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Simulation of River Discharge Upstream of Dez Dam Using Metaheuristic Models

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Abstract

Accurate river discharge measurement remains a fundamental challenge in water resource management. This study presents an innovative approach by developing hybrid intelligent models based on Support Vector Regression (SVR) to enhance river flow prediction. The key innovation of this research lies in the novel integration of SVR with three advanced optimization techniques—Wavelet Transform, Whale Optimization Algorithm (WOA), and Particle Swarm Optimization (PSO)—marking the first comprehensive application of these hybrid models in the Dez River Basin. Using data from four hydrometric stations (Tireh Marouk, Cham Chit, Sezar, and Tang-e Panj) from 2012 to 2022, the models were evaluated using statistical metrics, including correlation coefficient, root mean square error (RMSE), mean absolute error (MAE), and Nash-Sutcliffe Efficiency (NSE). Results demonstrated that the SVR-Wavelet model outperformed others, achieving a correlation coefficient of 0.898–0.985, RMSE of 0.008–0.088 m^3/s, MAE of 0.004–0.040 m^3/s, and NSE of 0.951–0.995 during validation. This study provides a precise tool for sustainable water resource management in the Dez Basin, which is critical for agriculture , industry, and drinking water supply. With a 30% decline in river discharge over the past decade, the proposed models offer vital insights for adaptive water management amid climate change and drought conditions. The findings serve as a benchmark for decision-making in water-stressed regions, particularly in arid and semi-arid environments.

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Introduction

Water resources management is a highly complex process comprised of various components, each with its own unique characteristics (Beirlant & Vries, 2013). Rivers are a major component of water resource systems, and monitoring their quantitative and qualitative parameters is of particular importance (Yildiz et al., 2022). Water flow is one of the most important indicators affecting river management, as its changes over time can have significant impacts on natural ecosystems (Mariella et al., 2022). For example, excessive reduction of river flow can lead to the destruction of aquatic life, while excessive increases in river discharge can cause destructive floods (Parisouj et al., 2020). Therefore, accurate methods should be used in river flow modeling and its prediction in the short and long term (Ghorani & Shabanlou, 2021). In the past, physical models have mainly been used to simulate river flow. These models are often time-consuming and do not have satisfactory accuracy (Zhao et al., 2021). In recent years, artificial intelligence-based methods have emerged, which require less time and cost to develop compared to physical models, and require less data compared to numerical models. Artificial intelligence methods are inspired by the nature of living organisms and can be used to model various linear and nonlinear systems (Mazare et al., 2024). These models have attracted the attention of researchers in the field of river flow simulation, including the following. Alizadeh et al. (2020) used a hybrid support vector regression-wavelet model to simulate runoff from the Souris River in the United States. This study used daily flow discharge data with different time lags from 1998 to 2018. The results showed that the hybrid model is more accurate than the single support vector regression model. Dehghani et al. (2020) used a hybrid support vector regression-artificial plant optimization algorithm to model the discharge of rivers in the Dez watershed in Iran. This study used flow discharge data with different time lags from 2008 to 2018 on a daily time scale. The results showed that the new hybrid support vector regression-artificial plant model is more accurate than the support vector regression-wavelet and support vector regression-Bayesian models examined. Sahoo et al. (2021) used artificial neural networks, support vector machines, back-propagation neural networks, and radial basis function networks to predict flood discharge in the Odisha basin in India. This study used discharge and precipitation data from 2010 to 2020 on a monthly time scale. The results showed that the support vector machine model performs better than the other models examined. Kohansalraz et al. (2024) used a hybrid model based on support vector regression with Harris, Gray Wolf, and Locust algorithms to model the discharge of the Gamasiab River in Kermanshah province in Iran. This study used discharge, precipitation, and temperature data from 2000 to 2021. The results showed that hybrid models based on support vector regression are a useful tool for simulating river flow, and the results also showed that the support vector regression-Harris algorithm has good accuracy compared to the other models examined. Overall, according to the research conducted, the support vector regression artificial intelligence model is an efficient tool in simulating river discharge and hydrological problems. Today, in order to increase the efficiency and improve the performance of the support vector regression model, the combination of this model with metaheuristic algorithms is used as a suitable solution for simulating river discharge. This study demonstrates the effectiveness of hybrid support vector regression (SVR) models for accurate river discharge prediction, introducing three novel hybrid approaches: wavelet-SVR (WSVR), whale optimization algorithm-SVR (WOA-SVR), and particle swarm optimization-SVR (PSO-SVR). The research makes significant contributions as the first comprehensive comparison and implementation of these advanced hybrid models for flow simulation in western Iran's Dez River basin, an area experiencing severe water stress with 30% flow reductions since 2010. The developed WSVR model showed particularly strong performance, providing water managers with a reliable tool for critical applications including: (1) drought early warning systems, (2) optimized agricultural water allocation, and (3) climate adaptation planning. The Tireh Marouk, Cham Chit, Sezar, and Tang Panj rivers studied here support vital economic activities including agriculture (>60% of regional GDP), fisheries, and eco-tourism, making accurate flow prediction essential for sustainable water management. This work establishes an important methodological framework for combining signal processing techniques (wavelet transform) and metaheuristic optimization algorithms with machine learning in hydrology. The results are especially valuable for data-scarce, water-stressed regions, offering both technical advances in modeling approaches and practical solutions for water resource management.

Materials and Methods

The Studied region

Iran has six main catchments: the Central Plateau, Hamoon, Sarakhs, the Caspian Sea, Lake Urmia and the Persian Gulf and the Sea of Oman. The Persian Gulf and the Sea of Oman are among the most important catchments in Iran. Several studies, including the Karun Bozorg basin, which is below the Dez basin, have been used in this study. Catchment area of Dez river as a third degree area is a subgroup for Karoun area in Iran country, and placed as a sub-group for Persian gulf area, and Oman sea. Sezar, and Bakhtiari are two main branches for Dez river. Sezar river is placed at northest of Dez area and comprised three branches of Marbereh, Tireh, and Sabzeh. Different waterways are joined, such as Azna river in Aligoodarz region and create Marbereh river. It flows in direction of western to eastern in Lorestan province. Dez catchment area in south-western is at semi-arid and mountain regions at lengths of 48º 9’15” to 50º 18’37” and widths of 31º 35’51” to 34º 7’46” northern. Figure 1 shows Dez catchment and selected stations. Station characteristics are shown in Table 1.

