Prediction of Parametric Value of Drinking Water of Hyderabad City by Artificial Neural Network Modeling

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Abstract: - In order to ascertain the quality of drinking water of the city of Hyderabad one of the significant parametric values of the drinking water was predicted. Like other parameters Electrical Conductivity (EC) is also imperative. The determination of electrical conductivity provides a prompt and expedient way to measure the accessibility of electrolytes in the water. There are swayed health effects on human life through these electrolytes, like disorder of salt and water balance in infants, heart patients, individuals with high blood pressure, and renal diseases. Salty taste is one of the aesthetic effects of EC if it exceeds 150 mS/m and if greater than 300 mS/m it does not slake the thirst. The drinking water supplied to Hyderabad city is taken from River Indus and the EC of this river remains questionable. The values of EC in drinking water of Hyderabad at selected locations were recorded. From 49 samples, the average values ranged from 658 to762. In order to determine the optimal value of EC with in the distribution system, where it deteriorates, it is necessary to predict it at different locations. The use of conventional methods to predict parametric values in the distribution systems is suffered from certain precincts. To get better drinking water quality by tumbling operational costs, Advance process control and automation technologies are the tools to be used normally. The application of Artificial Neural Networks in Water Supply Engineering is enticing and more accepted because of its high predictive accuracy. In this paper Radial Basis Neural Network has been demonstrated. The data sets were prepared for training the model. It was observed that the model has high predictive potentiality to predict the values of Electrical conductivity at 07 locations of distribution system of water supply in Hyderabad city. The removal of noisy and uninformative input variables from the data improved the efficiency of the network.

Key-Words: - Electrical Conductivity, Drinking water, Distribution System, ANNs, RBF, modeling, prediction Hyderabad.

1. Introduction

Hyderabad lies in the latitude 25^o 22` N and longitude 5$^o$-41`East. Geologically, the city is low flat-topped and typically of arid topography. The climate is subtropical, semi-desert type. It is characterized by low and highly erratic rainfall, low relative humidity, and high rate of temperature. The mean annual rain fall is 12.92 cm mainly concentrated in the months of July and August, which together accounts for 12.2 cm. [1]. River Indus is a major source of drinking water supplied to Hyderabad city having population of 1.8 million. Domestic water supply of Hyderabad comes from canals emanating from the river Indus, which receives an astonishing and spontaneous release of contaminated water from Manchhar Lake, one of the biggest natural fresh reservoirs in Asia. [2] In a study carried out by Pakistan Council of Research in Water Resources (PCRWR) in various cities of the country (Table 1-2) comprised of 6 rivers 10 reservoirs, including Indus. In 17 cities bacterial infectivity was greater than 50% while, the quality of drinking water of 4 cities within these, were declared incongruous for human consumption. In 2004, second study was carried out with a result that there was no improvement with respect to earlier study. From river Indus, at Jamshoro, water is supplied to the lagoons named North and South lagoons of 400 MG for pre-settlement and then brought to the “New treatment Plant” (NTP) with its capacity of 30 MGD. This plant and the pipeline distribution system came in being in the early 80s, in comparison with Old treatment Plant (OTP) with capacity of 10 MGD, commissioned in the early 60s, which is now out of work. It is observed that the most of waste water drainage pipe lines are also laid in parallel and are about 152-244 cm away from the drinking water pipeline, hence, often causing mixing of wastewater with drinking water [3] Under these conditions parametric pollution is evident from the distribution system of the city where all the samples were bacteriological positive at all seven locations concluded in a weeks study carried out by Pakistan Council for Research on water Resources (PCRWR) [4]. An overview of the Water Supply and distribution system of the drinking water of the city is shown in figure 1 and the current and projected population of the city is shown in table 3.

