Research Journal of Recent Sciences ISSN 2277-2502
Vol. **8(2),** 12-16, April **(2019)** *Res. J. Recent Sci.*

Prediction of irrigation water quality parameters by neural network technique in the Khed Taluka, India

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Available online at: www.isca.in, www.isca.me
Received 19th December 2018, revised 13th March 2019, accepted 20th March 2019

Abstract

The ANN model was developed with MLFBP with sigmoid transferred function. While developing ANN model for different input parameters, three steps were followed as identification of model structures, evaluate the performance and adopting model for forecasting. The ANN models were developed for prediction KR, Percent Na, PI, RSC, SAR and SSP using Neurosolutions. In ANN modeling KR, Percent Na, PI, RSC, SAR and SSP, selection of model parameters are very important i.e. input, output and model structure. In the present study, ANN were used to derive and to develop models for prediction KR, Percent Na, PI, RSC, SAR and SSP as groundwater quality parameters of Khed taluka by using post season values of existing groundwater quality parameters as input variables i.e. Na, Mg, K, $CaCO_3$, HCO_3. The post season data of groundwater quality parameters for time period 1999-2014 were selected for analysis. Model performance was assessed by statistical method included r, RMSE, Index of Agreement and MBE. In Khed taluka, 3-2-1 was best for predicting KR values and 4-2-1 model was best suited for prediction of percent Na values. In Khed taluka Taluka, for post monsoon season 4-6-1 model was best suited to predict PI and 4-4-1 was best suited to predict RSC. 3-6-1 was best suited to predict RSC and SSP in Khed taluka for post monsoon season.

Keywords: ANN, irrigation water quality, water quality parameters, MLFBP.

Introduction

An Artificial Neural Network is an extremely interrelated network of uncomplicated neurons, which were corresponding to biological neurons in human brain. Neuron was basic structural block of ANN. It receives input and produce output, which was to be passed to other neurons in next layers. The neuron in one layer was connected to adjoining layers, but not to those in same layer. Strong point is association between two neurons in adjoining layers was characterized by connection strength or weight/s. ANN is massively equivalent distributed information processing arrangement. It had assured performance characteristics similar to biological neural networks i.e. human brain[1].

An ANN trained from earlier data to predict future events, without caring physical factors which influence present and upcoming events. In ANN was adjusted depend on comparison of output and target, until network output matches the target. The network training perform of neural network is given in Figure-1.

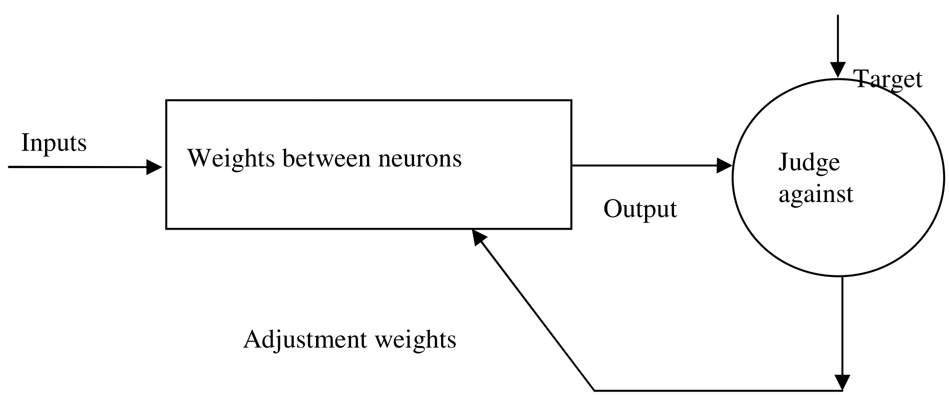

Figure-1: Training network inside the Neural Network.

Materials and methods

Data was normalized to range between 0 to 1 before analyzing data using ANN. For development of ANN architecture, creation of network topology and network training involved. The number of nodes present in input layer depends upon number of parameters used for calculating RSC, SAR, SSP, Permeability index, % Na and Kelly's ratio. In present study six input parameters namely, CO_3^{2-} , HCO_3^- , Ca^{2+}, Mg^2, K^+ and Na^+ were considered as nodes in input layer. In present study, nodes number in hidden layer ranged between nodes number in input layer and twice umber of nodes in input layer[2,3]. The nonlinear relationship among input and output data could be represents by one hidden layer[4]. Therefore, in present study only one hidden layer was taken. In this study, all ANN architectures trained to 5000 epochs and with aim of MSE of 0.001 for calculated during both training and validation.

The Levenberg–Marquardt, 2nd order optimization technique was widely in use for water quality modeling by ANN. LM algorithm was modification of Gauss–Newton method of approximation. The LM algorithm found better than standard back-propagation in terms of fast convergence so needed slighter learning cycles[5].