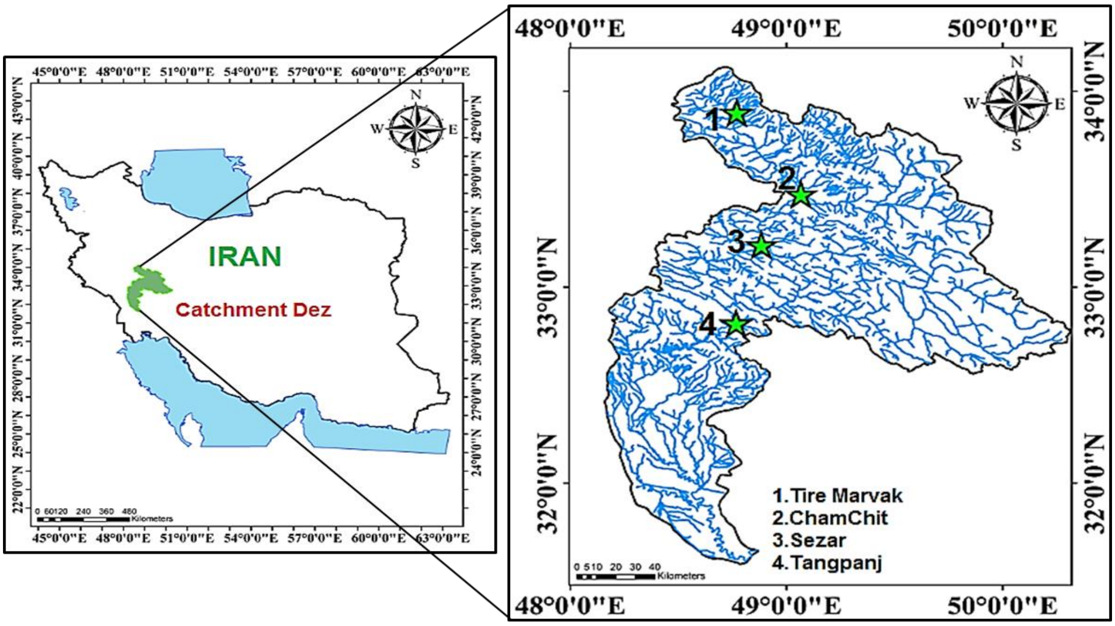

Figure 1. The studied region

Table 1. Station characteristics

	Station name	Area (Km^2)	Latitude	Longitude
1	Tireh marok	3400	33 ° 28′ 37 ″	49 ° 3′ 46 ″
2	Cham chit	345	33 ° 22′ 43 ″	47 ° 57′ 58 ″
3	Sezar	9434	33 ° 54′ 7 ″	49 ° 33′ 15 ″
4	Tang pangeh	555	32 ° 56′	48 ° 46′

Methodology

This study utilized daily time-series data obtained from the Lorestan Regional Water Company and Khuzestan Water and Power Authority. The Dez River basin contains an extensive network of hydrometric stations. For this research, we specifically selected stations meeting two critical criteria: (1) availability of long-term historical records, and (2) strategic positioning along primary tributaries. This selection methodology enabled accurate discharge estimation, resulting in our focus on four key stations (Tireh Marouk, Cham Chit, Sezar, and Tang-Pang) for comprehensive analysis. After identifying a complete statistical period without missing data, we normalized the dataset for integration. The processed data was then incorporated into intelligent models based on Support Vector Regression (SVR). To enhance model accuracy, we implemented parameter optimization using three advanced algorithms: wavelet transform, Whale Optimization Algorithm (WOA), and Particle Swarm Optimization (PSO). These techniques specifically optimized the activation functions (kernels) of the SVR model. The modeling process employed an 80:20 data split, with randomly selected training data (2012-2019) and validation data (2020-2022). The models incorporated time-lagged daily discharge parameters as input features to generate predictive outputs. Output responses were rigorously evaluated using quantitative performance metrics (correlation coefficient, RMSE, MAE, Nash-Sutcliffe Efficiency) complemented by qualitative diagram analysis. This systematic approach ensured robust assessment of model performance in simulating the Dez basin's hydrological dynamics.Figure 2 shows the research flowchart.

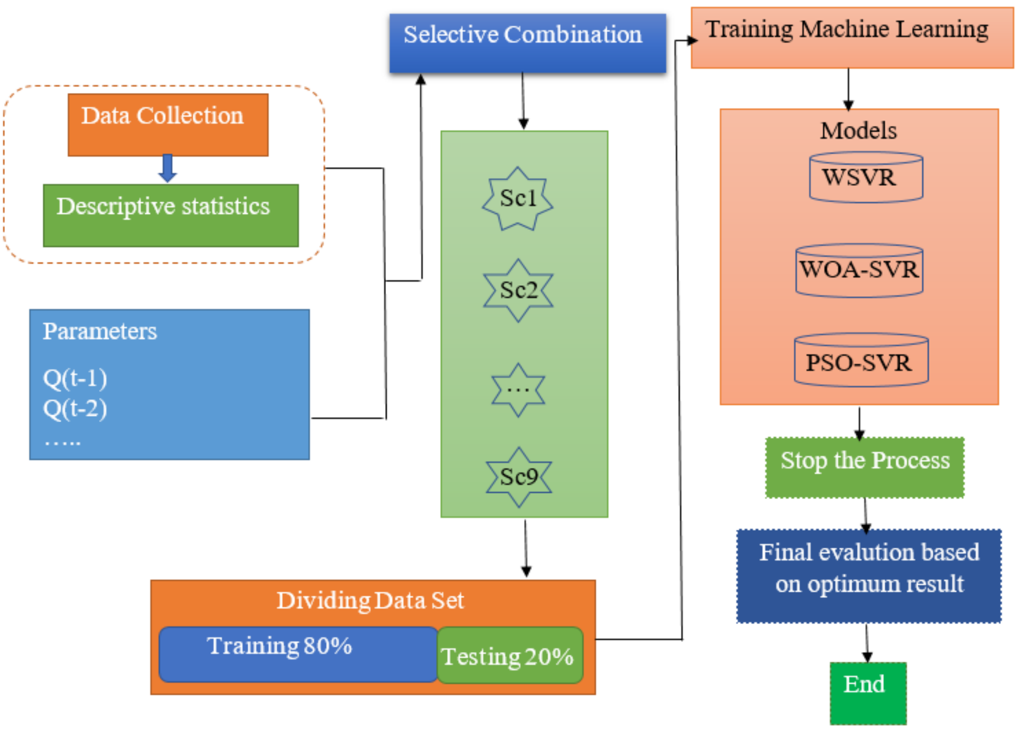

Figure 2. Research flowchart

Support Vector Regression (SVR)

Support Vector Regression is an artificial intelligence method based on optimization theory and follows the principle of minimizing error, which leads to a global optimal solution (Vapnik, 1995). In the SVR model, which includes a function with dependent variables Y, the dependent variable is composed of several independent variables X and an error term. As observed in regression problems, there is an algebraic relationship between the dependent and independent variables, as shown below in the structure of the Support Vector Regression model (Vapnik, 1998).

