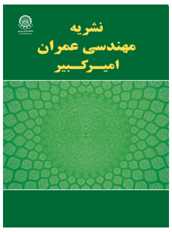

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Application of Optimized Neuro-Fuzzy Models for Estimation of Water Quality Index in Karun River

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ABSTRACT: Management of water quality is inextricably bound up with making good management decisions and this typical management is at the mercy of predicting the water quality index (WQI). The use of board range of artificial intelligence models for analyzing surface water quality is one of the most efficient techniques to predict water quality parameters and WQI. In the current research, at the first, datasets accumulated from nine hydrometry stations, located in Karun River, were included those of 13 water quality parameters (i.e., dissolved oxygen, chemical oxygen demand, biochemical oxygen demand, electrical conductivity, nitrate, nitrite, phosphate, turbidity, pH, calcium, magnesium, sodium, and water temperature) which was used to estimate WQI. So, to obtain an optimal selection of ANFIS model-feeding-input variables, gamma test (GT), forward selection (FS), and principal component analysis (PCA) evaluations were applied. Ultimately, constant coefficients of membership function used in the ANFIS model were computed by using evolutionary techniques including a genetic algorithm (GA), ant colony optimization (ACO), and particle swarm optimization (PSO) for training the structure of the ANFIS model. Results of statistical assessments indicated that the GT-ANFIS-PSO model with a correlation coefficient of 0.952, mean absolute error of 1.68, and root mean square error of 3.05 had a satisfying performance for prediction of WQI compared with other optimized ANFIS models. Moreover, values of WQI ranged from 30 to 58.4 which were indicative of being relatively poor to the good water quality of Karun River.

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1. INTRODUCTION

Prediction of water quality index (*WQI*) plays a key role in the monitoring of natural water bodies such as rivers, lakes, estuarine, and ocean environments. There are a variety of conventional methodologies for the estimation of *WQI* in natural rivers [1-3]. The most well-known *WQI* model is associated with the national sanitation foundation (NFS) which has been frequently applied for various real-world problems in water quality monitoring [1-3]. The current *WQI* methodology may occasionally experience several restrictions on water quality applications. The major drawback of the NSF model is related to the lack of available water quality parameters (WQPs) for the calculation of *WQI*. Nowadays, artificial intelligence (AI) models were used to predict *WQI* and WQPs with satisfying accuracy levels [1-3]. Accordingly, the most frequently-used AI models for water quality monitoring are artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS), gene-expression programming (GEP), M5 model tree (MT), and evolutionary polynomial regression (EPR) [1-3]. Hence, this study investigates *WQI* for Karun River by 200 recorded WQPs series data over 16 years beginning in May 1995. In this study, 13 WQPs are used to predict *WQI* based on NSF instructions. Furthermore, the optimal number of WQPs to estimate *WQI* value are obtained by using principal component analysis (PCA), gamma test (GT), and forward selection (FS). Afterward, the ANFIS model is improved in the training stages by three evolutionary algorithms, i.e., particle swarm optimization (PSO), ant colony optimization (ACO), and genetic algorithm (GA). Ultimately, the performance of various optimized ANFIS models is evaluated by different statistical benchmarks, and additionally, the water quality of Karun River is classified.

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2. METHODOLOGY

2.1. Case study

In the current study, 13 WQPs including dissolved oxygen (*DO*=3.1-29.4 mg/l), biochemical oxygen demand (*BOD*=3.7-40 mg/l), chemical oxygen demand (*COD*=1.06-34.2 mg/l), potential of hydrogen (pH=1.5-8.71), turbidity (Tur=1-25 NTU), sodium (Na^{+}=1.42-40 mg/l), magnesium (Mg^{2+}=2.1-60 mg/l), electrical conductivity (EC=1.7-2.2 dS/m), nitrite (NO_2^{-}=0.08-1.2 mg/l), nitrate (NO_3^{-}=0.34-2.7 mg/l), phosphate (PO_4^{3-}=0.13-3.21 mg/l), calcium (Ca^{2+}=1-35 mg/l), and temperature (T=9.3-30.3 ^{0}C) were used to predict monthly *WQI* based on NSF guidelines. All the water quality parameters were accumulated from nine hydrometry stations (i.e., 5th Bridge, Khoramshahr, Zergan, Kutamir, Deirfam, Marun, Mollasani, Darkhuien, and Nahr-e-Ghasbeh) in the Karun River. All the observational datasets have been ranged in May 1995- Jan 2012. According to the NSF guidelines, *WQI* values are obtained by recorded WQPs and there are seven classifications for *WQI* values: very poor (*WQI*<15), poor (*WQI*=15-29.9), relative poor (*WQI*=30-44.9), moderate (*WQI*=45-55), relative moderate (*WQI*=55.1-70), good (*WQI*=70.1-85), and very good (*WQI*>85). Furthermore, the following relationship is generally used to develop ANFIS:

$$\text{WQI}=\varphi\,(\text{DO, BOD, COD, pH, Tu, EC, } Ca^{2+}, Na^{+}, Mg^{2+}, NO_2^-, NO_3^-, PO_4^{3-}, T) \quad (1)$$

