in reservoir, and (5) time series on power production and turbine flow. All data is obtained through a simulation model of the water resources system, constructed as part of the research, with the use of HEC ResSim software. All time-series are 20 years long, with daily time step of the analyses. The analyses are conducted for the period between year 2021 and 2040. The operational policy of management of the reservoirs is defined according to current status – primary allocation of water goes to water supply and irrigation, whereas production of electricity has the latest priority for water allocation.

One of the most important data in water management is the amount of accessible water. That said, estimation of inflow hydrographs for each reservoir is paramount, especially when working with ungauged basins, as is the case with the studied basins of each dam site. As follows, brief description is given on the process of definition of the inflow hydrographs used in the research.

Inflow hydrographs are constructed according to data from measuring station ‘Shtip’ by scaling the existing hydrograph according to basin area of each reservoir, as well as average above sea level of the basin for each reservoir. Kalimanci reservoir basin, for instance, is 38% of the total basin of Bregalnica River down to measuring station ‘Shtip’, or 1107 km^2. This number, for Razlovci reservoir, is 15% or 447 km^2, for Loshana – 0.4% or 12.8 km^2, and for Ratevo – 2% or 54.49 km^2. However, building an upstream dam and forming a reservoir means water will be stored and the basin that would naturally flow towards a downstream point is reduced, and the expected hydrograph at all reservoirs is a sum from sub-basin flow and managed water flow from upstream reservoirs. That said, sub-basins for each of the dams’ sites, are: Kalimanci dam – 647.40 km^2, Razlovci dam – 392.31 km^2, Loshana dam – 12.80 km^2, and Ratevo dam – 54.49 km^2. Additionally, the average elevation above sea level of each sub-basin, is: for Kalimanci dam basin – 984 m a.s.l., for Razlovci dam basin – 1088 m a.s.l., for Loshana dam basin – 1131 m a.s.l., and for Ratevo dam basin – 1260 m a.s.l. With regard of both the area and average above sea level of each sub-basin, unit flow is determined for each dam site according to Figure 3. Figure 3 represents a mathematical correlation curve derived from data of five different measuring stations in the basin of Bregalnica River. The curve shows information on unit flow (M) for a basin based on its average above sea level (Z_{average}). This curve is formed as part of the current study, and it presents the initial step in formation of hydrographs on ungauged basins within the basin of Bregalnica River. After reading the unit flow, the gauged hydrograph from measuring station ‘Shtip’ is scaled through a coefficient between the derived unit flow for the analysed site, its basin area and the average flow from the gauged hydrograph. The mathematical iteration is given in Equations (1) and (2).

$$K_i = \frac{Q_i}{Q} \tag{1}$$

$$Q_i = M \cdot F_i \tag{2}$$

where: K_i = correlation coefficient, Q_i = average flow from analysed basin (m^3·s^{-1}), Q = average flow from gauged hydrograph from measuring station ‘Shtip’ (m^3·s^{-1}), M = unit flow (dm^3·s^{-1}·km^{-2}), F_i = basin area down to analysed dam site (km^2).

Inflow hydrographs defined for each reservoir are given in Figure 4. The average inflow in Ratevo reservoir is 0.546 m^3·s^{-1}, for Loshana reservoir – 0.074 m^3·s^{-1}, for Kalimanci reservoir – 7.452 m^3·s^{-1}, and for Razlovci reservoir – 3.049 m^3·s^{-1}.

Hydrographs on delivered water for water supply goes to Ratevo and Loshana reservoirs, both reservoirs in operation. The

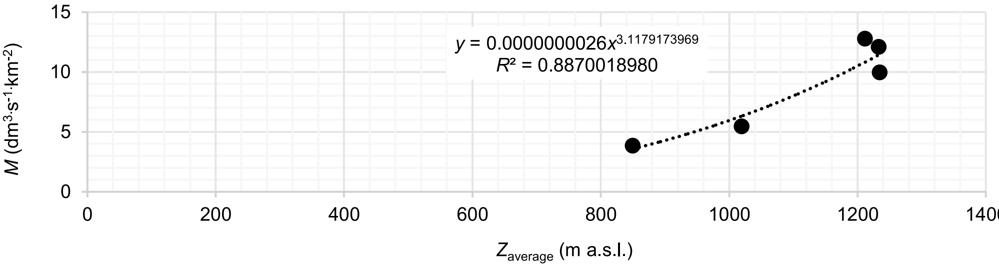

Fig. 3. Unit flow (M) in the basin of Bregalnica River, based on average elevation above sea level (Z_{average}) of the whole analysed basin; source: own study

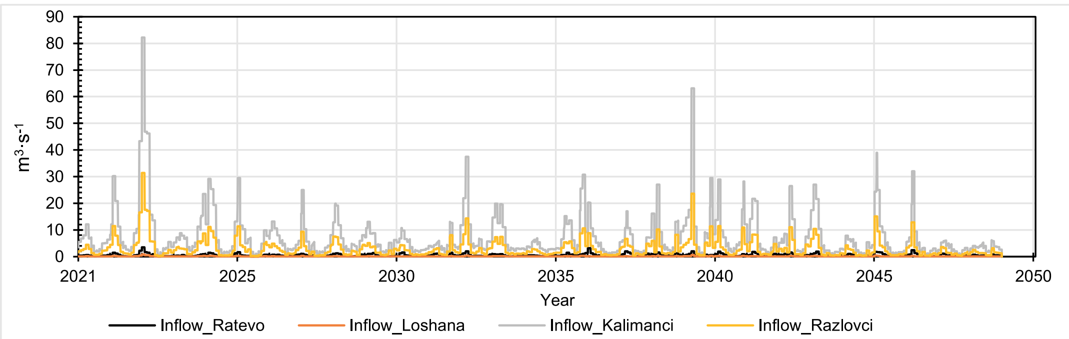

Fig. 4. Inflow hydrographs for Ratevo, Loshana, Kalimanci and Razlovci reservoir; source: own study

