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Evaluation of Hybrid Metaheuristic Models in Estimating Electrical Conductivity (Case Study: Kakarza River, Lorestan Province)

Ebrahim Nohani[1], Hamidreza Babaali[2*], Reza Dehghani[3]

1- Department of Civil Engineering, Materials and Energy Research Center, Dez. C., Islamic Azad University, Dezful, Iran.

2- Department of Civil Engineering, Islamic Azad University, Khorramabad branch, Khorramabad, Iran.

3- Department of Soil Conservation and Watershed Management, Lorestan Province Agriculture and Natural Resources Research and Education Center, Areeo, Khorramabad, Iran.

***Corresponding Author: h-babaali@khoiau.ac.ir**

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Abstract

Electrical conductivity (EC) is an important indicator for monitoring water quality in rivers. Electrical conductivity is inherently related to the concentration of dissolved ionic compounds in aquatic environments, including various salts and minerals. Estimating electrical conductivity is crucial for environmental monitoring and assessing the health of aquatic ecosystems. In this study, a hybrid intelligent model based on the support vector regression approach was developed to estimate the electrical conductivity of river water. For this purpose, three optimization algorithms, including wavelet, whale, and particle swarm optimization , were utilized for modeling the electrical conductivity of river flow. For modeling, data and statistics from the Kakareza hydrometric station located in Lorestan province were used as a case study in seven combined scenarios consisting of input parameters for the years 2003-2023. To evaluate the performance of the models, criteria such as correlation coefficient, root mean square error, mean absolute error, and Nash-Sutcliffe coefficient were employed. The results indicated that increasing the amount of effective parameters in the modeling process improves the results. Furthermore, the results obtained from the evaluation criteria showed that the wavelet support vector regression model had a correlation coefficient of 0.980, a root mean square error of 0.344 (ppm), a mean absolute error of 0.172 (ppm), and a Nash-Sutcliffe coefficient of 0.85 during the validation phase. Overall, the findings indicated that the use of intelligent models based on the support vector regression approach can serve as an effective method for the sustainability of river engineering.

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Introduction

Clean and healthy water is essential for human consumption, hygiene, and health maintenance. Contaminated water harbors harmful microorganisms, pathogens, and pollutants that cause waterborne diseases (Nemčić-Jurec et al., 2022). Water quality is essential for maintaining the health of aquatic ecosystems, including rivers, lakes, wetlands, and oceans. Aquatic organisms, such as fish, plants, and other wildlife, depend on clean water for survival and growth. Polluted water, containing chemicals, toxins, or excessive nutrients, can lead to habitat destruction, species loss, and the disruption of ecological balance (Bhat et al., 2022). Water quality is crucial for agriculture and food production. Contaminated water used for irrigation negatively impacts the health and productivity of agricultural products. It also leads to the accumulation of harmful substances in food, posing risks to human health. Maintaining good water quality in irrigation systems is crucial for sustainable agriculture and safe food production (Mensah-Akutteh et al., 2022). Water quality is of paramount importance for human health, ecosystem function, sustainable development, and various economic activities. Monitoring, managing, and maintaining water quality are vital for protecting human health, safeguarding the environment, and ensuring the sustainable use of this valuable resource (Giri et al., 2022).

Electrical Conductivity (EC) is an important parameter used to assess and monitor water quality. It is a measure of the water's ability to conduct electrical current and is influenced by the concentration of dissolved ions in the water (Naiel et al., 2022). Electrical conductivity serves as an estimate of the concentration of Total Dissolved Solids (TDS) in water. TDS represents the total concentration of dissolved mineral and organic substances in water, including salts, minerals, metals, and other dissolved solids. Higher electrical conductivity values generally indicate elevated TDS levels, which can affect the taste, odor, and overall palatability of the water (Ezea et al., 2022). High electrical conductivity values also indicate higher levels of salinity, which can have adverse effects on aquatic life, irrigation practices, and the suitability of water for various uses (Liu et al., 2023). Measuring and predicting electrical conductivity can aid in identifying identify potential sources of pollution and assess overall water quality (Lakrout et al., 2022).