$$f(x)=W^{T}.\emptyset(x)+b \quad (1)$$

$$y=f(x)+noise \quad (2)$$

Like other artificial intelligence models, Support Vector Regression has activation functions called kernels. These kernels include the Polynomial kernel, Radial Basis Function (RBF) kernel, and Linear kernel, and are estimated according to the following relationships (Vapnik & Chervonenkis, 1991; Basak et al., 2007). These three kernel functions were also used in this research. The Support Vector Regression model was also coded in MATLAB software.

$$k(x,x_j)=(t+x_i.x_j)^d \quad (3)$$

$$K(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \quad (4)$$

$$k(x,x_j)=x_i.\,x_j \quad (5)$$

Wavelet Transform

Wavelet transform is presented as an alternative to short-time Fourier transform, and its purpose is to overcome the problems related to frequency resolution in short-time Fourier transform. In wavelet transform, as in short-time Fourier transform, the signal is divided into windows, and wavelet transform is performed separately on each of these windows (Vapnik, 1998). However, the most important difference between them is that in wavelet transform, in addition to the frequency resolution of a signal or the length of a window changing in proportion to the type of frequency, the window width or frequency scale also changes in proportion to the type of frequency. In other words, in wavelet transform, there is a scale instead of frequency. That is, wavelet transform is a type of time-scale transform. Accordingly, using wavelet transform, the signal is expanded in high scales and the details of the signal can be analyzed, and in low scales, the signal is contracted and the generalities of the signal can be examined (Wang et al., 2000). A wavelet, meaning a small wave, is a part or window of the original signal whose energy is concentrated in time. Using wavelet transform or analysis, a signal or mother time series can be decomposed into wavelets with different levels of resolution and scales. Therefore, wavelets are translated and scaled samples of the mother signal that have oscillations in a finite length and are highly damped. Based on this important feature of wavelet transform, non-stationary and transient time series can be analyzed locally (Shin et al., 2005).

Particle Swarm Optimization (PSO)

The Particle Swarm Optimization algorithm is a metaheuristic algorithm that was first introduced by Kennedy and Eberhart (1995) (Eberhart and Kennedy, 1995). These researchers first examined computational intelligence based on social relations, then conducted these studies on groups of animals and humans, and finally, this algorithm was inspired by the nature of the behavior of birds and fish. This algorithm is inspired by the collective behavior of a group of birds or fish. Like other optimization algorithms, this algorithm helps a group of birds and fish find the most suitable path to reach the nest and food without obstructing the movement of other particles. The steps of this algorithm in this research are such that the initial population is first generated, the velocity vectors of the particles are initially zero, and the location vector is randomly selected. In the next step, the value of the particle is evaluated, and then the best individual position and velocity of the particle are updated (Shrivatava et al., 2015). The flowchart of this algorithm is shown in the figure below.

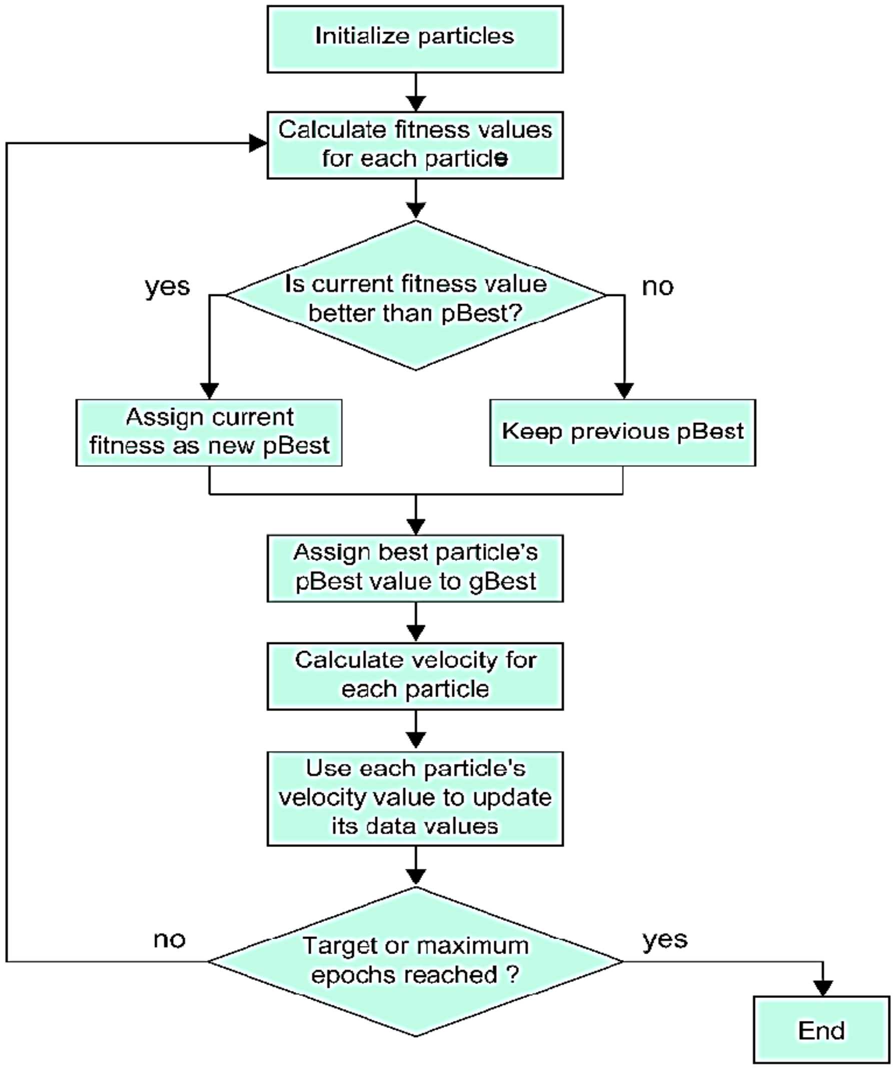

Figure 3. Flowchart of the particle swarm algorithm

Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm is a metaheuristic algorithm inspired by the nature and behavior of living organisms and is used in various fields. It was first introduced by Mirjalili and Lewis (2016). This algorithm originates from the behavior of whales during hunting, in such a way that the whale identifies the hunting location and surrounds it. In this algorithm, it is assumed that the most suitable solution is to hunt the target. In this algorithm, after the best hunting target is searched, other search agents try to update their location relative to the best prey (Reddy and Saha, 2022). The behavior of this algorithm follows the following relationships:

$$\vec{D} = \left|\vec{C}.\vec{X} - \vec{X}(t)\right| \quad (6)$$

$$\vec{X}(+1) = \vec{X^*}(t) - \vec{A}.\vec{D} \quad (7)$$

“where A and C are coefficient vectors, X^* is the position vector of the best solution obtained so far, and X is the position vector. The vectors C and A are calculated as follows:”

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (8)$$

$$\vec{C} = 2\vec{r} \quad (9)$$

In the above formulas, ‘a’ linearly decreases from a value between 2 and 0 in each iteration, and ‘r’ is a random vector in the range of 0 to 1. The flowchart of this algorithm is shown in the figure below.