Table1
Experimental values taken from Dams, Canals & Lakes of Pakistan

Source	pH	Turbidity (NTU	TDS (mg/l)	Coliform (MPN/100ml)	E. coli (MPN/100ml)
Simly Dam	8.2	6	192	>16	>16
Rawal Dam	7.9	24	208	>16	>16
Mangla Dam	8.2	4	93	>16	>16
Lahore Canal	7.6	647	126	>16	>16
Khanpur Dam	8.1	2	222	>16	>16
Tarbela Dam	7.9	52	94	>16	>16
Hanna Lake	7.5	11	385	>16	>16
Hub Dam	7.2	5	743	>16	>16
Hamal Lake	7.3	12	4652	>16	>16
Manchhar Lake	7.6	134	5318	>16	>16
Torkhezai Dam	7.7	400	150	>16	>16
Chashma lake	7.8	183	132	>16	>16

Table 2
Experimental values taken from rivers of Pakistan

Source	pH	Turbidity (NTU	TDS (mg/l)	Coliform (MPN/100ml)	E. coli (MPN/100ml)
Sutlej River	7.5	694	580	>16	>16
Ravi River	7.5	670	127	>16	>16
Swat River	7.3	36	46	>16	>16
Indus River	7.6	76	84	>16	>16
Kabul River	6.1	774	120	>16	>16
Hub River	7.2	6	756	>16	>16
Chenab River	7.6	580	115	>16	>16

The existing and proposed distribution system of the drinking water to the city is shown in figure 1. In this study, the locations selected for predicting the value of

Electrical conductivity are taken within the existing distribution system of the city. 07 locations were selected randomly, in order to check the quality of the drinking water through out the distribution system, up to the end users.

Globally it is evident that the increase in population is a burning issue. In 2004, Pakistan was at a growth rate of 1.9%, and the projected population by 2010 is indicated as 173 million and may be extended to 221 million by the year 2025. This alarming situation will bring the country below the limit of 1000m^3 of water per capita per day (PCPD), and this may go to still more rapid in the areas outside of the river basin, where annual average is below this limit of 1000m^3 PCPD [5]. Table 3 represents the current and projected population of Hyderabad city.

Table 3
Current and Projected population of the city

CURRENT AND PROJECTED POPULATION

(ALL FIGURES IN THOUSAND)

TALUKA	1998	2005	2008	2015	2020
HYDERABAD CITY	525	606	650	732	793
QASIMABAD	115	171	186	247	284
LATIFABAD	564	670	720	840	922
SUB-TOTAL	1204	1447	1656	1819	1999
HYDERABAD RURAL	290	329	349	393	426
TOTAL	1494	1776	2005	2212	2425

Courtesy (WASA, Hyderabad)

Indus River is major source of keeping people alive gratifying their desires for drinking and agriculture as well, but generally it provides drinking water in cities around like Hyderabad. In 1994, 90% of highly tainted water with alarming concentrations of pollutants was discharged into this river, through many sources and it was learnt that the Indus River water pollution was increasing constantly due to industrial waste and urbanization.[6]. However the availability of raw water storage in the city of Hyderabad is shown in the table 4.