average delivered water from Ratevo reservoir is 0.014 $m^3 \cdot s^{-1}$ and for Loshana reservoir – 0.005 $m^3 \cdot s^{-1}$. According to the available data on water needs in the region where water is taken from these two reservoirs, over 90% of the total needs is fulfilled with the operational policy adopted in the simulation model. Respected time-series are given in Figure 5. Delivered water (almost identical to planned water needs for the upcoming period) has a steady decline for both Ratevo and Loshana reservoirs, resulting from constant gradual reduction in population in North Macedonia.

parameter in the models. In Figure 7, fluctuation of water level in Ratevo reservoir is given. In Figure 8, fluctuation of water level in Razlovci reservoir is given. In Figure 9, fluctuation of water level in Loshana reservoir is given, and in Figure 10 – for Kalimanci reservoir. For the smaller reservoirs Ratevo and Loshana, during the simulation period water level is very close to the normal operating water level. For Razlovci and Kalimanci reservoirs this is not the case – water level varies significantly and this is due to the large amount of water drawn from these reservoirs compared to the inflow of water in them.

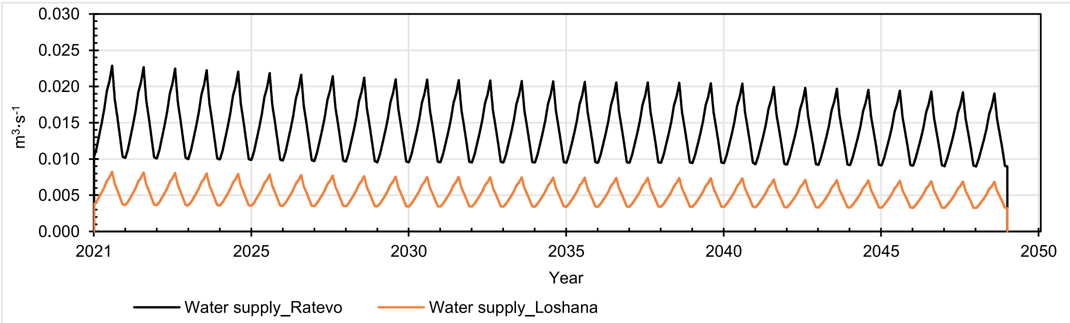

Fig. 5. Delivered water for water supply hydrographs for Ratevo and Loshana reservoir; source: own study

Hydrographs on delivered water for irrigation goes to Ratevo, Kalimanci and Razlovci reservoirs. The average delivered water varies according to the season, with over 78% of all needs for irrigation being fulfilled with the operational policy adopted in the simulation model. The time-series on delivered water are given in Figure 6.

The time-series on water fluctuation in the reservoirs during the time span of the analyses is also used as an operational

At Kalimanci reservoir, a hydropower plant is installed and functioning. The installed turbine flow is 18 $m^3 \cdot s^{-1}$ and the installed power is 13.80 MW. In Figure 11, time-series on turbine flow for the time period from 2020 to 2050 is given. On average, the turbine flow for the analyses is 1.178 $m^3 \cdot s^{-1}$ with 0.809 MW of power production. The power production time series is given in Figure 12.

In summary, the input data for the machine learning models are five different time-series for the operation of the water

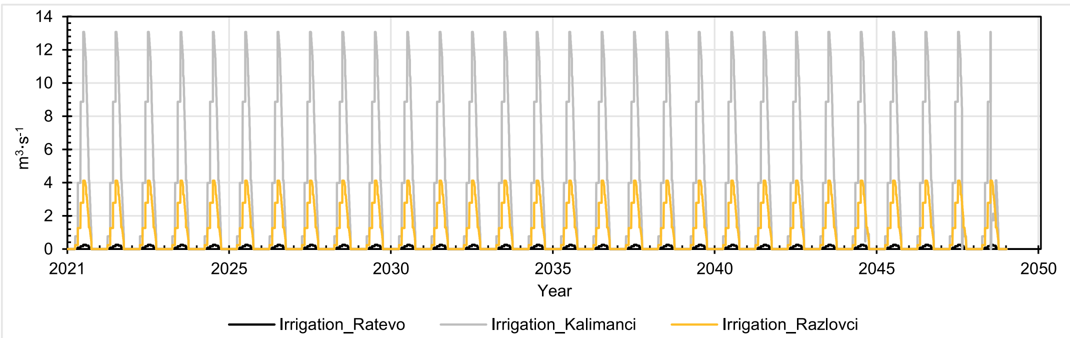

Fig. 6. Delivered water for irrigation hydrographs for Ratevo and Loshana reservoir; source: own study