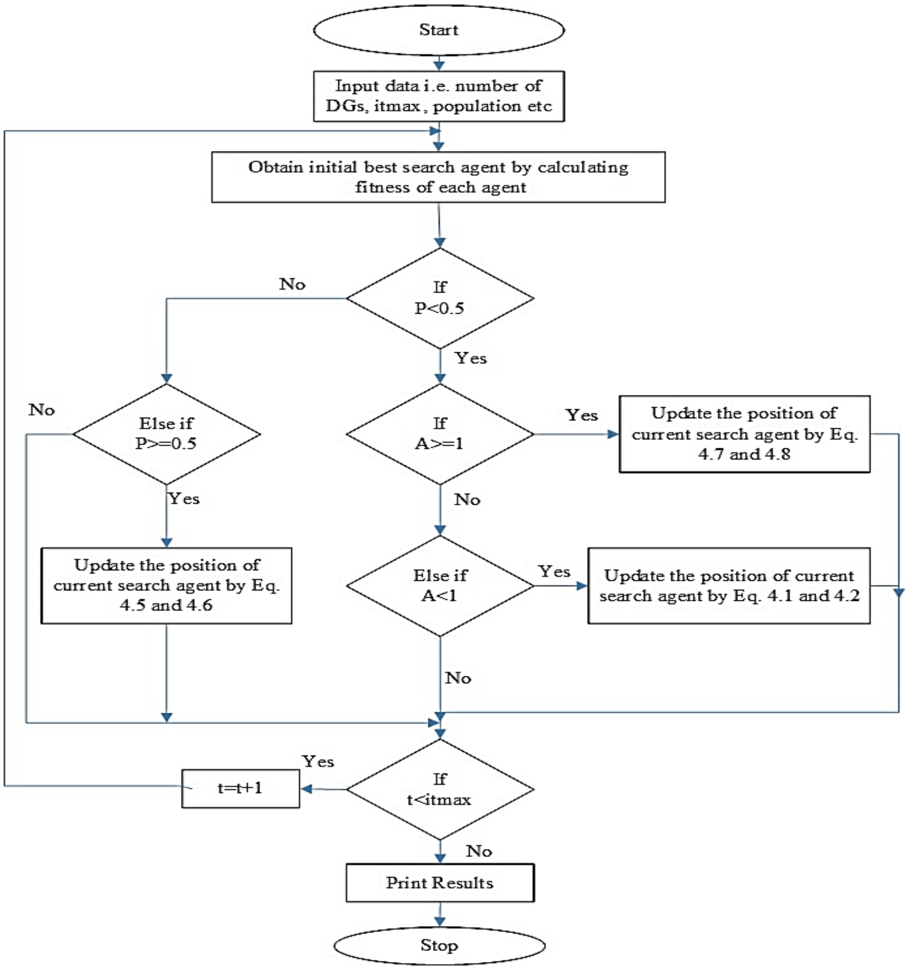

Figure 4. Whale algorithm flowchart

Evaluation Criteria

In this study, the following evaluation indices were used to evaluate the models under investigation for simulating the discharge of rivers in the Dez watershed

$$R=\frac{\sum_{i=1}^{N}(x_i-\bar{x})\,(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2\;\sum_{i=1}^{N}\,(y_i-\bar{y})^2}}\quad 1\leq R\leq 1 \qquad (10)$$

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\,(x_i-y_i)^2} \qquad (11)$$

$$MAE=\frac{\sum_{i=1}^{n}|x_i-y_i|}{n} \qquad (12)$$

$$NS=1-\frac{\sum_{i=1}^{N}\,(x_i-y_i)^2}{\sum_{i=1}^{N}\,(x_i-\bar{y})^2}\quad \infty\leq NS\leq 1 \qquad (13)$$

In the above relations, R is the correlation coefficient, RMSE is the root mean square error in m3/sm3/s, and NSNS is the Nash-Sutcliffe efficiency. x_i and y_i represent the observed and computed values at the i-th time step, respectively. N is the number of time steps, while x¯ and y¯ are the mean values of the observed and computed data, respectively. In addition to these metrics, scatter plots and time series graphs of the observed-computed values over time are also used for further comparison and analysis.

Results and Discussion

In this study, Support Vector Regression (SVR) models with Wavelet, Whale Optimization Algorithm (WOA), and Particle Swarm Optimization (PSO) were used to simulate the discharge of rivers in the Dez watershed, including Tireh Marouk and Cham Chit in Lorestan province, and Sezar and Tang-e Panj in Khuzestan province. The parameters of delayed discharge Q(t), Q(t-1), Q(t-2), and Q(t-3) were considered as model inputs, and the parameter Q(t) was considered as the model output during the years 2012-2022. It is worth noting that the time lag of the discharge parameters and the river discharge rate are based on the correlation coefficient of these parameters with the model output, in such a way that the time lag was performed up to the point where there was a significant correlation between the parameters (Rajaei et al., 2011). Table 2 presents the correlation coefficient of the flow discharge parameter at different time lags. For the modeling process in this study, 80% of the data were selected for training and the remaining 20% for testing, completely randomly (Nagai et al., 2002; Casey and Carhan, 2006). One of the most important steps in the modeling process is selecting appropriate scenarios of model input parameters. For this purpose, different combinations of input parameters were used to achieve the optimal model, which are presented in Table 3.

To simulate the river discharge of hydrometric stations in the Dez watershed, the Support Vector Regression (SVR) model with Wavelet, Whale Optimization Algorithm (WOA), and Particle Swarm Optimization (PSO) algorithms were used. Also, in the Support Vector Regression model, activating functions called kernels were used; these functions include Radial Basis Function (RBF), Polynomial, and Linear functions, which were investigated in this study. For this purpose, the normalized values of river flow discharge are then entered into the Support Vector Regression model. In recent years, due to the fact that in the Support Vector Regression model, the parameter values for adjusting the kernel functions are chosen randomly, optimization algorithms have been used to increase the accuracy and reduce the error of the model (Dehghani and Torabi, 2021). In this study, in order to increase the performance of the model, Wavelet, Whale, and Particle Swarm algorithms were used to optimize the values of the adjustment parameters. Therefore, in this research, after entering the input parameter information into the model and optimizing the adjustment parameters, the hybrid model structure is formed, which leads to the computational response of the model. Since the stopping criterion in training artificial intelligence models is the amount of error, the model stops at the lowest amount of error and the output is obtained.