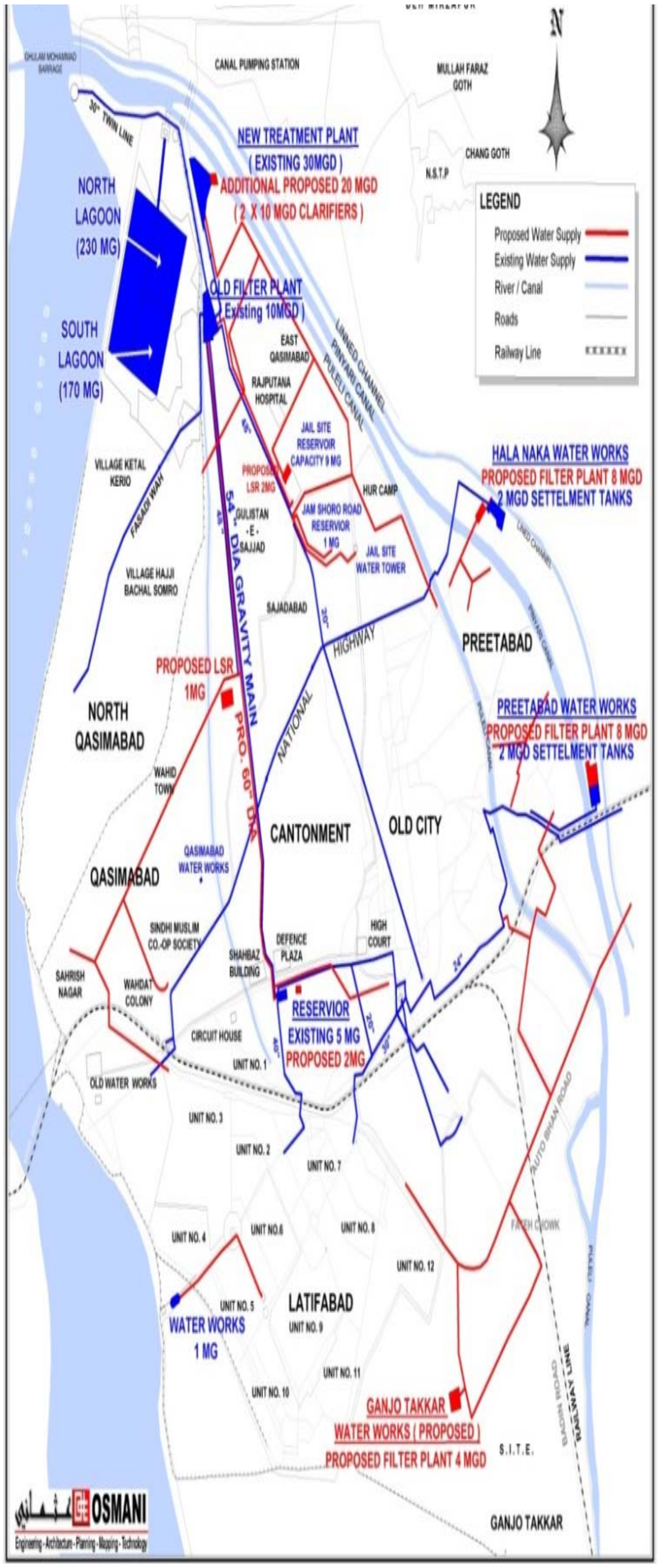

Figure 1
Water Supply and Distribution System of the city of Hyderabad (Courtesy: WASA Hyderabad)

Table 4
Raw water storage facilities in Hyderabad

AVAILABLE RAW WATER STORAGE FACILITIES			
S.#	LOCATION	EARLIER CAPACITY	RECENTLY ENHANCED CAPACITY
1	JAMSHORO LAGOONS	400 MG	500 MG
2	HALA NAKA TANKS	35 MG	108 MG
3	PREETABAD TANKS	28 MG	102 MG
4	HUSSAINABAD TANKS	2 MG	2 MG
5	LATIFABAD UNIT No.4 TANKS	10 MG	10 MG
6	LATIFABAD UNIT No.6 TANKS	1 MG	1 MG
	TOTAL	476 MG	723 MG

The drinking water supplied to the city is stored at the various locations of the city as shown in table 5 and water intake facilities are shown in table 6

Table 5
Clear Water Storage facilities available in the city

AVAILABLE CLEAR WATER STORAGE FACILITIES		
S.#	LOCATION	CAPACITY
1	THANDI SARAK RESERVOIR	5.00 MG
2	JAMSHORO ROAD RESERVOIR	1.00 MG
3	RESERVOIR AT NEW WATER TREATMENT PLANT (NTP)	0.05 MG
4	RESERVOIR AT OLD WATER TREATMENT PLANT (OTP)	1.00 MG
5	RESERVOIR AT PREETABAD	1.00 MG
6	RESERVOIR AT HALA NAKA	1.00 MG
7	FORT RESERVOIR (LSR)	1.00 MG
8	FORT RESERVOIR (HSR)	0.80 MG
9	QASIMABAD RESERVOIR	0.05 MG
10	AMANI SHAH LATIFABAD RESERVOIR	0.30 MG
11	UNIT No.10 LATIFABAD RESERVOIR	0.30 MG
12	HEERABAD RESERVOIR (HSR)	0.50 MG
13	UNIT No.11 LATIFABAD DEGREE COLLEGE RESERVOIR	0.30 MG
	TOTAL	12.30 MG

Table 6
Water Intake Facilities in the city

WATER INTAKE FACILITIES			
S.#	SOURCE	CAPACITY	RECENTLY UPGRADED CAPACITY
1	HEAD REACH (RIVER INDUS)	15 MGD	50 MGD
2	HALA NAKA	10 MGD	20 MGD
3	PREETABAD	10 MGD	20 MGD
4	INTAKE P.S. AT COMBINED CHANNEL	60 MGD	60 MGD
5	UNIT NO.04 (D/S KOTRI BARRAGE)	08 MGD	08 MGD
6	HUSSAINABAD (D/S KOTRI BARRAGE)	02 MGD	02 MGD
	TOTAL	105 MGD	160 MGD