Accurate measurement of electrical conductivity in the laboratory is challenging, time-consuming, and requires skilled manpower, and also involves high costs. Nowadays, Given thenonlinear and complex nature of river water quality issues, artificial intelligence approaches are increasingly being used. These models are inspired by the nature of living organisms and are capable of solving problems with great complexity and scope. These models have garnered significant attention from researchersin the field of predicting the qualitative parameters of rivers, particularlyelectrical conductivity, which can be mentioned below. Machine learning algorithms offer a promising approach to address these challenges and enhance the accuracy and efficiency of EC prediction. Khadr & Elshemy (2017) investigated the capabilities of the support vector regression model in comparisonto empirical models for predicting various water quality factors based on electrical conductivity, turbidity, discharge, water temperature, dissolved oxygen, total suspended solids, total dissolved solids, and pH parameters. The results showed that artificial intelligence models have higher accuracy than empirical models. Najah Ahmed et al. (2019) used support vector regression and artificial neural network models to predict surface water electrical conductivity in the Johor river basin. The results showed that the support vector regression model has less error rates compared to conventional models such as artificial neural networks. Similarly, Ekemen Keskin et al. (2020) used machine learning and regression-based techniques to predict groundwater electrical conductivity. The results demonstrated that models based on the machine learning approach, especially support vector regression, are suitable models for predicting electrical conductivity. Mokhtar et al. (2022) used multiple regression and support vector regression models to predict the electrical conductivity of the Mead River in Turkey. The results showed that the support vector regression model is more accurate than statistical models. showed for predicting the irrigation water quality index. These models served as rapid decision-making tools for modeling irrigation water quality and assisting in water resource management strategies. Kumar et al. (2023) used a hybrid support vector regression model combined with metaheuristic algorithms to predict the electrical conductivity of the Ganges River in India. The results showed that the hybrid support vector regression model with metaheuristic algorithms performs better than the single support vector regression model.

Wang et al. (2024) conducted a study comparing hybrid models based on support vector regression performance against single models for predicting water quality in the Jinqing River in China. The results showed that hybrid models outperformed single models. Shams et al. (2025) compared hybrid models including random forest, extreme gradient boosting, gradient boosting, adaptive boosting, K-Nearest neighbors regression, decision tree regression, support vector regression, and multi-layer perceptron regression with metaheuristic algorithms to predict river water quality in India. The results indicated that Support Vector Regression had higher accuracy compared to the other models studied.

Overall, considering the research conducted, the effectiveness of artificial intelligence models in estimating river water quality and other water resources studies has been confirmed. Therefore, artificial intelligence models, including support vector regression, can be used as an efficient tool for estimating river water quality and hydrological issues. In recent years, numerous studies have been conducted on the use of single support vector regression for modeling river water quality, and the results have been associated with reduced model accuracy (Rajaee et al., 2022). Nowadays, in order to increase accuracy, reduce error, and improve the efficiency of the support vector regression model, combining this model with metaheuristic optimization algorithms has been used as a suitable solution for predicting river water quality, which has yielded favorable results (Jalalkamali & Jalalkamali, 2018). In this study, hybrid models of support vector regression-wavelet, support vector regression-whale optimization algorithm, and support vector regression-particle swarm optimization were used to model the water quality of the Kakarza River located in Lorestan Province. The Kakarza River is one of the important rivers in Lorestan Province in terms of agriculture, drinking water, and aquaculture. Given that the water quality of this river has faced problems in recent years, such that the water quality of this river has decreased annually in the past, endangering the health of living organisms. Therefore, the analysis and investigation of the water quality of the Kakarza River is necessary considering the economic investment conditions, aquaculture production, tourism, and special geographical location of Lorestan Province's planning. On the other hand, although the use of support vector regression has been widely used to predict river quality. So far, no research has been done on the use and comparison of whale and particle swarm metaheuristic algorithms in this region. Therefore, in this research, optimization algorithms were used with the aim of combining with the support vector regression model to estimate the electrical conductivity of the Kakarza River.

Materials and Methods

Study Area

The study area is the Kakarda Station, located in Lorestan Province. This station is situated along the Kakarda River, which is one of the permanent rivers in Lorestan Province. It originates from the southeastern mountains of Alishtar County and the Chaghalondi (Harood) district, and is known as Kakarda within the boundaries of Alishtar County. The river is located between 48°15' to 49° latitude and 32° 22' to 33° 52' north latitude, in Lorestan Province, to the east of Khorramabad County, and forms part of the tributaries of the Karkheh River in the Zagros region. The Kakarda River lies at an elevation of 1550 meters above sea level. The catchment area of Kakarda spans 1148 square kilometers and features a river that is 85 kilometers long. After merging with the Kashkan, Simreh, and Karkheh rivers, the Kakarda River ultimately flows into the Persian Gulf. Figure 1 illustrates the geographical location of the study area. In this research, to model the electrical conductivity of the Kakarda River in Lorestan Province, monthly data, including sodium, magnesium, calcium, sulfate, chloride, bicarbonate, and pH, were used for the statistical period of 2003-2023. Table 1 presents the statistical characteristics of the parameters used.