As specified in Table 4, hybrid models in scenario number four, which includes all input parameters to the model, have less error than other scenarios; therefore, increasing the number of effective parameters in hybrid models based on Support Vector Regression leads to increased model performance. Also, all models have better accuracy in the Radial Basis Function kernel. The results of the models studied in scenario number four are shown in Table 4. As can be seen in the table, the Support Vector Regression-Wavelet model at Tireh Marouk station has a correlation coefficient of 0.952-0.968, Root Mean Square Error (RMSE) (m3/s) of 0.033-0.052, Mean Absolute Error (MAE) (m3/s) of 0.021-0.027, and Nash-Sutcliffe Efficiency (NSE) of 0.967-0.987. At Cham Chit station, it has a correlation coefficient of 0.855-0.898, RMSE (m3/s) of 0.088-0.098, MAE (m3/s) of 0.040-0.058, and NSE of 0.891-0.917. At Sezar station, it has a correlation coefficient of 0.938-0.960, RMSE (m3/s) of 0.021-0.057, MAE (m3/s) of 0.011-0.041, and NSE of 0.944-0.981. And at Tang-e Panj station, it has a correlation coefficient of 0.902-0.985, RMSE (m3/s) of 0.008-0.073, MAE (m3/s) of 0.004-0.054, and Nash-Sutcliffe coefficient of 0.921-0.995, showing better performance in the validation stage.

In Figures 5-7, the scatter plot of observed and calculated values is shown. As can be seen, the Support Vector Regression-Wavelet model, compared to the hybrid models of Support Vector Regression-Whale and Support Vector Regression-Particle Swarm, has shown acceptable accuracy in estimating most points, including minimum, maximum, and median, in such a way that in all stations under study, it has estimated these values close to the observed values.

As shown in Figures 5 to 7, the proximity and alignment of data points to the dashed line in each plot serve as a key indicator for evaluating the model’s performance. The closer these points are to the diagonal line, the higher the prediction accuracy of the model, indicating that the Support Vector Regression-Wavelet (SVR-Wavelet) model has effectively reproduced the observed data trends at each of the four investigated hydrometric stations. Overall, these plots clearly illustrate the efficiency and accuracy of the aforementioned model in predicting values under various conditions and locations, providing valuable visual information regarding its performance quality. In summary, it can be stated that the performance of the WSVR model is superior to the other models examined, with the WOA-SVR and PSO-SVR models ranking second and third, respectively.

Also, in Figures 8 and 9, the diagrams of the correlation coefficient and Root Mean Square Error of the studied models are shown. As can be seen, the Support Vector Regression-Wavelet model has less error and a higher correlation coefficient compared to other models in all stations. As can be seen, at Cham Chit station, the studied models have a lower correlation coefficient and higher error compared to other stations. The reason for this can be stated that the area of this station is smaller than the other hydrometric stations studied.

Therefore, the Support Vector Regression-Wavelet model has better performance than the other models studied, which is consistent with the research of Zeidali Nejad and Dehghani (2023) and Babaali and Dehghani (2022). In the analysis of these results, it can be stated that the superiority of this model is due to the Wavelet transform, which divides the received signals into two categories, high-pass and low-pass, and in the high-pass category, the resolution power increases, which causes the maximum values of the signal to be analyzed with good accuracy.

The Support Vector Regression-Whale and Particle Swarm models have discrete optimization, which reduces the time to reach an optimal solution in a wide search area and gets trapped in local optimal points, thus increasing the error of the model.

Figure 10 shows the Taylor diagram of the models under investigation. This diagram illustrates the performance of three different models (PSO-SVR, WOA-SVR, WSVR) across four different regions (Tiremarvak, Chamchit, Sezar, and Tangpang) based on the metrics of standard deviation and correlation. The Taylor Diagram is a visual tool for comparing model performance against observed data. In this diagram, the closer the points representing the models are to the "Observed" point, the better the model's performance. The radial distance from the center indicates the standard deviation, and the angle represents the correlation coefficient.

Generally, all three models have demonstrated acceptable performance in most regions, as most points are located near the circle with a correlation coefficient of 1. However, differences between models and regions are observed. For instance, in the Tiremarvak region, the PSO-SVR and WOA-SVR models appear to perform better than WSVR, as they are closer to the "Observed" point. In the Chamchit region, all three models exhibit similar performance and are close to the observed data. In the Sezar region, WSVR and WOA-SVR have performed slightly better than PSO-SVR. In the Tangpang region as well, WSVR and WOA-SVR show better performance than PSO-SVR.

Table 2. Correlation cross between input and output variables

Station	Output	Q(t-1)	Q(t-2)	Q(t-3)	Q(t-4)
Tirmarvak	Q(t)	0.941	0.895	0.862	0.810
Chamchit		0.893	0.833	0.804	0.750
Sezar		0.954	0.798	0.862	0.821
Tangpang		0.933	0.887	0.845	0.792

Table 3. Selected combinations of input parameters

Number	Input structure	Output
1	Q(t-1)	Q(t)
2	Q(t-1),Q(t-2)	Q(t)
3	Q(t-1),Q(t-2),Q(t-3)	Q(t)
4	Q(t-1),Q(t-2),Q(t-3),Q(t-4)	Q(t)

Table 4. Results of the Analyzed Models

Station	Model	Training				Testing			
		R	RMSE (m3/s)	MAE (m3/s)	NS	R	RMSE (m3/s)	MAE (m3/s)	NS
Tiremarvak	WSVR	0.93	0.071	0.028	0.947	0.968	0.033	0.021	0.987
	WOA-SVR	0.928	0.074	0.032	0.944	0.965	0.036	0.025	0.984
	PSO-SVR	0.925	0.074	0.031	0.948	0.952	0.052	0.027	0.967
Chamchit	WSVR	0.85	0.118	0.076	0.874	0.898	0.088	0.04	0.917
	WOA-SVR	0.846	0.126	0.084	0.868	0.89	0.094	0.045	0.911
	PSO-SVR	0.824	0.125	0.081	0.849	0.855	0.098	0.058	0.891
Sezar	WSVR	0.936	0.038	0.028	0.966	0.96	0.021	0.011	0.981
	WOA-SVR	0.932	0.042	0.031	0.96	0.948	0.025	0.017	0.965
	PSO-SVR	0.922	0.081	0.032	0.931	0.938	0.057	0.041	0.944
Tangpang	WSVR	0.953	0.018	0.009	0.988	0.985	0.008	0.004	0.995
	WOA-SVR	0.917	0.055	0.018	0.938	0.94	0.035	0.016	0.954
	PSO-SVR	0.892	0.104	0.062	0.915	0.902	0.073	0.054	0.921