The parameters include pH, Turbidity, Electrical conductivity, HCO_3, Cl, SO_4, Ca, Mg, Na, K, Hardness and Bacteriology. In this study the Electrical Conductivity is undertaken, being an important parameter of drinking water quality. The adverse health effect include disturbance of salt and water balance in infants, heart patients, persons with high blood pressure, and renal disease. Aesthetic effects include a salty taste to the water (if conductivity > 150 mS/m) while water with conductivity > 300 mS/m does not slake thirst. [7] The dissolved or soluble fraction of the water's total solids load is referred to as total dissolved solids, known

as TDS, normally the weight of this material. The Electrical conductivity EC provides a simple measure of TDS and is the measure of the water's ability to conduct an electric conductivity. A relationship between TDS and EC may be considered with respect to the following relationship. This relationship gives an idea about the approximate calculation of Total Dissolved solids (TDS) when Electrical conductivity EC is taken with respect to a specific temperature of 25^{o} C.
The relationship is given as under:
TDS (mg/l) = 0.67x EC 25 (1)
It is observed that the Electrical conductivity EC is temperature sensitive. It increases with increasing temperature. This is maintained automatically when measured with latest equipment having probes. These modern probes automatically standardize all the readings to 25^{o}C temperature, and this EC is called as EC_{25} [8].

2. ANNs in Water Supply Engineering

Recent research indicates towards the use of new technologies and computer based applications for predicting the Drinking Water Pollution Level (DWPL) for all its measurable parameters. Over the last two decades, artificial neural networks have been a primary focus of interest for research in computer based civil and environmental engineering by providing convenient and often highly accurate solutions to problems from all branches including drinking water related issues. At first momentary look, artificial neural networks appear to be one of the great accomplishments in the history of computing in civil engineering. Replying to the question : "why there has been such a high and sustained level of interest in applying artificial neural networks to civil/environmental engineering", the answer is that ANNs ,despite their presently elementary form, are very good at solving direct mapping problems that are non-linear and comprise several independent variables, a common class of problems in civil engineering. In this context they often provide more accurate solutions than the alternative modeling techniques and place a little demand on the modeler in terms of understanding the basic form of the function being represented [9].
Quite a lot of thriving applications in environmental engineering have been reported in literature as well. Maier and Dandy provided an extensive review of literature on the use of ANNs in water resource modeling. [10]. For finding optimal pumping operation for successful remediation of a polluted aquifer, feed-forward artificial Neural Network and genetic algorithm(GA) was used by Rogers and Dowla in 1994[11]. In 1999 Zhang and Stanley used artificial neural Network for real-time control system for coagulation, flocculation and sedimentation process [12]. Same year, Brion and Lingireddy used artificial neural networks for identifying non-point source of microbial contamination [13]. Again, in the same year Tay and Zhang modeled the complex process of anaerobic biological treatment of wastewater using neural-fuzzy technique. [14]. Peak concentrations of cryptosporidium were predicted by using the artificial neural networks in 2001 [15]. The atmospheric ozone concentration in Seoul was forecasted using an artificial neural network and spatial-temporal analysis. [16].
Artificial neural network models are capable of modeling data whose functional relationship are not known in advance. By choosing appropriate architecture and activation, neural networks can be trained to capture knowledge from the data available with acceptable performance. In general Multilayer Perceptron MLP Artificial Neural Networks are commonly used in almost every filed of engineering. This type of ANN is supposed to perform well in a number of hydrologic and water resources applications [17]. The most commonly used algorithm for training multilayer feed-forward networks is the 'error back-propagation algorithm'. Often it is referred as back-propagation training algorithm. This algorithm involves calculating the derivatives of the network training error with respect to the weights by the application of chain-rule and gradient decent optimization to adjust the weights to minimize the errors [18]. It is well known that MLPs and a variety of kernel-based networks [such as radial basis function RBF] are universal function approximators, in some sense. [19] A.R. Barron proved that MLPs are better than linear basis function systems like Taylor series in approximating smooth functions [20]. Despite its popularity, the back propagation algorithm suffers from the following disadvantages.

- It is slow.
- It may stuck to global minima of the error surface rather than the global minimum during the training.
- While using this algorithm, the number of the hidden layer neurons is to be selected manually; this may be far from the optimal.