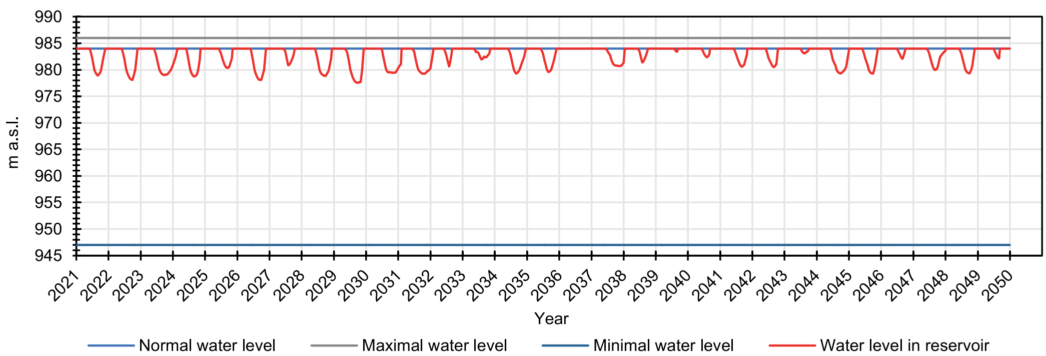

Fig. 7. Fluctuation of water level in Ratevo reservoir; source: own study

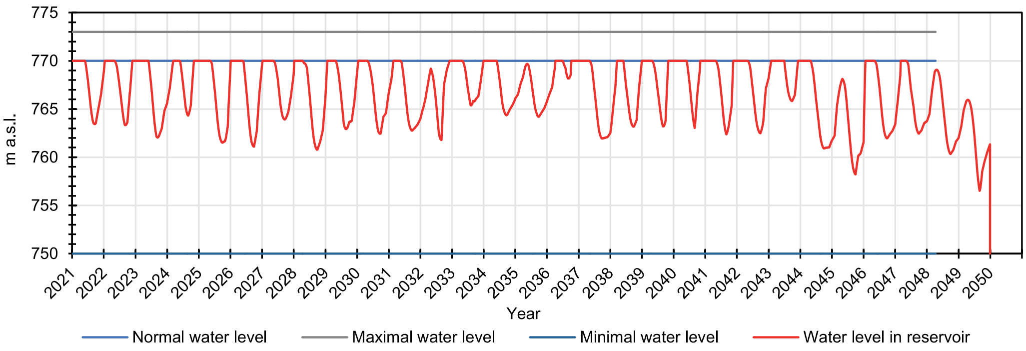

Fig. 8. Fluctuation of water level in Razlovci reservoir; source: own study

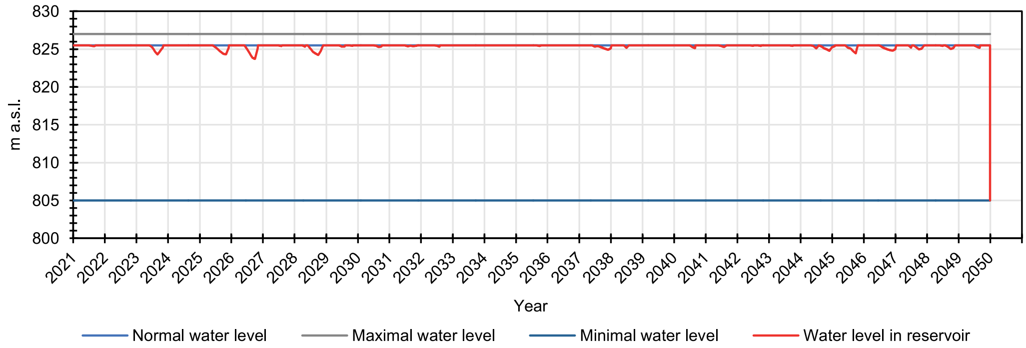

Fig. 9. Fluctuation of water level in Loshana reservoir; source: own study

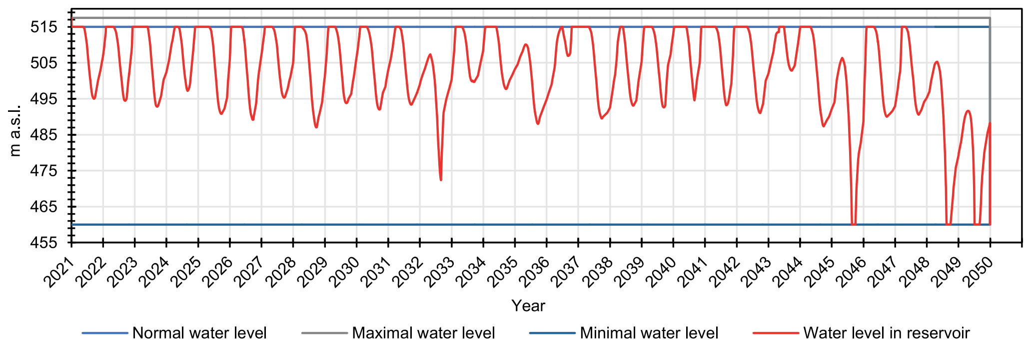

Fig. 10. Fluctuation of water level in Kalimanci reservoir; source: own study

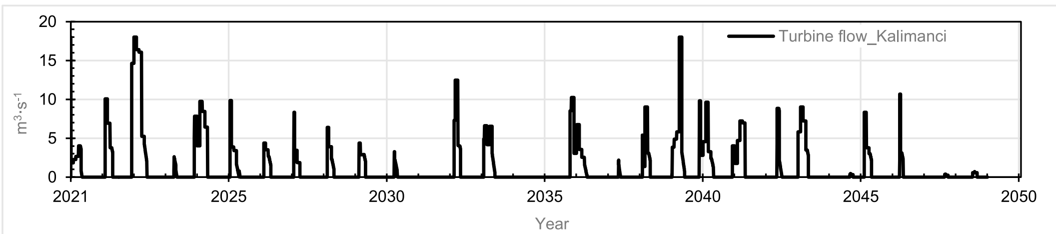

Fig. 11. Time-series on turbine flow for Kalimanci hydropower plant; source: own study