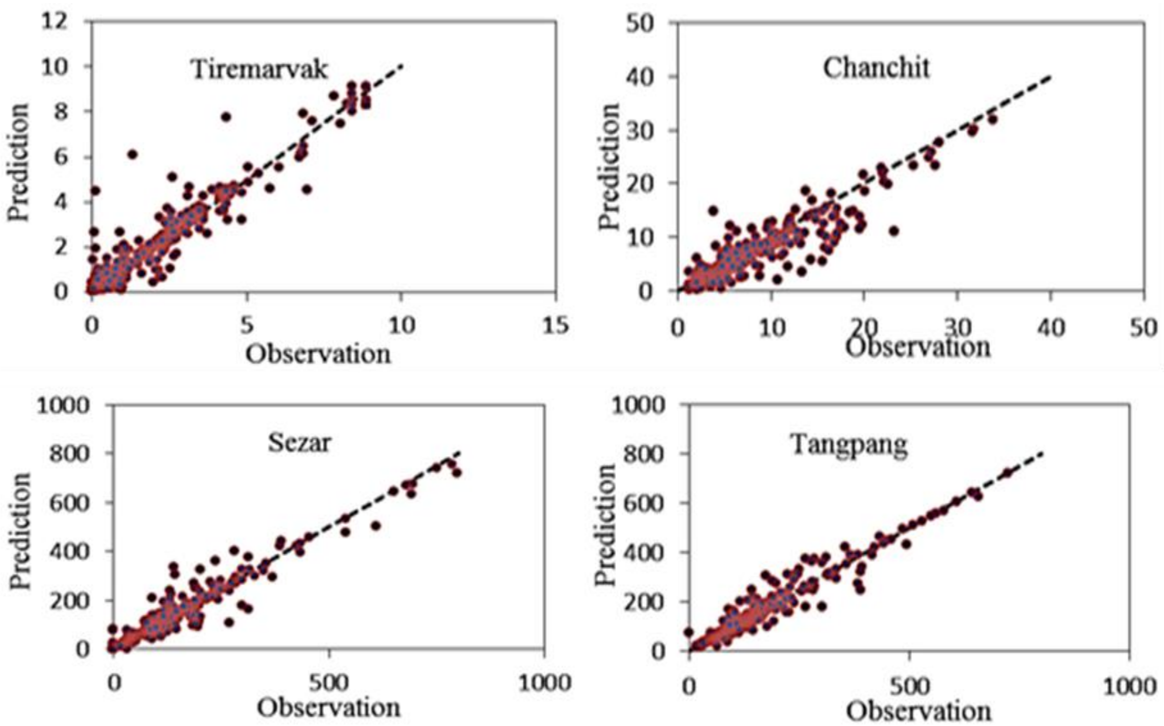

Figure 5. Scatter Plot of Observed and Computed Values for the Support Vector Regression-Wavelet Model

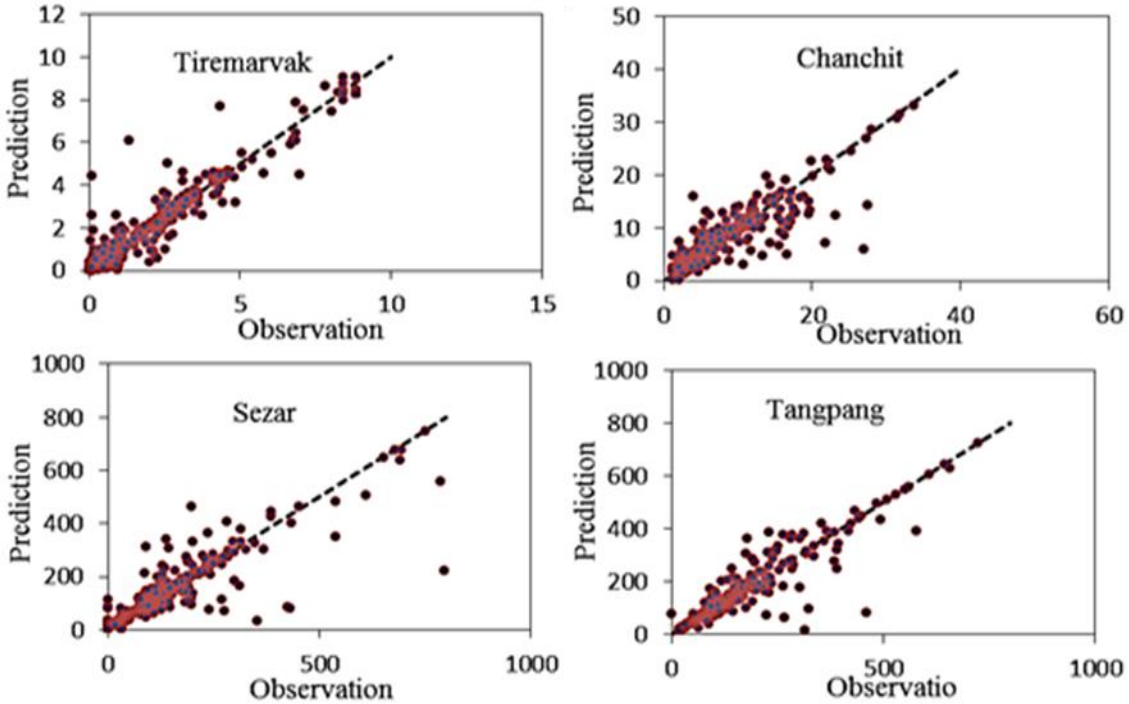

Figure 6. Scatter Plot of Observed and Computed Values for the Support Vector Regression-Whale Algorithm Model