Latest research confirms that the error back propagation algorithm remains a signified milestone in neural network research area of interest though known as an algorithm with poor convergence rate, while many attempts have been made to speed up this algorithm.
Better results have been obtained with artificial enlarging of errors for neurons operating in the saturation region. [21]

2.1 Selection of Model (RBF)

Different neural networks have been developed in latest years together with Radial Basis Function models. In 1997, Yingwei and Billings proposed different adaptation algorithms for radial Basis Function network structures to recursively train the network for system identification and were not considered as system controlled but the model was trained to fulfill the requirements.[22] Predictive performance of a model is always an essential aspect in artificial intelligence; hence the proposed models performance was not well thought-out in particular when the new centers were added probably due to the fact that the new centers were not trained by the previous measurement data starting from the initial condition.[23] Another adaptive RBF network with Lyapunov method was presented in 1999 by Lieu [24] In 2000, Pereria suggested adaptive RBF network for controlling an experimental process.[25]

In 2001, Paulin Coulibaly presented two variants of Radial Basis Function(RBF) in his study, a generalized radial basis function network(GRBF) and a variation of RBF network named probabilistic neural network (PNN). Among these, the former represented the general and typical form of RBF network, and the latter was a variation of RBF that uses a soft competitive activation function derived from the Bayesian classification theory. According to him, both the network assumes Gaussian (Radial) basis function for their hidden units. The typical RBF network looks like the conventional three layer feedforward network topology; however its operation is fundamentally different. Temporal and probabilistic neural networks are effectual at predicting monthly groundwater level fluctuations in aquifer. The general form of RBF network (GRBF) is not apposite to deep water table modeling. [26]

In this study an RBF network has been used which does not suffer from any of the above mentioned disadvantages and is therefore a powerful alternative to MLP network. The RBF networks were originally applied to the multivariable interpolation problems [27].

An RBF network is essentially a three layers network. That is, it has input layer, a hidden layer and an output layer, as shown in figure 2.

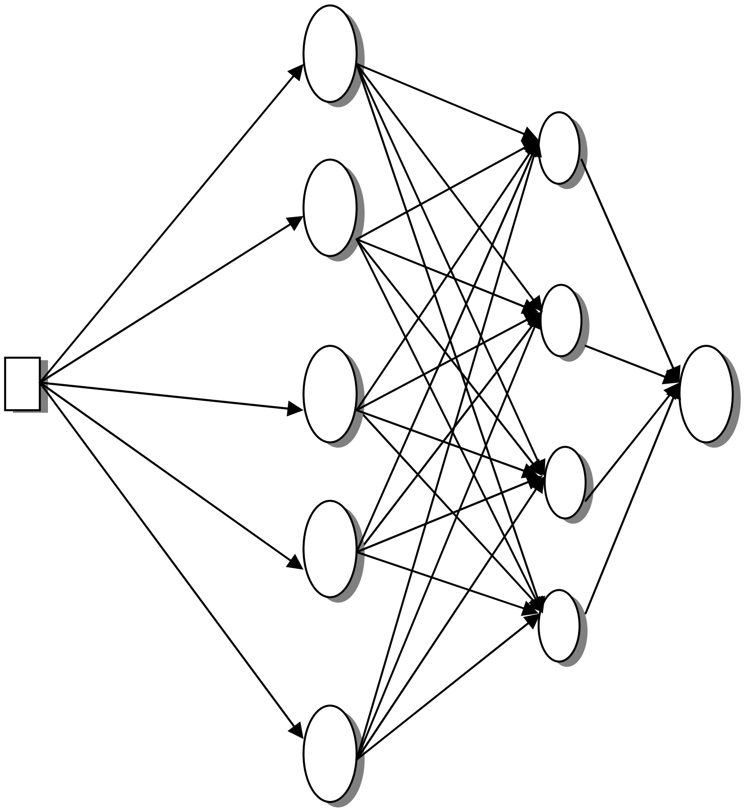

Fig.2:
Structure of an RBF Network

The output layer is always linear because each neuron of this layer has a linear activation function. The hidden layer is always non-linear. The neurons in this layer use a radial basis function as an activation function. A most widely used radial basis function is the Gaussian function which is defined as follows:

$$g_k(\vec{x}) = \exp\left(-\frac{\left\| \vec{x} - \vec{c}_k \right\|^2}{\sigma_k^2} \right) \quad (2)$$

In the above equation, $\vec{x}$ is the input vector, c_k is the centre of the kth Gaussian Function and σ_k^2 is the corresponding variance.