Artificial Neural Networks Methodology: The available data was separated into a model improvement and assessment data. The data was then normalized in order to train network. The model improvement data were again sub-divided in training, testing, and cross validations as 70:15:15 proportions[6, 7]. Calculating and bring up to date the network weights and biases 1st data set was utilized. 2nd data set was utilized for cross validation. The error occurred in validation was observed throughout the training course of action. As validation error raise to particular numeral at that time training process stopped. When Validation errors amount was at least then returned weights and biases.

Performance Evaluation of ANN Model: Different ANN model was checked for different station was done using statistical method. The statistical performance indicators viz Coefficient of correlation (r), Index of agreement (I.A), Mean bias error and RMSE were employed to carry out analysis[8-10].

Results and discussion

Performance of ANN for different neurons for SAR: The R for training (0.98), testing and cross validation (0.97) was observed. An index of agreement for training (0.97), testing (0.90) and Cross Validation (0.91) was observed. Mean bias error close to zero. The negative value of Mean Bias Error gives underestimation. RMSE was close to zero for training, testing and cross validation during post monsoon season for Khed Taluka.

Therefore, Model 3(3-6-1) was best suited to predict RSC in Khed Taluka for post monsoon season among three models. It is also depicted from Figure-2 that, comparison of actual SAR value and predicted SAR value from neural network.

Performance of ANN for different neurons in hidden layer for PI: It is observed from Table-1 that, correlation coefficient (R) for training and testing and cross validation 1.00, 0.98 and 0.99 was observed. There was very close index of agreement for training, testing and Cross Validation 1.00, 0.99 and 0.99, respectively for model 3. Mean bias error was close to zero in negative direction. RMSE was observed lowest among all the models for training, testing and cross validation in post monsoon season for Khed Taluka. In Khed Taluka, for post monsoon season model 3 (4-6-1) model was best suited to predict PI.

It is also depicted from Figure-3 that, comparison of actual PI value and predicted PI value from neural network.

Performance of ANN for different neurons in hidden layer for RSC: Data pertaining to performance indices viz. R, IA, MBE and RMSE of different models for changing number of neurons is given in Table-1. It was observed that, training, testing and cross validation, R value was nearly equal for all considered models. In the case of IA that, performance of models improved when change the number of neurons in hidden layer.

But MBE and RMSE values changes more comparatively in training, testing and validation to R values. The value of correlation coefficient and IA was equal in model 2, 3 and 4. MBE and RMSE was low as in model 2 compared to other three models. This was reflected in the Figure-4 given below. Model 2 (4-4-1) was best suited to predict RSC in Khed Taluka for post monsoon season among four models.

Performance of ANN for different neurons in hidden layer for percent Na: It is observed from Table-1 that, R and IA values found to be constant for training, testing and cross validation in all cases. But values of MBE and RMSE changes more comparatively in training, testing and cross validation to R and IA values. It may due to the fact that MBE was found to be nearer to zero and therefore changes were more visible on small scale. MBE was lowest in model 1. MBE values indicate negative sign that's means it underestimating the values of percent Na. RMSE was lowest among all models. Performance of Model was better as compared to model 2 and model 3. Therefore, for post monsoon season model 1 (4-2-1) model was best suited for prediction of percent Na values during post monsoon season for Khed Taluka. This was reflected in the Figure-5.

Performance of ANN for different neurons in hidden layer for SSP: It is observed from Table-1 that, the correlation coefficient for training, testing and cross validation was observed 0.99 and index of agreement for training, testing and cross validation was observed 1.00 for model 3. Mean bias error close to zero and lowest among all models. The MBE correspond to underestimation when its value became negative. RMSE was also lowest among the entire model for training, testing and cross validation during post monsoon season for Khed Taluka. Therefore Model 3 (3-6-1) was best suited to predict SSP in Khed Taluka for post monsoon season among three models.

It is also depicted from Figure-6 that, comparison of actual SSP value and predicted SSP value from neural network.

Performance of ANN for different neurons in hidden layer for Khed Taluka KR: Correlation coefficient (R) of model 2 was highest among all three models but the IA was high in model 1. Mean bias error and RMSE for model 1 was lowest among all. MBE values indicate negative sign that's means it underestimating the values of KR. Therefore, model 1 (3-2-1) was better for predicting KR values during post monsoon season in Khed Taluka (Table-1). It is also depicted from Figure-7 that, comparison of actual KR value and predicted KR value from neural network.