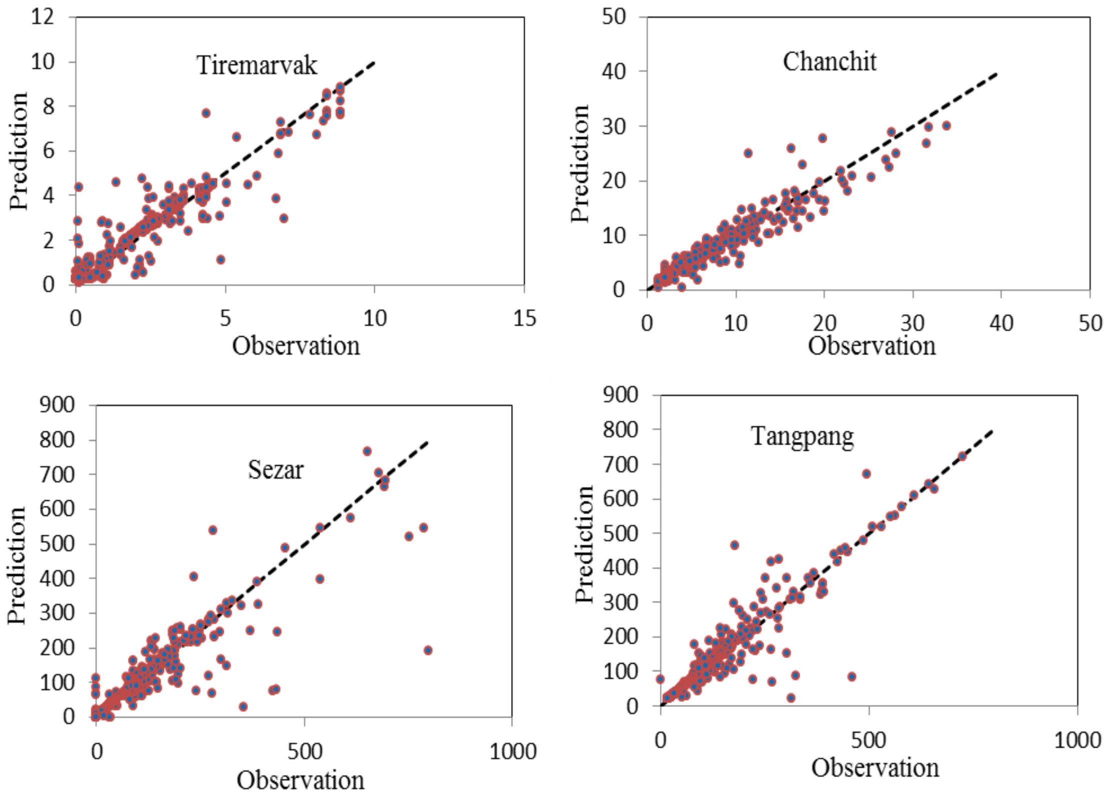

Figure 7. Scatter Plot of Observed and Computed Values for the Support Vector Regression-Particle Swarm Algorithm Model

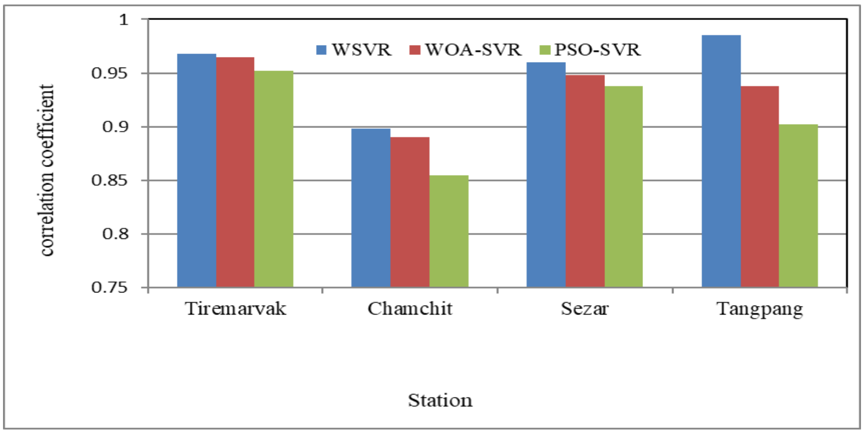

Figure 8. Correlation coefficient of models at the accuracy verification stage

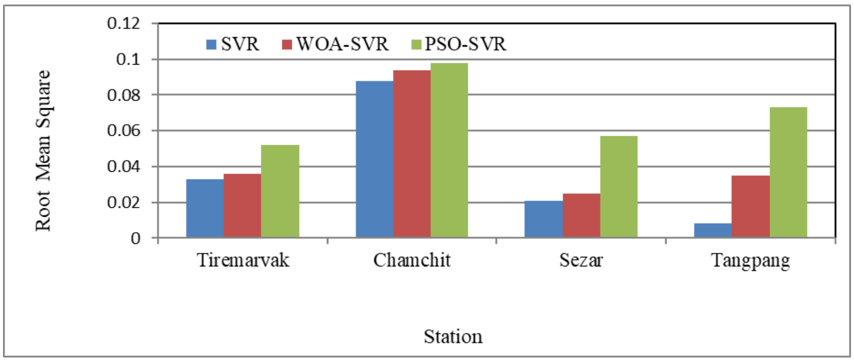

Figure 9. Root Mean Square Error of the Models in the Validation Phase

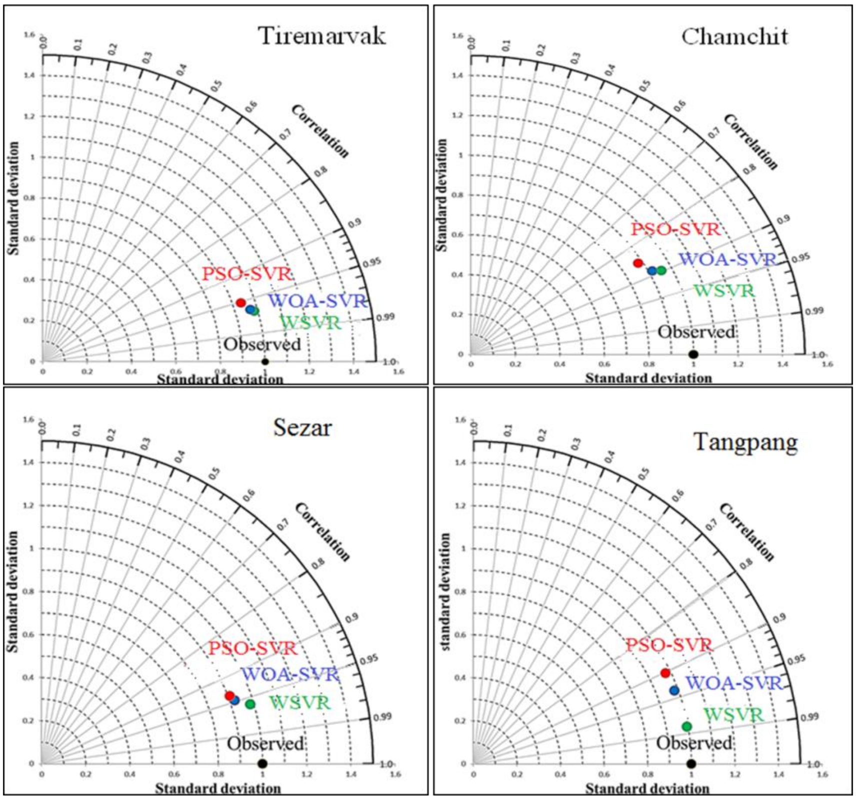

Figure 10. Taylor diagram of the models under study

Conclusion

The simulation of river discharge using hybrid models based on Support Vector Regression (SVR) serves as an effective tool in the design of hydrological systems and river engineering. This study presents a case evaluation of the performance of the hybrid metaheuristic SVR model for estimating the discharge of hydrometric stations in the Dez watershed, including Tireh Marouk, Cham Chit, Sezar, and TangPang. For this purpose, nature-inspired algorithms such as Wavelet, Whale Optimization, and Particle Swarm Optimization were integrated with the SVR model. Additionally, various time-lagged discharge parameters were used as input for modeling. To construct the optimal hybrid SVR model, 80% of the data was allocated for training and the remaining 20% for testing.