The overall output of the network is computed as

$$f(\vec{x}) = \sum_{k=1}^{M} w_k \cdot g_k(\vec{x}) \quad (3)$$

Where M is the number of RBFs and Wk is the kth weight.
Like other feed forward neural networks, the RBF network is trained in such a way that the error between the desired and actual output(s) of the network is minimum. In other words, the weights are optimized during training so that the actual output is sufficiently close enough to the desired output. Before optimization of the weights, the network must select an appropriate number of RBFs. Moreover, the centers and width of the RBFs must also be optimized to get good approximation.
In this paper, the orthogonal least Mean Squares Algorithm (LMS) proposes of Chen et al [28] has been used to train the RBF network. This algorithm automatically selects the number of hidden layer neurons by optimizing the centers of the RBFs of a given width.

3. Case Study

Water Pollution has turn out to be a somber issue worldwide, particularly in the urban areas, though the houses are now equipped with a local water filter system. However WHO [29] estimated that there will be 4 billion cases of diarrhea and 2.2 million deaths per annum. It is crystal clear that the users are concern with the pollution in drinking water due to the presence of heavy metals and toxic chemical, they are taking daily. It may be presumed that the filtered water is the main source of safe and reliable drinking water. However debates are continued to confirm that efficiency of the filtration system complies with the established regulations keeping the fact up that the drinking water looking colorless physically, odorless and may be tasteless even, is not the authorization that the water is safe for consumption, there fore the drinking water should be tested for physicochemical and microbiological quality[30]. WHO recommended in its report of 2000 that the physical parameters that are likely to raise the complaints from the consumers are color, taste, and turbidity, pH has the effect of corrosion if less than the standard and it has effect on the taste of water if it exceeds than the maximum contaminant level (MCL)

This case study was conducted for prediction of one of the important parameter of Electrical Conductivity (EC) of drinking water of Hyderabad, the 4th biggest city of Pakistan with 2.28 million souls. The drinking water is treated in the filter plant bearing the capacity of 30 MGD. Analytical /experimental observations on the drinking water of Hyderabad city were available with the concerned quarters like Water and Sewerage Authority (WASA), Environmental Protection Agency (EPA), and Pakistan Council for Research in Water Resources (PCRWR) Lahore. Successful application of artificial neural network model requires proper input data preparation [31]. Proper selection of input variables (parameters) is an essential process in any modeling activity of ANNs. Eliminating unnecessary or least influencing input variables not only simplifies the models predictive abilities, but also reduces the burden on data collection .If these variables are well chosen and if the problem is simple enough, the model could be designed from the data. Usually all the variables available may not be equally informative; some of them may be noisy, meaningless or irrelevant to the task. Thus selecting a subset of the input variables, which are relevant to the given problem, is important. The neural network while performing in general, do not provide information about the underlying task to identify and remove the useless input variables. Thus the removal of these useless variables helps to understand the prediction and give important information only to the model. Removal of useless variables allows simplifying the model structure itself and speeds up the training and prediction process and may provide better estimates. It is important as well to notice that using less number of input variables speeds up data acquisition process. [32]
In this study complete data sets were prepared according to the specifications normally used for input data preparation. The data were based on the results of experimental analysis carried out by PCRWR and WASA, during last 5 years. The data sets include the observations of the samples taken at the locations K.B.Federal Police Station Khurshid Colony, City water supply tank Kotri, Hussainabad Pacca Tank HDA-8, Board of Intermediate Secondary Education, Latifabad Number 7, Tayab Masjid Unit 12 Latifabad, New Wahdat Colony, Qasimabad, and Mustafa Town,Qasimabad.
Normalization (scaling) of the data is a process to get it useable for training a neural network model trained with back propagation algorithms. In this paper two parameters , i) Electro conductivity and ii) Turbidity were normalized in order to optimize the weights and train the network for desired outputs.