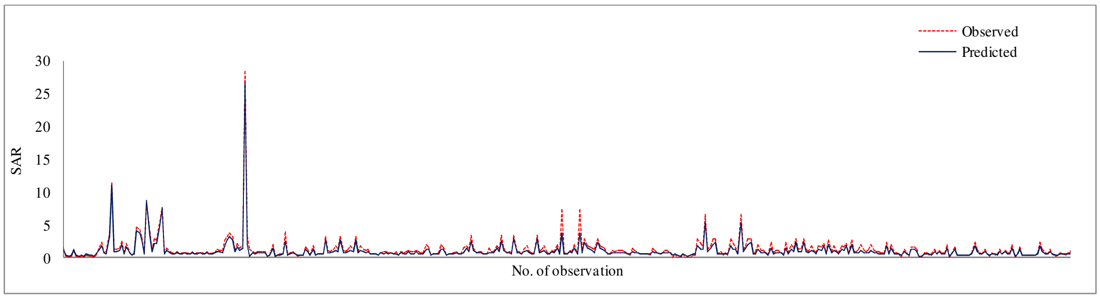

Figure-2: Comparison of actual SAR value and predicted SAR value from neural network.

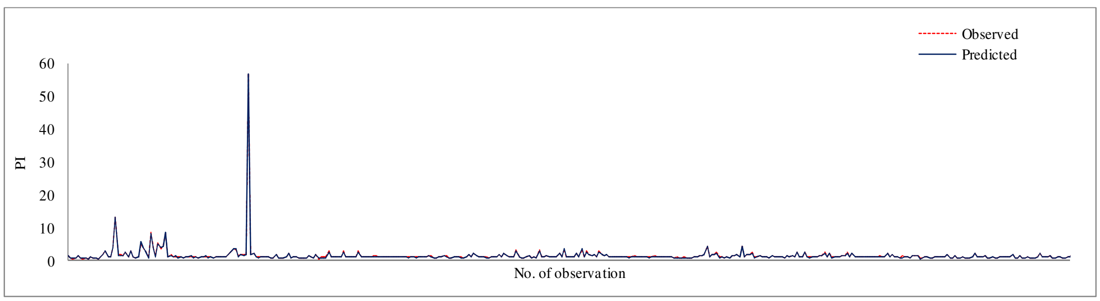

Figure-3: Comparison of actual PI value and predicted PI value from neural network

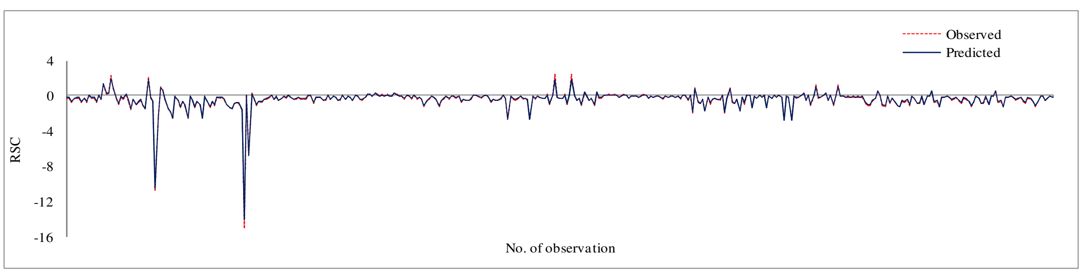

Figure-4: Comparison of actual RSC value and predicted RSC value from neural network.

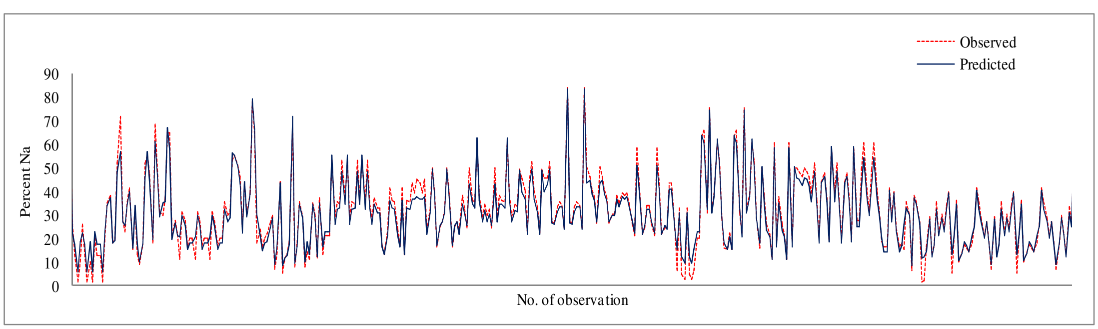

Figure-5: Comparison of actual perNa value and predicted perNa value from neural network.