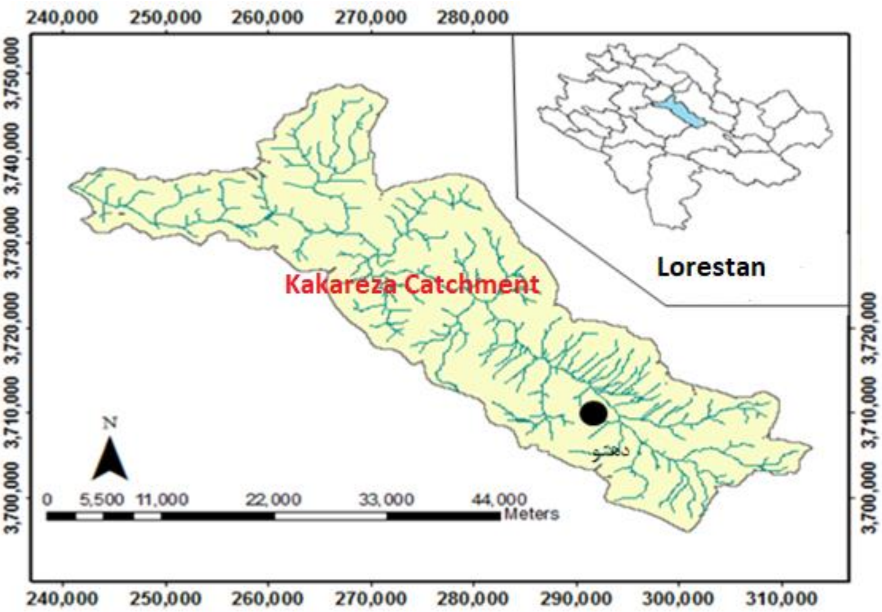

Fig 1. Study Area

Table 1. Statistical Characteristics of the Parameters Studied

Parameters	Training			Testing		
	Minimum	Mean	Maximum	Minimum	Mean	Maximum
Na(mg/l)	0.02	0.215	0.81	0.06	0.22	0.45
Mg(mg/l)	0.30	1.18	3.70	0.50	1.22	3.60
Ca(mg/l)	1	2.37	4.49	1.9	2.97	4.50
SO4(mg/l)	0	0.40	3.74	0.03	0.56	2.43
CL(mg/l)	0.1	0.28	1	0.21	0.39	1
Hco3(mg/l)	1.25	3.05	5.80	1.90	3.43	5.30
PH(mg/l)	6.6	7.80	8.57	6.90	7.99	8.30
EC(mg/l)	180	380.10	675	180	390.72	632

Methods

In this study, the data used initially included Electrical Conductivity (EC), Bicarbonate (HCO3), Chloride (Cl), Sulfate (SO4), Calcium (Ca), Magnesium (Mg), Sodium (Na), and the concentration of hydrogen ions (pH) measured monthly at the Kakarza hydrometric station located in Lorestan Province during the years 2003-2023, obtained from the Lorestan Province Regional Water Company. It is worth noting that during the period under review, the time series data had no missing data, were homogeneous, and did not contain outliers. Then, in order to integrate statistics and information, a normalization process was performed on the input data obtained. Nowadays, due to the increased efficiency of intelligent models, including support vector regression, optimization algorithms are used to optimize the tuning parameters of the model. In this study, wavelet, whale optimization algorithm, and particle swarm optimization algorithms were used to optimize the tuning parameters of the support vector regression model. The support vector regression model has kernel or activation functions, and these functions consist of variables t, d, and δ. In the process of hybridizing the model, these variables are estimated to the most optimal value possible by the aforementioned optimization algorithms. Then, the hybrid model structure is formed, and finally, the input parameters are entered into the model, leading to the output response. Overall, the model results are examined based on evaluation criteria and time series plots, box plots, and Taylor diagrams. The models and algorithms under review are briefly described below.In this study, water quality data from the river during the years 2003 to 2023 was used, such that 80% of the data from 2003 to 2018 was randomly selected for training, and the remaining 20% from 2019 to 2023 was used for testing. Additionally, for the training process of the model, a total of 1000 iterations were considered, and this model was implemented in MATLAB. The flowchart of the research is shown in the Figure 2.

Support vector regression

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).

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

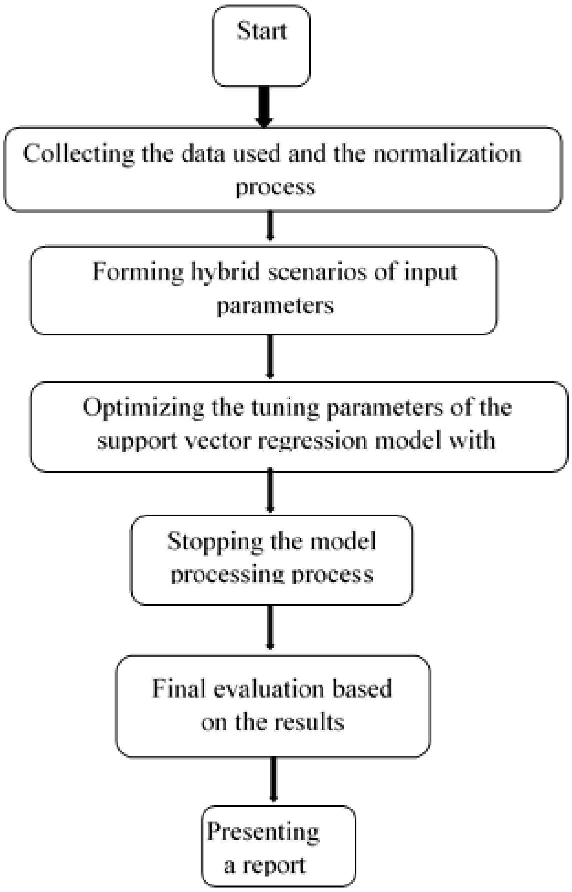

Fig 2. The research flowchart

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

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.