This study systematically evaluated hybrid Support Vector Regression (SVR) models for river discharge simulation, demonstrating that the SVR-Wavelet approach outperformed other configurations with exceptional accuracy (NSE = 0.951–0.995, RMSE = 0.008–0.088 m^3/s). The integration of wavelet decomposition significantly enhanced the model's ability to capture non-linear hydrological patterns, while metaheuristic optimization algorithms (WOA, PSO) effectively fine-tuned SVR parameters. These results establish a new benchmark for discharge modeling in semi-arid regions, particularly where data scarcity and climate variability pose challenges. The research makes three key scientific contributions: (1) development of a novel hybrid modeling framework combining signal processing and machine learning for hydrological applications; (2) quantitative demonstration of parameter optimization benefits through multi-criteria performance metrics; and (3) creation of a transferable methodology applicable to other stressed river basins. The models' robust performance across four hydrometric stations confirms their reliability for operational water management, including drought prediction and allocation planning. From a practical perspective, these AI-driven models offer water authorities a powerful decision-support tool to address the Dez basin's critical challenges, including 30% flow reductions and agricultural water shortages. The study provides a template for modernizing hydrological forecasting in Iran, with immediate applications for climate adaptation strategies and long-term potential for national water governance reforms. Future work should focus on real-time implementation and integration with emerging climate projection datasets to further enhance predictive capabilities.

References

Alizadeh, F., Gharamaleki, A., Jalilzadeh, M. and Akhoundzadeh, A. 2020. Prediction of river stage-discharge process based on a conceptual model using EEMD-WT-LSSVM Approach, Water Resources. 47(2), 41-53

Basak, D., Pal, S., and Patranabis, D.C. 2007. Support vector regression. Neural Information Process. 11(2), 203-225.

Brierley, G.J., and Fryirs, K.A 2013. Geomorphology and river management: applications of the river styles framework. John Wiley & Sons. 6(3), 645-652.

Dehghani, R., and Babaali, H. 2023. Evaluation of Statistical Models and Modern Hybrid Artificial Intelligence in Simulation of Runoff Precipitation Process. Sustainable Water Resources Management, 8, 154-172.

Dehghani, R., Torabi Poudeh, H., Younesi, H., and Shahinejad, B. 2020.. Daily streamflow prediction using support vector machine-artificial flora (SVM-AF) hybrid model. Acta Geophysica. 68(7), 1763–1778 .

Dehghani, R., Torabi Poudeh, H., Younesi, H., and Shahinejad, B.(2020). Daily Streamflow Prediction Using Support Vector Machine-Artificial Flora (SVM-AF) Hybrid Model. Acta Geophysica. 68(6), 51-66.

Dehghani, R., and Torabi, H. 2021. Dissolved oxygen concentration predictions for running waters with using hybrid machine learning techniques. Modeling Earth Systems and Environment, 6(2), 64-78.

Eberhart R., and Kennedy J. 1995. A New Optimizer Using Particle Swarm Theory Proc. Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, Piscataway, NJ: IEEE Service Center, 39-43.

Goorani, Z., and Shabanlou, S. 2021. Multi-objective optimization of quantitative-qualitative operation of water resources systems with approach of supplying environmental demands of Shadegan Wetland. Journal of Environmental Management. 292, 112-131.

Kisi, O., Karahan, M., and Sen, Z. 2006. River suspended sediment modeling using fuzzy logic approach. Hydrological Processes. 20(2), 4351-4362.

Kohansarbaz, A., Yaghoubi, B., Shabanlou, S. Yosefvand. F.,Izadbakhsh, M.A., and Rajabi, A. 2024. Simulation of monthly river flow using SVR neural network improved with population-based optimization algorithms. Model. Earth Systems and Environment. 10(4), 4525–4547.

Marlia, M., Syaharuddin, S., Handy, M.R.N., Subiyakto, B., and Ilhami, M.R. 2022. Changes in the behavior of the riverside community of Banua Anyar Village towards river management policies. The Kalimantan Social Studies Journal. 4(1), 48–55.

Mazraeh, A., Bagherifar, M., Shabanlou, S., and Ekhlasmand, R. 2024. A novel committee-based framework for modeling groundwater level fluctuations: a combination of mathematical and machine learning models using the weighted multi-model ensemble mean algorithm. Groundwater for Sustainable Development. 24, 101-126.

Mirjalili, S., and Lewis, A. 2016. The whale optimization algorithm. Advances in Engineering Software .95(6), 51-67

Nagy, H., Watanabe, K., and Hirano, M. 2002. Prediction of sediment load concentration in rivers using artificial neural network model. Journal of Hydraulics Engineering. 128, 558-559.

Parisouj, P., Mohebzadeh, H., and Lee, T. 2020. Employing machine learning algorithms for streamflow prediction: a case study of four river basins with different climatic zones in the United States. Water Resources Management. 34(13), 4113–4131

Rajaee, T., Nourani, V., Zounemat-Kermani, M., and Kisi, O. 2011. River suspended sediment load prediction: application of ANN and wavelet conjunction model. Journal of Hydrologic Engineering. 16(2), 613–627

Reddy, K., and Saha, A.K. 2022. A modified Whale Optimization Algorithm for exploitation capability and stability enhancement. Heliyon. 8(10), 425-441

Sahoo, A., Singh, U. K., Kumar, M. H., and Samantaray, S. 2021. Estimation of Flood in a River Basin Through Neural Networks: A Case Study. In Communication Software and Networks (pp. 755-763). Springer, Singapore.

Shin, S., Kyung, D., Lee, S., Taik & Kim, J., and Hyun, J. 2005. An application of support vector machines in bankruptcy prediction model. Expert Systems with Applications. 28(4),127-135.

Vapnik, V., and Chervonenkis, A.1991. The necessary and sufficient conditions for consistency in the empirical risk minimization method. Pattern Recognition and Image Analysis.1(3), 283-305.

Vapnik, V.N. 1995.The nature of statistical learning theory. Springer, New York. 3(1), 250-320.

Vapnik, V.N.1998. Statistical learning theory. Wiley, New York. 4(1), 250-320.

Wang, D., Safavi, A.A., and Romagnoli, J.A. 2000. Wavelet-based adaptive robust M-estimator for non-linear system identification. AIChE Journal. 46(4), 1607-1615.

Yildiz, B.S., Pholdee, N., Bureerat, S., Yildiz, A.R., and Sait, S.M. 2022. Enhanced grasshopper optimization algorithm using elite opposition-based learning for solving real-world engineering problems. Engineering with Computers. 38(5),4207–4219.

Zeidalinejad, N., and Dehghani, R. 2023. Use of meta-heuristic approach in the estimation of aquifer's response to climate change under shared socioeconomic pathways. Groundwater for Sustainable Development. 20(4), 112-132.

Zhao, G., Bates, P., Neal, J., and Pang, B. 2021. Design flood estimation for global river networks based on machine learning models. Hydrology and Earth System Sciences. 25(11), 5981–5999.