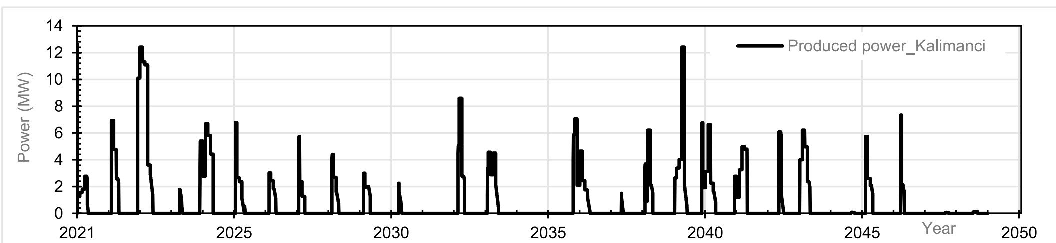

Fig. 12. Time-series on power production for Kalimanci hydropower plant; source: own study

resources system. All time series are variable parameters, except inflow in Kalimanci reservoir, which is posed as target parameter in the analyses. From all 30 years long data series, data from the first 15 years – from year 2021 to year 2035 is used for training and testing the model, and the last 15 years from 2036 to 2049 is used for prediction. The train and test split during the training process is 80% for train and 20% of data used for testing. In order to understand the methodological approach better, a workflow chart is presented in Figure 13 with all steps during the modelling and evaluation process.

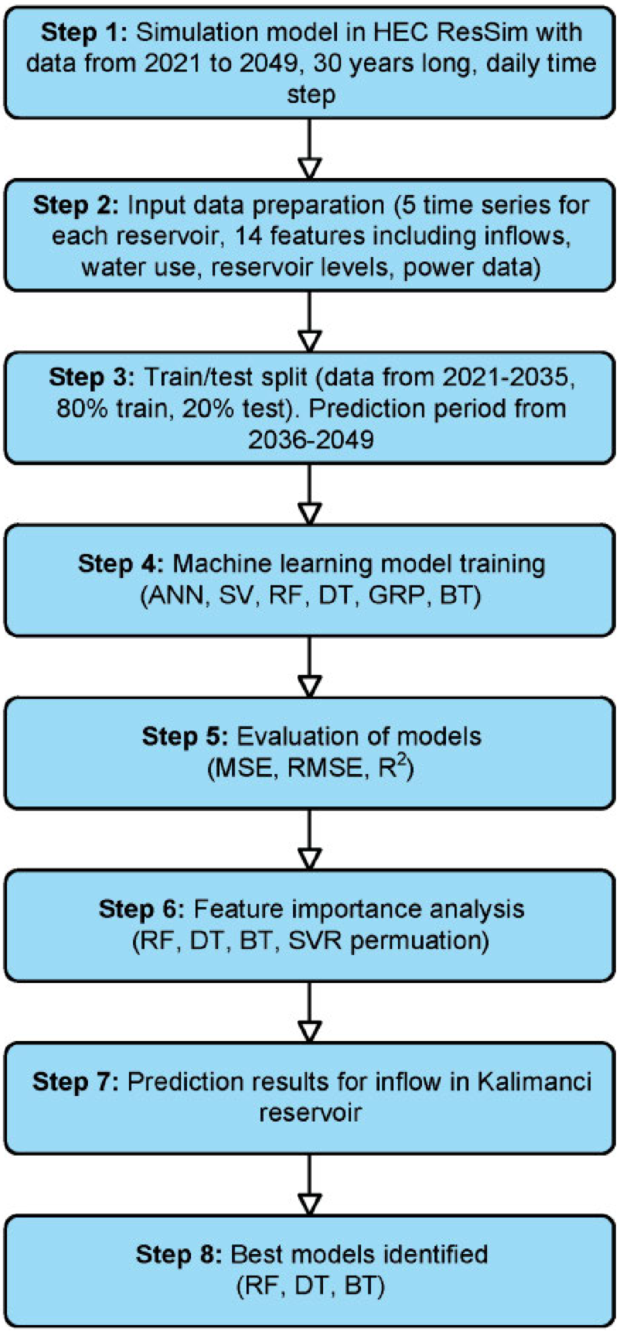

Fig. 13. Workflow chart of the methodology used in the analyses; ANN = artificial neural network, SVR = support vector regression, RF = random forest, DT = decision trees, GPR = Gaussian process regression, BT = boosted trees, *MSE* = mean squared error, *RMSE* = root mean squared error, R^2 = coefficient of determination; source: own study

In order to evaluate the machine learning models, four parameters for evaluation of the metrics are calculated – the mean squared error (*MSE*), the root mean squared error (*RMSE*), mean absolute error (*MAE*) and coefficient of determination (R^2).

MSE measures the average of the squares of the error, i.e. the average squared difference between the actual and predicted values. The formula of *MSE* is given in Equation 3. The lower the *MSE*, the better the model's performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^{'}\right)^2 \tag{3}$$

where: y_i = the actual value, y_i' = the predicted value, n = number of observations.

RMSE is the square root of the *MSE*. It brings the error measure back to the same units as the original data, making it easier to interpret than *MSE*. The formula of *RMSE* is given in Equation 4. The lower the *RMSE*, the accuracy of the prediction is better.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^{'}\right)^2} \tag{4}$$

MAE is the average of the absolute differences between actual and predicted values. Unlike *MSE* and *RMSE*, it does not square the errors, making it more robust to outliers. The formula of *RMSE* is given in Equation 5. The closer to 0, the better the model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i^{'}\right| \tag{5}$$

R^2 represents the proportion of variance in the dependent variable that is predictable from the independent variables. It measures how well the model explains the variability of the output. The formula of R^2 is given in Equation 6. R^2 ranges from 0 to 1, with values closer to 1 showing better prediction.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i^{'}\right)^2}{\sum_{i=1}^{n}\left(y_i - y_{aver}\right)^2} \tag{6}$$

where: y_{aver} = the mean of the actual values.