2.2. Optimal selection of WQPs

In this research, three well-known sensitivity analyses were used to choose the optimal number of WQPs. In the first place, FS techniques select 10 water quality parameters (i.e., *BOD*, *COD*, *DO*, PO_4^{3-}, *EC*, pH, NO_3^-, Mg^{2+}, Ca^{2+}, *Tu*) among 13 WQPs, as the most contributory factors on the prediction of *WQI* values. Additionally, the results of the gamma test (GT) indicated that *COD* and Mg^{2+} have the lowest level of contribution on the estimation of *WQI*. Hence, the rest of the WQPs (11 input variables) can be used to develop the ANFIS technique. Finally, the PCA technique converted 13 WQPs into four components as 4 input variables.

3. Development of ANFIS model

In this section, Fuzzy C Mean (FCM) was used to generate the structure of the ANFIS model. Several clusters in the ANFIS model are in close connection with some input variables. In this way, there are 4, 10, and 11 clusters (or fuzzy rules) for the application of preprocessing-data-strategies: PCA, FS, and GT, respectively. Moreover, weighting coefficients associated with Gaussian Membership Functions were optimized by GA, PSO, and ACO.

4. RESULTS AND DISCUSSION

To assess the performance of ANFIS models underlying evolutionary algorithms, three statistical benchmarks such as the correlation of coefficient (*R*), root mean squared error (*RMSE*) and mean absolute error (*MAE*) were employed. Under applying PCA, ANFIS-PSO had the best performance (*R*=0.88, *RMSE*=3.45, and *MAE*=2.54) in the training stage compared with the ANFIS-ACO and ANFIS-GA techniques. Also, in the testing phase, ANFIS-PSO with *R* of 0.89, RMSE of 3.41, and *MAE* of 2.69 predicted the *WQI* with most accuracy level than ANFIS-GA (*R*=0.84, *RMSE*=3.7, and *MAE*=2.84) and ANFIS-ACO (*R*=0.83, *RMSE*= 3.51, and *MAE*=2.95).

In the case of FS application, the performance of the training phase demonstrated that ANFIS-GA (*R*=0.942, *RMSE*=3.16, and *MAE*=1.82) had the most accurate estimation for the *WQI* in comparison with ANFIS-ACO and ANFIS-GA techniques. From testing results, it was found that the application of PSO into the structure of the ANFIS model (*R*=0.943, *RMSE*=3.13, and *MAE*=1.87) provided a compromising estimation of *WQI* rather than ANFIS-GA (*R*=0.88, *RMSE*=3.5, and *MAE*=2.1) and ANFIS-ACO (*R*=0.889, *RMSE*=3.49, and *MAE*=2.21). As GT was applied as a preprocessing-data-technique, statistical results of the training phase showed that ANFIS-PSO (*R*=0.88, *RMSE*=3.45, and *MAE*=2.54) had superiority to other optimized ANFIS models. Furthermore, it was inferred from testing results that the ANFIS-PSO model (*R*=0.89, *RMSE*=3.41, and *MAE*=2.69) produced the most convincing efficiency for *WQI* estimation when compared to ANFIS-GA (*R*=0.84, *RMSE*=3.7, and *MAE*=2.84) and ANFIS-ACO (*R*=0.83, *RMSE*=2.95, and *MAE*=3.51). Overall, statistical benchmarks given by training and testing stages demonstrated that GT-ANFIS-PSO had the most successful performance in the *WQI* estimation than other ANFIS models fed by PCA and FS.

5. CONCLUSION

In this research, the *WQI-NSF* values of Karun River were predicted by using optimized ANFIS techniques. Results of statistical assessments indicated that FS and GT strategies had the highest impact on reducing the number of WQPs, leading to the optimal selection of input variables for feeding the ANFIS technique. Furthermore, the application of PSO to train GMFs utilized in ANFIS had the most accurate performance when compared with ANFIS-GA and ANFIS-ACO. In addition to this, Moreover, *WQI* for Karun River was between 30 and 58.4 which have been classified into relatively poor to good quality. Concerning the best ANFIS model, it can be used to monitor and management the water quality of Karun River as a cost-effective method.

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