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

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

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

Wavelet Transform

Wavelet transform has been presented as an alternative method to the short-time Fourier transform, and its goal is to overcome the issues related to frequency resolution in the short-time Fourier transform. In the wavelet transform, similar to the short-time Fourier transform, the signal of interest is divided into windows, and the wavelet transform is performed separately on each of these windows (Vapnik, 1998). However, the most important difference between them is that in the wavelet transform, in addition to the frequency resolution of a signal or window length changing according to the type of frequency, the width of the window or the frequency scale also changes according to the type of frequency. In other words, in wavelet transform, scale exists instead of frequency. Therefore, the wavelet transform is a type of time-scale transformation. Accordingly, using the wavelet transform, at higher scales, the signal is expanded, allowing detailed analysis of the signal, while at lower scales, the signal is compressed, enabling examination of the overall structure of the signal (Wang et al, 2000). A wavelet, meaning 'small wave', is a segment or window of the original signal that concentrates its energy in time. Using wavelet transform or analysis, one can decompose a parent signal or time series into wavelets with different resolution levels and scales. Thus, wavelets are transferred and decomposed samples of the parent signal that exhibit oscillations over a finite length and are highly localized. Based on this important property of the wavelet transform, non-stationary and transient time series can be analyzed locally (Shin et al, 2005).

In this research, various wavelet functions, including Haar, Mexican Hat, and Morlet, were used. The Morlet wavelet function was selected because it is the second derivative of the Gaussian function, which yields better performance. The Morlet wavelet transform, with its ability to provide precise time-frequency analysis, adjustable central frequency, suitable shape for analyzing vibrational signals, and capability for extracting phase information, is a powerful tool for signal analysis in various domains, even capable of removing noise from signals. Noise removal methods based on wavelets generally perform better than traditional methods because they can eliminate noise without losing important details of the signal

Particle Swarm Optimization

The Particle Swarm Optimization algorithm is a metaheuristic algorithm that was first introduced by Kennedy and Eberhart (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 3.

Whale Optimization Algorithm

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 & Saha, 2022). The behavior of this algorithm follows the following relationships:

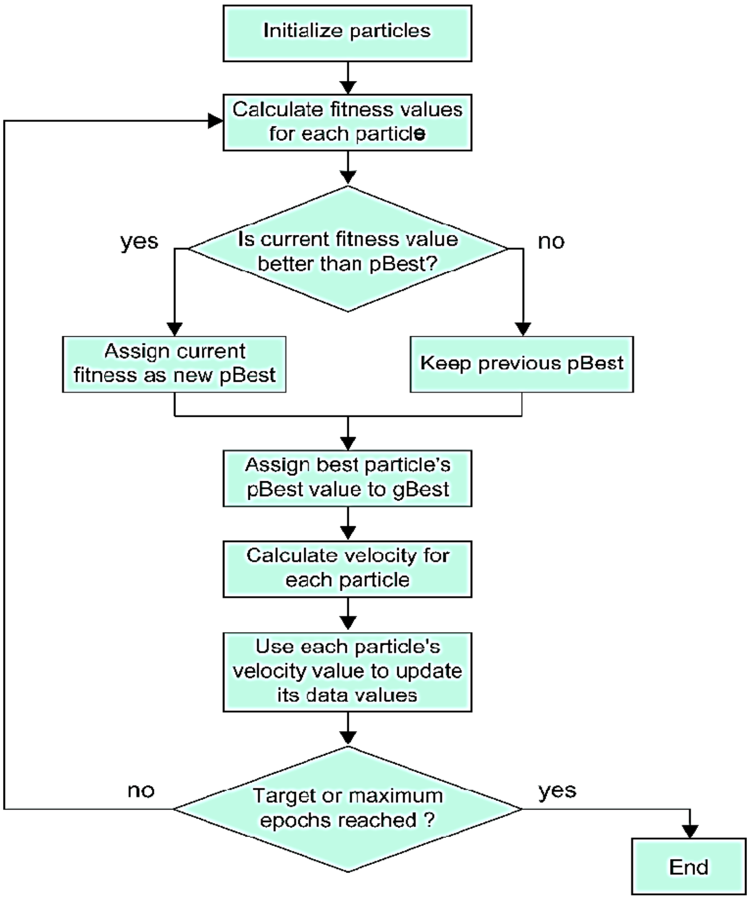

Fig 3. Flowchart of the particle swarm algorithm

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

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

"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 4.