RESULTS AND DISCUSSION

Six different machine learning algorithms are analysed with the data from operation of the four dams with reservoirs Ratevo, Razlovci, Kalimanci and Loshana. The algorithm is prepared in Python, as part of the research. The methods used, are: artificial neural networks (ANNs), support vector machines/support vector regression (SVM/SVR), random forest (RF), decision trees (DT), Gaussian process regression (GPR) and boosted regression trees (BRT).

During the development of the models, two phases are distinguished – at first, train and test input data, and second – observe prediction. The first phase is conducted with 15 years-long data, from 2021 to 2035. The second phase of prediction is conducted with 15 years-long data, from 2036 to 2049. In the train and test period, 80% of the input data is for training, and 20% – for testing.

Target parameter in the models is the inflow in Kalimanci reservoir. Variable parameters, used as time-series, are:
1) inflow in Ratevo reservoir,
2) inflow in Loshana reservoir,
3) inflow in Razlovci reservoir,
4) delivered water for water supply from Ratevo reservoir,
5) delivered water for water supply from Loshana reservoir,
6) delivered water for irrigation from Ratevo reservoir,
7) delivered water for irrigation from Kalimanci reservoir,
8) delivered water for irrigation from Razlovci reservoir,
9) fluctuation of water level in Ratevo reservoir,
10) fluctuation of water level in Kalimanci reservoir,
11) fluctuation of water level in Razlovci reservoir,
12) fluctuation of water level in Loshana reservoir,
13) delivered power from Kalimanci hydropower plant, and
14) turbine flow from Kalimanci hydropower plant.

From the analyses during the train and test period, the first overview of the models is done through the four parameters for evaluation of the metrics: *MSE*, *RMSE*, *MAE* and R^2. Their values are given in Table 2.

Table 2. Values of the parameters for evaluation of the metrics obtained during train and test of ML models

Model	*MSE*	*RMSE*	*MAE*	R^2
Decision tree	0.003	0.059	0.011	1.000
Random forest	0.004	0.067	0.014	1.000
ANN	0.051	0.226	0.142	1.000
Boosted trees	0.066	0.257	0.171	0.999
SVR	0.107	0.328	0.115	0.999
GPR	183.576	13.549	8.373	–0.618

Explanations: *MSE* = mean squared error, *RMSE* = root mean squared error, *MAE* = mean absolute error, R^2 = coefficient of determination, ANN = artificial neural network, SVR = support vector regression, GPR = Gaussian process regression.

The *MSE* parameter has best value calculated for the DT model with value of 0.003, whereas the highest value is calculated for the GPR model as 183.575860. The *RMSE* parameter has best value for the DT model with value of 0.058, whereas the highest value is calculated for the GPR model as 13.549017. The *MAE* parameter has very good values for both the DT and RF models with value of 0.011 for DT and 0.013 for RF, highest value, again, is calculated in the results of the GPR model. R^2 parameter has very good values for DT, FP, ANN, BT and SVR – all over 0.999, and lowest value for the GPR model with negative value of –0.617. The achieved values of metrics for the GPR model paints a picture of a model that fails to explain the variance in the target parameter. This is probably due to the GPR's sensitivity to noisy, high-dimensional and non-stationary data. The nonlinearity and noise is due to the 14 sets of input variables with large input range and variance, with patterns that change across seasons and years. After analysing all parameter's values, the GPR model is not furtherly used for prediction.

Feature importance is also analysed in the train and test period for RF, DT and BT models.

In RF model, highest importance for the target parameter has the value of 'Loshana inflow', followed by 'Razlovci inflow' and 'Ratevo inflow'. The values of 'Razlovci reservoir level', 'Kalimanci power' and 'Kalimanci turbine flow' have very little importance in the model. Values are given in Figure 14.

In DT model, highest importance for the target parameter has the value of 'Loshana inflow', followed by 'Razlovci inflow' and 'Ratevo inflow', with very little importance of the values of 'Kalimanci reservoir level' and 'Razlovci reservoir level'. Values are given in Figure 15.

The BT model has the same order of importance for parameters as in the RF model. Values are given in Figure 16.

For the SVR model, permutation importance is calculated for all the variable parameters. The values are given in Figure 17. From the data, it can be observed that the highest permutation importance have the values for 'Razlovci inflow', 'Loshana inflow' and 'Ratevo inflow'. Secondary importance have the values of