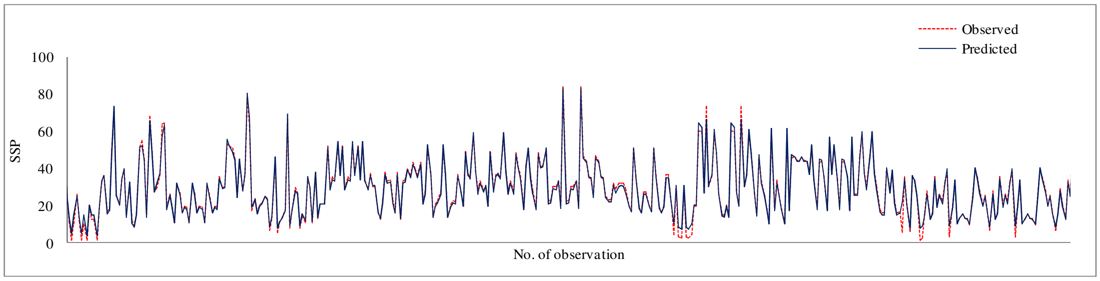

Figure-6: Comparison of actual and forecasted SSP from neural network.

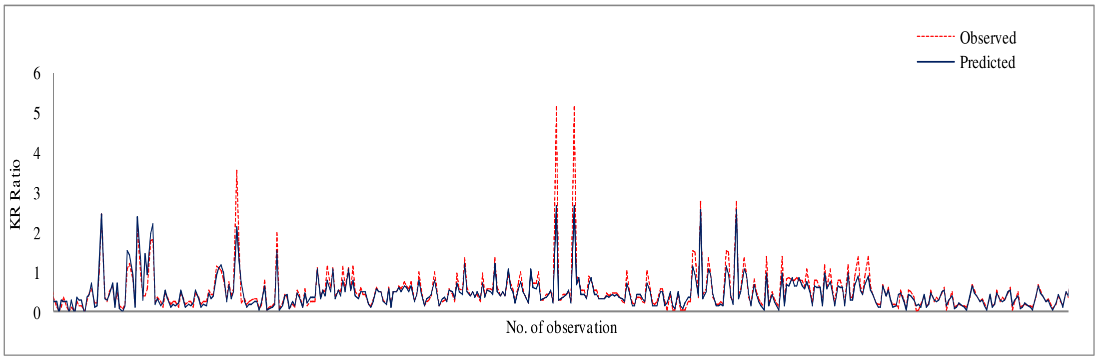

Figure-7: Comparison of actual KR value and predicted KR value from neural network.

Table-1: Best fit model performance of the various groundwater parameters.

Data set	IA	Correlation	MBE	RMSE	Parameter	Architecture
Training	0.97	0.98	-0.2176	0.3698	SAR	3-6-1
Testing	0.90	0.97	-0.1348	0.2482		
Cross validation	0.91	0.97	-0.2137	0.3438		
Training	1.00	1.00	-0.0270	0.0719	PI	4-6-1
Testing	0.99	0.98	-0.0173	0.0725		
Cross validation	0.99	0.99	-0.0144	0.0629		
Training	1.00	1.00	0.0379	0.0713	RSC	4-4-1
Testing	1.00	0.99	0.0225	0.0579		
Cross validation	1.00	1.00	0.0335	0.0599		
Training	0.99	0.98	-0.4682	3.2246	percent Na	4-2-1
Testing	0.99	0.99	-0.4081	2.0632		
Cross validation	0.99	0.99	-1.0383	2.6365		
Training	1.00	0.99	0.0440	1.7385	SSP	3-6-1
Testing	1.00	0.99	-0.4797	1.4172		
Cross validation	1.00	0.99	-0.2450	1.7354		
Training	0.94	0.92	-0.0478	0.1674	KR	3-2-1
Testing	0.94	0.94	-0.0211	0.1005		
Cross validation	0.95	0.95	-0.0759	0.1451		

Conclusion

In this paper ANN models were recognized for calculation of KR, % Na, PI, RSC, SAR and SSP concentration in groundwater of the Khed Taluka. The recognized models were trained, validated and tested for Na, Mg, K, $CaCO_3$, HCO_3 concentration. A good agreement between actual data and the ANN outputs was seen for training, validation and testing data sets. Hence, it can be indicated that the ANN model explained in this study is an applied tool to predict the KR, % Na, PI, RSC, SAR and SSP concentration. It was proposed that ANN is useful tool for working out of groundwater quality and it could be also utilized in other fields to get better the understanding of groundwater pollution indexes. The results confirmed that developed ANN models found suitable for prediction of water quality indicators used for irrigation purpose. The recommended node numbers included in hidden layer can be used for modelling of water quality indicators under limited data conditions. The Artificial Neural Network can be one of the powerful projecting substitutes to conventional modeling techniques.

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