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

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

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

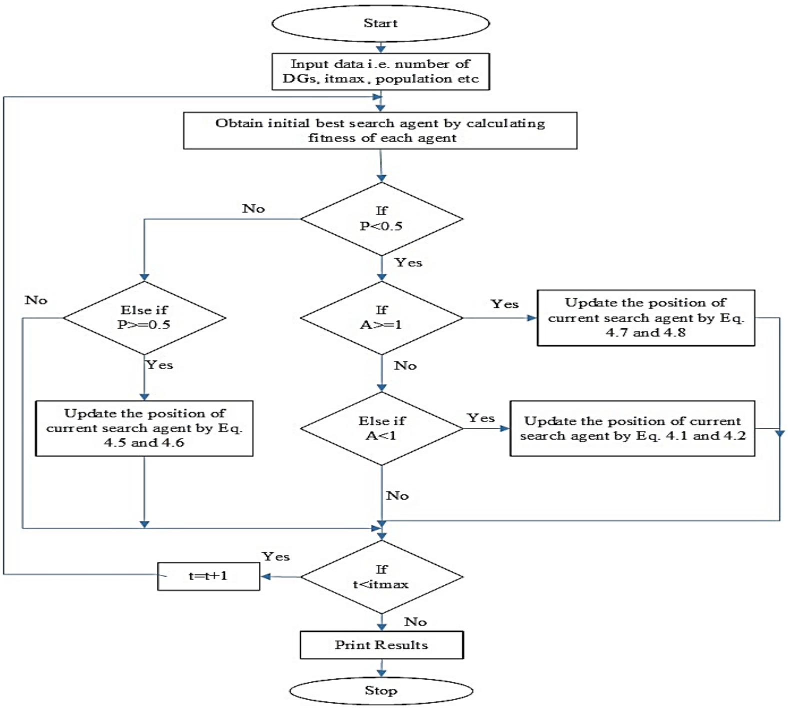

Fig 4. Whale algorithm flowchart

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

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

In the above relations, R is the correlation coefficient, RMSE is the root mean square error in $m^3/sm^3/s$, and NS 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 and 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, a hybrid artificial intelligence method based on the Support vector regression model with whale optimization algorithm, and particle swarm optimization were used to model the electrical conductivity of the Kakarza River. Data from the Kakarza station located in Lorestan Province was used for modeling. The parameters Sodium (Na), Magnesium (Mg), Calcium (Ca), Sulfate (SO_4), Chloride (Cl), Bicarbonate (HCO_3), and pH were selected as inputs, and the Electrical Conductivity (EC) parameter was selected as the model output, with monthly data spanning from 2003 to 2023. Given the complex and non-linear nature of river electrical conductivity and the various parameters affecting it, a combination of effective parameters under different scenarios is necessary (Nagy et al., 2002; Kisi et al., 2006). Table 2 shows the combination of effective parameters under different scenarios. It is worth mentioning that for modeling, 80% of the input data was used for training and the remaining 20% was used for testing.

To model the electrical conductivity of the Kakarza River flow, the Support vector regression model with wavelet, whale optimization algorithm, and particle swarm optimization algorithms were used. In the support vector regression model, kernel functions were also used, including Radial Basis Function (RBF), polynomial, and linear functions, which were investigated in this study. For this purpose, the values of the quality parameters of the Kakarda hydrometric station were normalized and then entered into the support vector regression model. In recent years, because the parameter values of the kernel functions in the support vector regression model are selected randomly, optimization algorithms have been used to increase accuracy and reduce model error (Dehghani et al., 2020). In this study, wavelet, whale optimization algorithm, and Particle Swarm Optimization algorithms were also used to improve the performance of the model in order to optimize the values of the tuning parameters. Therefore, in this study, after entering the input parameter information into the model and optimizing the tuning parameters, the hybrid model structure is formed, leading 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.

In Table 3, the estimated values of the tuning parameters using wavelet, whale, and particle swarm optimization algorithms are shown. In Table 4, the sensitivity analysis or the impact of each of the input parameters according to the selected scenarios is shown. As observed, in scenario one, the effect of magnesium on sodium has improved the model's performance. Additionally, in the fourth scenario, the inclusion of sulfate has also significantly changed the model's performance compared to other scenarios, and it has shown a suitable accuracy in scenario seven. Therefore, in this research, the results of scenario seven have been discussedAs shown in Table 5, the hybrid models in scenario number 7, which includes all input parameters to the model, have better performance than the other scenarios. Also, all models in the Radial Basis Function kernel have better accuracy, and the results of the models according to the combined scenarios are shown in Table 5 with the Radial Basis Function kernel. As shown in the table, the support vector regression-wavelet model in the combined scenario number 7 has the highest correlation coefficient of 0.980, the lowest root mean square error of 0.344 (ppm) , the lowest mean absolute error of 0.172 (ppm) , and the highest Nash-Sutcliffe coefficient of 0.985 in the validation stage, shows better performance.