4. Results and Discussions

A single hidden layer Radial Basis Function (RBF) model with Gaussian function as an activation function in hidden layer neurons, and linear function in output neurons was selected and trained. The data sets were prepared from the available results of the PCRWR and WASA authorities taken during the last 5 years. One complete set was reserved for training and the other data set was prepared to testify and verify the validity of the model. The Input parameters were EC, pH, Turbidity, Alkalinity, HCO_3 and Cl. and the targeted value to be predicted out was Electrical conductivity. These results showed that this RBF model doesn't require any scaling of the data. The Sum of the squared errors SSE was 0.0397799 during the training. It was found that 2 neurons in hidden layer are sufficient for successful training. As there is one output so the number of the neurons in output layer is one. The output (predicted EC values) of the trained network is shown in Figure 2.

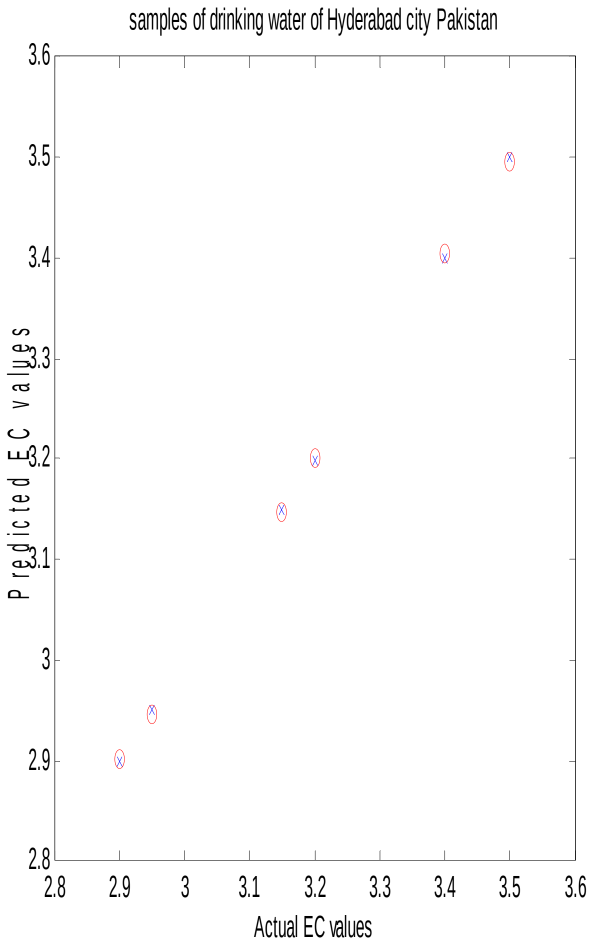

Figure 2
Actual and predicted values of EC

The experimental results are also plotted in the same graph for comparison purpose. The input weights, output weights, input bias, output bias, the time elapsed during training and the SSE is given in table 5.The model was tested for using different testing sets and each time the results were satisfactory because the error in each sample for each testing set was negligible.

Table 5
Predicted and Tested values of EC at 07 locations of the city

Location	**1**	**2**	**3**	**4**	**5**	**6**	**7**
EC predicted	**2.9472**	**3.2003**	**2.9015**	**2.9015**	**3.4969**	**3.1478**	**3.4049**
EC Tested	**3.7221**	**3.6817**	**3.7158**	**3.7158**	**3.5081**	**3.6988**	**3.5770**
Input Weights	**3.4000 , 3.000**						
Output weights	**6.2861 , 7.0283**						
Input Bias	**0.8326, 0.8326**						
Output Bias	**2.7113**						
Time elapsed during training	**0.281000 seconds**						
Sum of square Error (SSE)	**0.0397799**						

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5. Conclusions

The study conducted showed that the use of Artificial Neural Networks for predicting the parametric value of drinking water is viable. This research advocated that Radial Basis Function (RBF) Model has the powerful looming of predicting the precise EC values of drinking water ; in the distribution system ; having amalgamation of the parameters like Turbidity, pH, Cl; at an assortment of locations in the water supply distribution system of Hyderabad. This has specified the potential of RBF model to be implemented as an online tool to aid the determination of EC values in drinking water distribution network of the city. This Model does not require any robust training termination even in small data sets because of its fast training efficiency which was recorded as low as 0.281000 seconds. It was evident that the removal of uninformative input variables from the data collected, speeds up the training process of the model and predictive potentiality as well. This may be due to the fact that the physical process behind the modeling errand was well known which helped to make it easy for selecting the input variables used in this model. This learning proves the advantages, competence, capability and knack of applying the Artificial Neural Network Modeling for monitoring the quality of Drinking water of Hyderabad city of Pakistan.

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