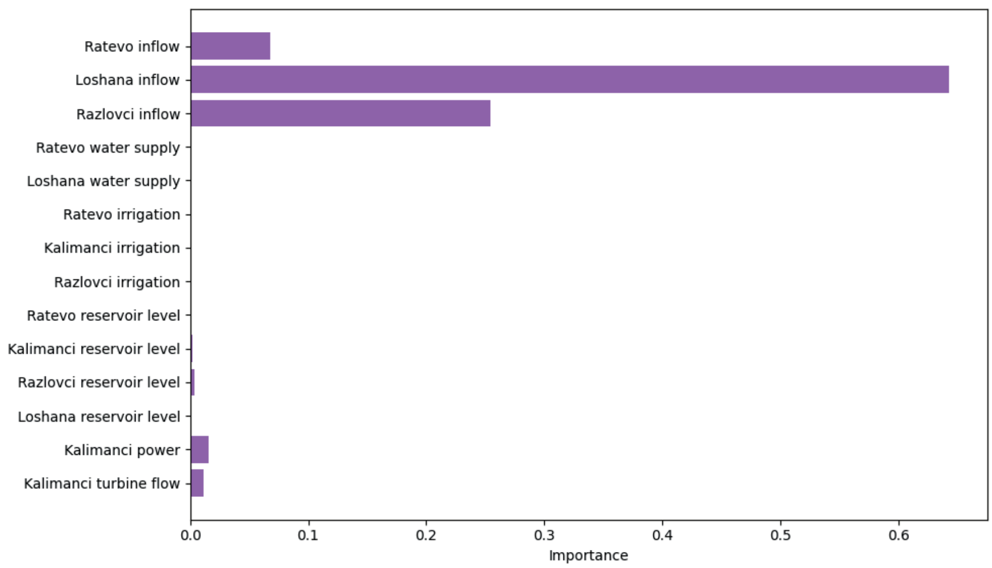

Fig. 14. Feature importance for the random forest (RF) model; source: own study

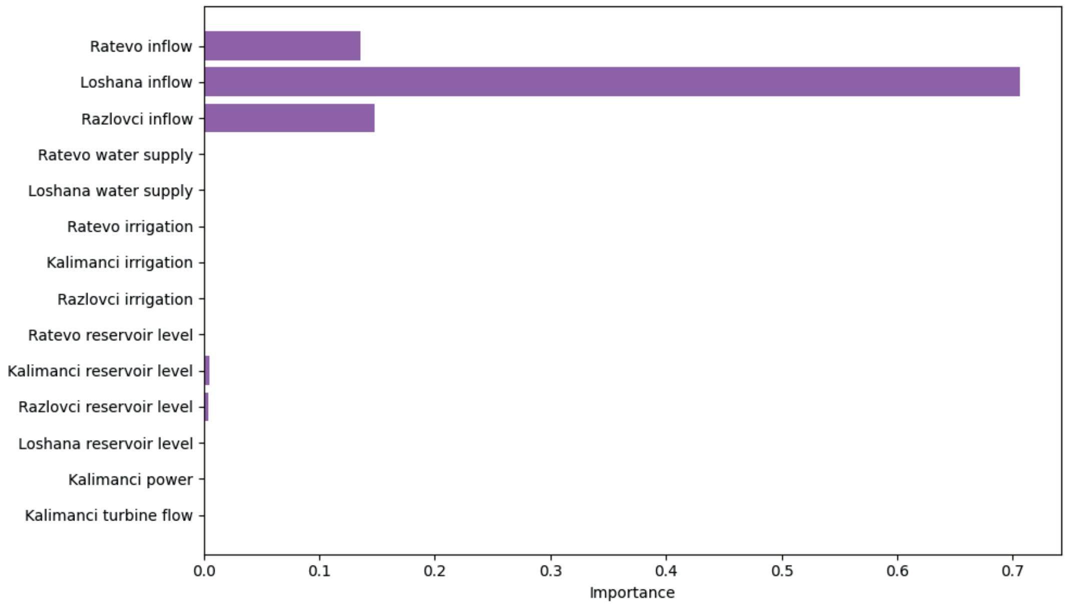

Fig. 15. Feature importance for the decision tree (DT) model; source: own study

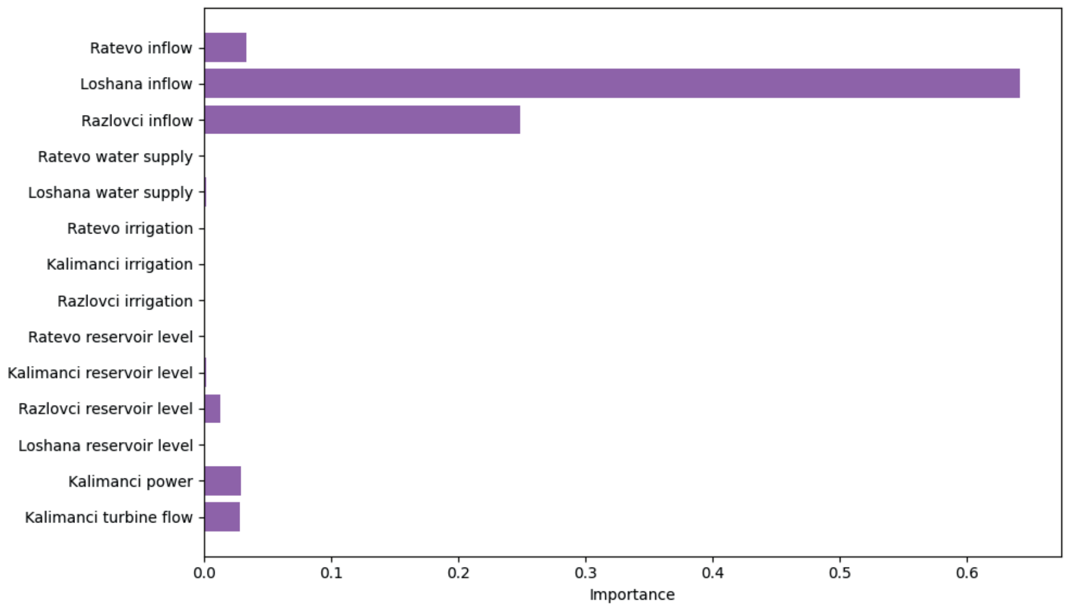

Fig. 16. Feature importance for the boosted tree (BT) model; source: own study

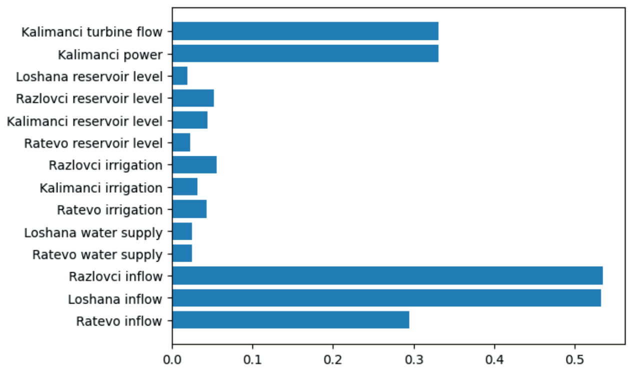

Fig. 17. Permutation importance for the support vector regression (SVR) model; source: own study

'Kalimanci turbine flow' and 'Kalimanci power'. All the other parameters have smaller importance values in the model.