Figure 5 shows the time series chart of observed and calculated values. As observed, the support vector regression-wavelet model shows acceptable accuracy in estimating most points, including minimum, maximum, and median, compared to the hybrid support vector regression-whale and support vector regression-particle swarm models. Also, the support vector regression-whale and particle swarm models have relatively good performance in estimating median values and performed poorly in estimating minimum and maximum values.

In Figure 6, the box plot of the models under study is shown. As observed, the support vector regression-wavelet model shows better performance in estimating the first quartile and median values compared to the observed data, while the support vector regression-particle swarm model performed poorly, and the support vector regression-whale model also has good accuracy and is in second place.

In Figure 7, the Taylor diagram of the models under study is visible. The support vector regression-wavelet model has better performance because the standard deviation of the predicted electrical conductivity of the river flow has the closest distance to the standard deviation of the observed data and the correlation coefficient also shows the highest value.

As shown in Figures 6 and 7, the support vector regression-wavelet model has a good performance because the range of computed values is close to the estimated observed values. Additionally, the first and third quartile values have been estimated in such a way that it has resulted in a high standard deviation for this model. However, the support vector regression-particle swarm model has not covered the range of computational data adequately, and its standard deviation is lower compared to the other models

The support vector regression model - whale algorithm is a discrete optimization that reduces the time to reach an optimal solution in a wide search area because it avoids local optimal solutions. This makes the algorithm suitable for solving non-linear problems with large dimensions with an appropriate speed in converging towards an acceptable optimal answer. These results are consistent with the research by Zeidalinejad & Dehghani (2023) and Dehghani et al. (2022) and Nohani et al (2025). it can be said that the hybrid model of support vector regression with the wavelet algorithm has a favorable ability because the wavelet algorithm divides the signal or time series into two categories, high-pass and low-pass, and in the high-pass category, it examines the details of the time series with high resolution at the minimum and maximum points, which improves the model results. In general, it is recommended to use the hybrid support vector regression-wavelet model as a model with negligible error to solve non-linear problems with large dimensions with an appropriate speed in convergence towards an optimal answer. It can also be used as a novel approach to predict the electrical conductivity of river water flow to make appropriate management decisions to improve water resources, prepare land, economic investment, and produce aquatic products.

Conclusion

Estimating the electrical conductivity of river water using hybrid models based on support vector regression serves as an effective tool in the design of hydrological systems and river engineering. In the present study, a case study was conducted to evaluate the performance of a hybrid metaheuristic model of support vector regression for estimating the electrical conductivity of the Kakarza River located in Lorestan Province. To achieve this, nature-inspired algorithms including wavelet, whale, and particle swarm optimization were combined with the Support vector regression model. Parameters such as Sodium (Na), Magnesium (Mg), Calcium (Ca), Sulfate (SO4), Chloride (Cl), Bicarbonate (HCO3), and pH were utilized as inputs, while electrical conductivity (EC) was used as the output parameter of the model. For constructing the hybrid support vector regression model, 80% of the data was allocated for training, and the remaining 20% was used for testing. To evaluate the models under consideration, statistical indicators such as correlation coefficient, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Nash-Sutcliffe efficiency were employed. Furthermore, time series plots, box plots,

Table 2. Combination of Input Parameters

Number	Input	Output
1	Na	EC
2	Na, Mg	EC
3	Na, Mg, Ca	EC
4	Na, Mg, Ca,SO4	EC
5	Na, Mg, Ca,So4, Cl	EC
6	Na, Mg, Ca,So4, Cl, HCO3	EC
7	Na, Mg, Ca,So4, Cl, HCO3, PH	EC

Table 3. The values of the adjustment parameters of the studied algorithm

Alghorithm	t	d	δ
Wavelet	10	0.1	0.18
WOA	10	0.2	0.25
PSO	10	0.3	0.28

Table 4. The error rate of the input scenarios of the model during the training and testing phases

Senario	Training RMSE (ppm)	Testing RMSE (ppm)
1	0.643	0.441
2	0.618	0.422
3	0.601	0.411
4	0.584	0.393
5	0.561	0.377
6	0.545	0.362
7	0.521	0.344

Table 5. Results of the models under review

Model	Kernel	Training				Testing			
		R	RMSE (ppm)	MAE (ppm)	NS	R	RMSE (ppm)	MAE (ppm)	NS
WSVR	RBF	0.960	0.521	0.250	0.970	0.980	0.344	0.172	0.985
	Poly	0.951	0.534	0.261	0.960	0.970	0.352	0.185	0.975
	Line	0.940	0.547	0.273	0.950	0.955	0.368	0.197	0.960
WOA-SVR	RBF	0.945	0.540	0.270	0.955	0.960	0.355	0.191	0.965
	Poly	0.938	0.551	0.278	0.940	0.945	0.374	0.202	0.950
	Line	0.921	0.564	0.288	0.930	0.930	0.388	0.214	0.935
PSO-SVR	RBF	0.930	0.556	0.281	0.940	0.950	0.376	0.207	0.945
	Poly	0.922	0.562	0.290	0.930	0.935	0.389	0.218	0.935
	Line	0.912	0.575	0.301	0.920	0.921	0.398	0.227	0.927

and Taylor diagrams were used to analyze the results. Findings from the study, based on the evaluation of scenarios consisting of input parameters, indicated that increasing the number of effective parameters across different modeling scenarios resulted in better performance in estimating electrical conductivity. Additionally, the results from the evaluation criteria showed that the SVR-Wavelet model exhibited high accuracy and minimal error. According to the analyzed diagrams, the SVR-Wavelet model estimated electrical conductivity values closely resembling their actual values, which was evident in the box and Taylor plots. Overall, the results of