During the prediction phase, the trained model for ANN, SVR, RF and BT models are used. All results including the data from simulation model for the target parameter – inflow in Kalimanci reservoir, are given in Figure 18. Visually, all models give good predictions, close to the real values. The SVR model has more skewing on the prediction rather than the other models.

Residual analysis was performed to assess the accuracy and bias of the machine learning models in predicting inflow to the Kalimanci reservoir. Residuals are defined as the difference between the observed values from the simulation model and the predicted values from each ML model. Ideally, residuals should be symmetrically distributed around zero, with no apparent pattern, indicating a well-fitted model with minimal bias.

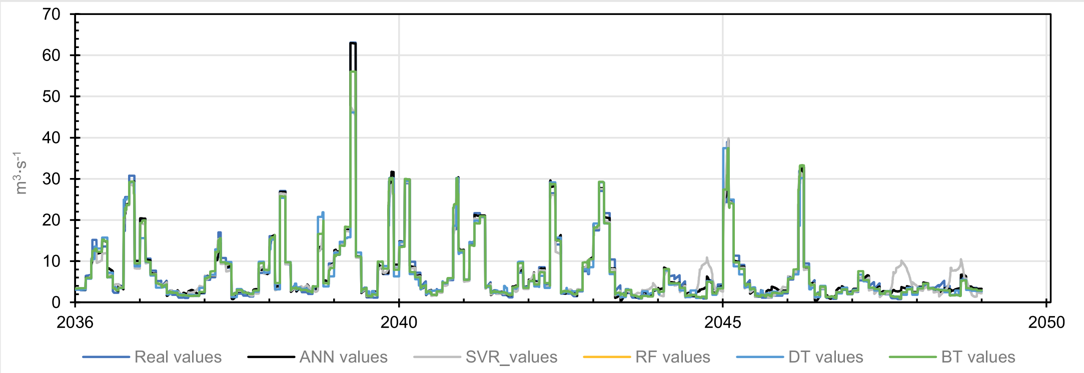

Fig. 18. Actual vs. predicted target parameter – time series; ANN = artificial neural network, SVR = support vector regression, RF = random forest, DT = decision trees, BT = boosted trees; source: own study

The ANN model demonstrates a relatively balanced residual distribution, with values tightly clustered around the zero line, suggesting good predictive accuracy and minimal systematic error (Fig. 19a). In contrast, the SVR model exhibits a clear tendency toward negative residuals, indicating that the model systematically overestimates inflow values. This skewed distribution highlights potential overfitting or model bias, reducing its reliability for long-term inflow forecasting (Fig. 19b).

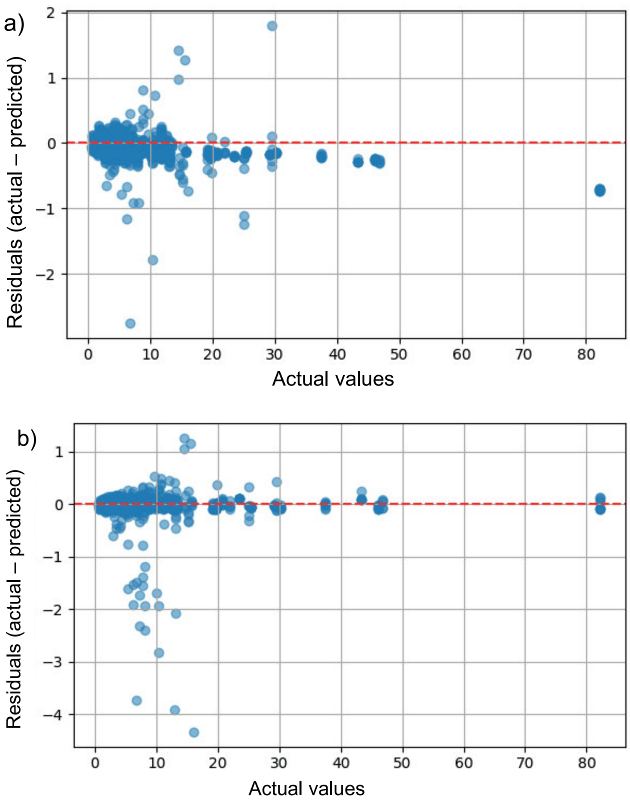

Fig. 19. Calculated residuals for the: a) artificial neural network (ANN) and b) support vector regression (SVR) model; source: own study

Both random forest (RF) and decision tree (DT) models display tight residual clouds centred around zero, with low dispersion. This behaviour is consistent with their excellent performance metrics ($R^2 \approx 1.000$, low *MAE*/*RMSE*) and confirms their robustness and generalization ability across the prediction set. No significant bias or variance patterns were observed, supporting their suitability for real-time operation (Fig. 20).

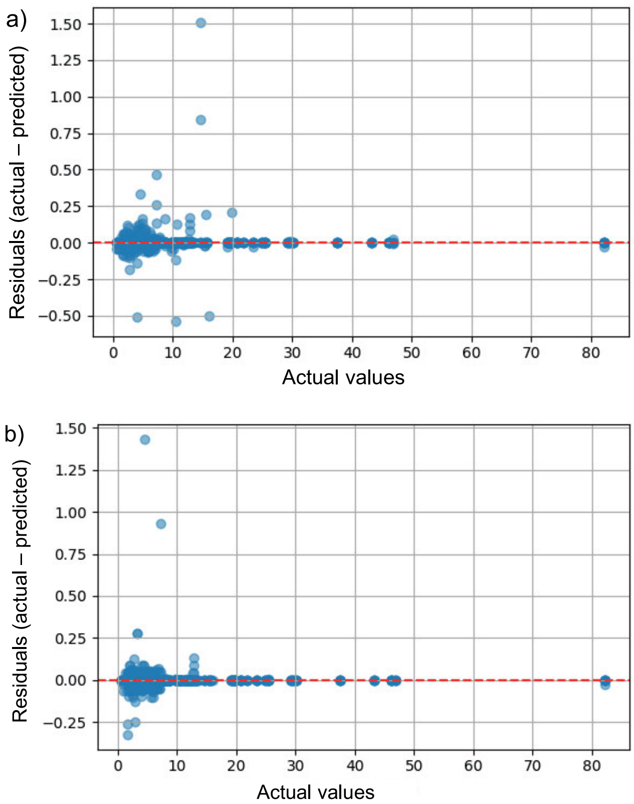

Fig. 20. Calculated residuals for the: a) random forest (RF) and b) decision trees (DT) model; source: own study

The boosted trees (BT) model also shows a well-balanced residual distribution, although with slightly broader spread compared to RF and DT (Fig. 21). Despite this, the residuals remain within acceptable bounds, reinforcing BT's position among the top-performing models. This is consistent with its high R^2 and low error metrics.

From the analyses, the models of RF, DT and BT are recommended for further use in real-time operation with the system. These models have the best results during the train and testing period, as well as during the prediction period. The analyses are conducted for target parameter – inflow in Kalimanci reservoir in order to oversee how would the management of the upper three reservoirs Ratevo, Razlovci and Loshana impact the management of Kalimanci reservoir. Namely, today three of the reservoirs are functioning – Loshana, Ratevo and Kalimanci,

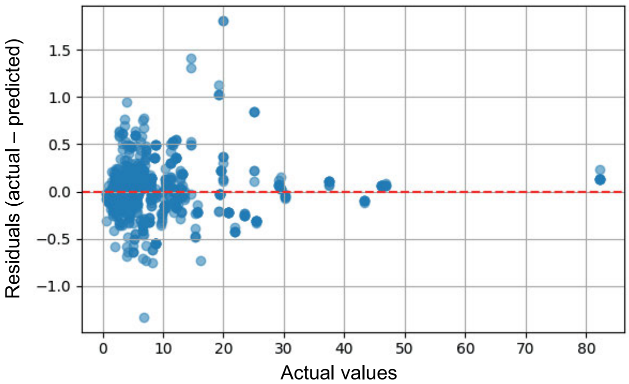

Fig. 21. Calculated residuals for the boosted trees (BT) model; source: own study

with Razlovci still in design phase. Including this reservoir in the scheme would mean major regulation of the inflow towards Kalimanci reservoir. Kalimanci reservoir is the largest one in the analysed water resources system, with active volume of 127 mln m^3. Today Kalimanci reservoir is facing major demands for irrigation supply, and electricity production is majorly put on hold. The reservoir is closer to the minimal water elevation most of the year, which means the inflow and outflow are in great difference, i.e. the needs surpass the available water. With this research, we have created a simulation model for prospective upgraded version of the system, including Razlovci reservoir. The results show that the inflow in Kalimanci reservoir is greatly influenced by the inflows in Loshana reservoir, Ratevo reservoir and Razlovci reservoir.

CONCLUSIONS

This study evaluated the effectiveness of six machine learning models – artificial neural networks (ANNs), support vector machines/support vector regression (SVM/SVR), random forest (RF), decision trees (DT), Gaussian process regression (GPR), and boosted trees (BT) – for inflow prediction in a complex cascade reservoir system on the Bregalnica River, North Macedonia. Input data for the models were derived from a 30-year simulation using HEC-ResSim, and included 14 time-series variables related to inflows, water supply, irrigation, reservoir levels, and power production. The target variable was the inflow into the Kalimanci reservoir, the largest and most downstream reservoir in the system.

Model performance was evaluated using four standard metrics: mean squared error (*MSE*), root mean squared error (*RMSE*), mean absolute error (*MAE*), and coefficient of determination (R^2). Among the tested models, the decision tree (DT) and random forest (RF) achieved the best results during both training and testing, with R^2 = 1.000, *MAE* = 0.011–0.014, and *RMSE* = 0.059–0.067, indicating extremely high accuracy and reliability. The boosted trees (BT) model also performed well, with R^2 = 0.999 and *RMSE* = 0.257. In contrast, the Gaussian process regression (GPR) model showed very poor performance (R^2 = −0.618, *RMSE* = 13.549) and was excluded from the prediction phase.

During the prediction period (2036–2049), the RF, DT, and BT models continued to demonstrate robust performance with accurate inflow estimates and minimal residuals. Feature importance analysis confirmed that upstream reservoir inflows (particularly from Loshana and Razlovci) had the greatest influence on Kalimanci inflow. Based on these findings, the RF, DT, and BT models are recommended for integration into real-time water system operation to support efficient and sustainable reservoir management.

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CONFLICT OF INTEREST

All authors declare that they have no conflict of interest.

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