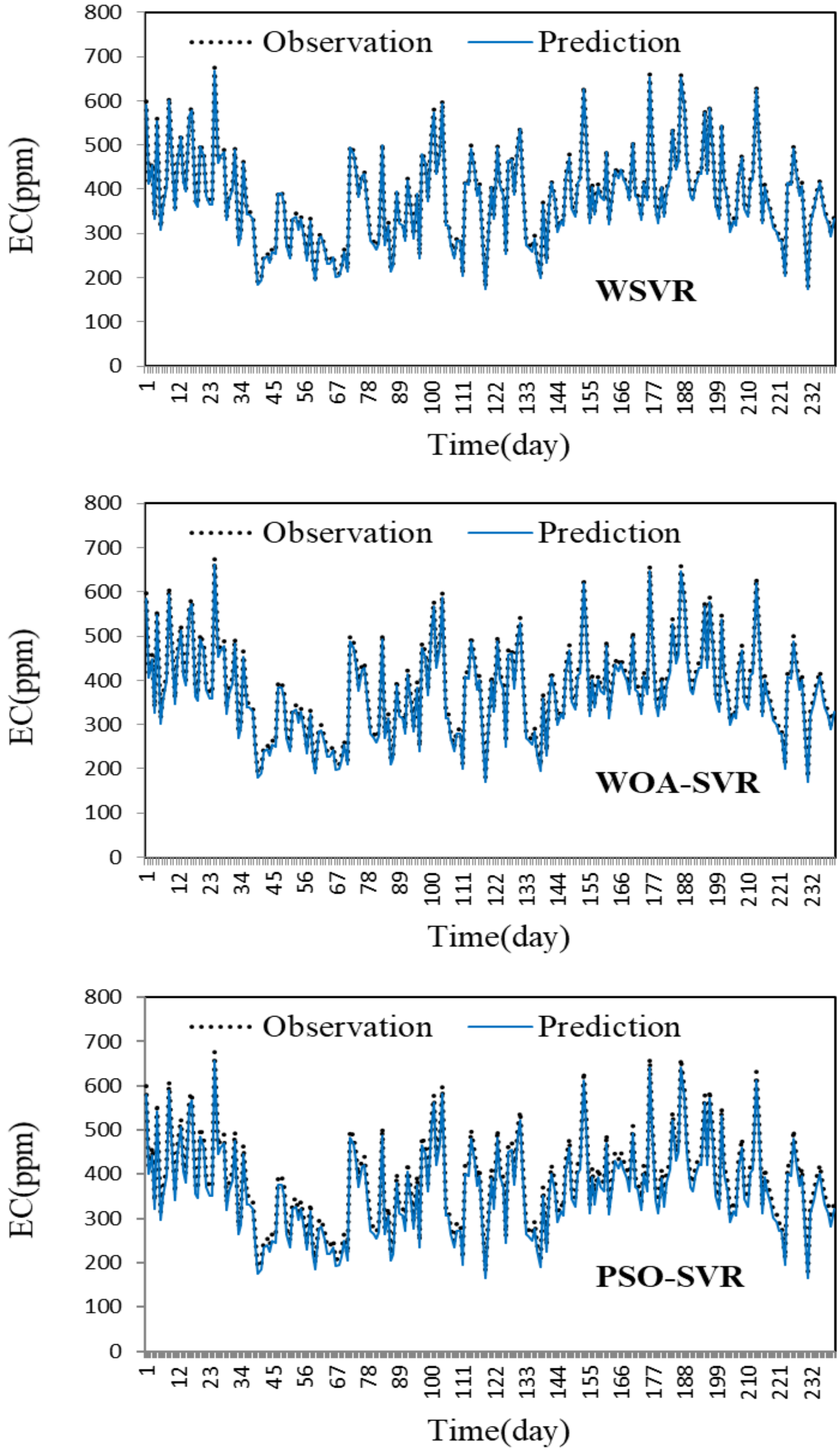

Fig 5. Time series chart of the models under review

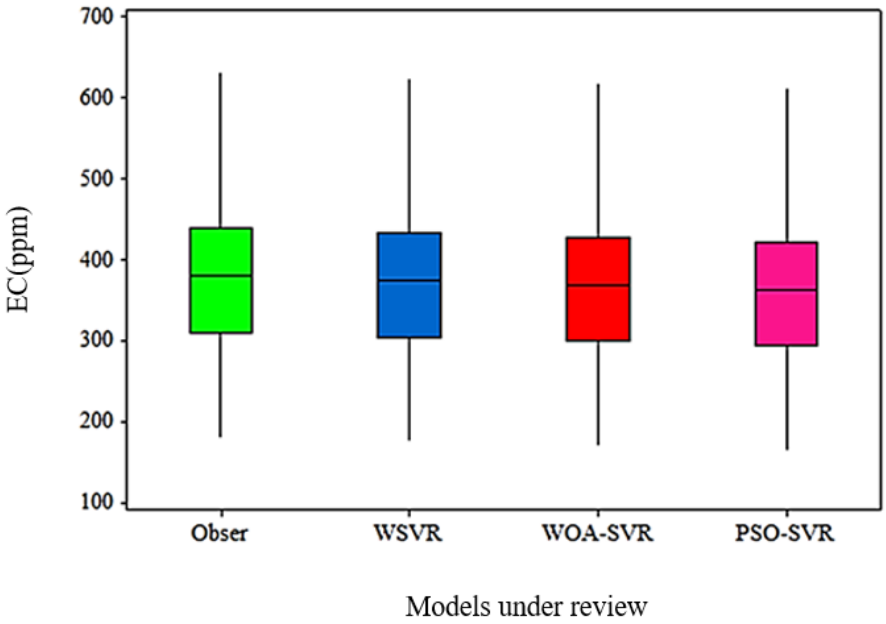

Fig 6. Box plot of the models under review

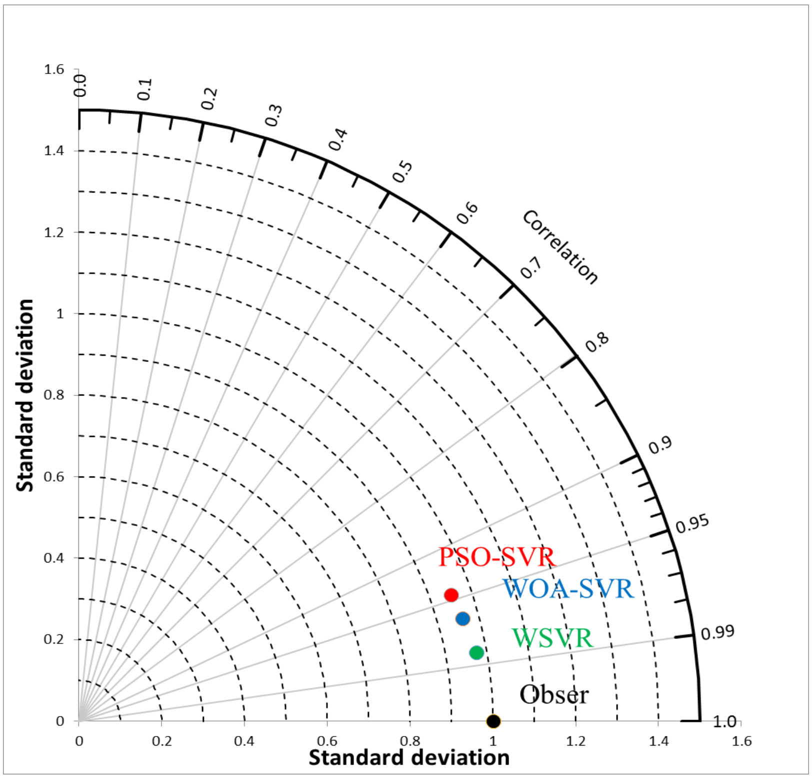

Fig 7. Taylor diagram of the models under review

this study demonstrate that the use of artificial intelligence models based on the support vector regression approach can be utilized for estimating the electrical conductivity of river water over a 20-year statistical timeframe for other regions of the country and is a step toward making appropriate management decisions.In conclusion, it is suggested to utilize new algorithms that combine continuous and discrete optimization, which do not get trapped in local optima, to improve model performance. Additionally, this modeling should be applied in other regions of the country.

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