Water Level Prediction using Simulated Annealing

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Abstract- India's rapidly rising population and changing lifestyles has also increased the domestic need for water. The water requirement for the industries also shows an overall increase. Intense competition among users of agriculture, industry, and domestic sectors is driving the groundwater table lower. Thus, constant monitoring of the ground water levels is extremely important. The water levels if properly predicted well in advance can help the administration to plan better ground water utilization.The overall objective of the present work is to use Adaptive Neuro Fuzzy Inference System (ANFIS) and Simulated Annealing (SA) optimization techniques for the development of groundwater level prediction models in order to overcome groundwater related problems mentioned above. For this Sarojini Nagar Block of Lucknow district has been taken up as a case study. MATLAB platform will be used for the development of the model.

I. INTRODUCTION

The importance of groundwater for the existence of human society cannot be overstated. Groundwater is the major source of drinking water in both urban as well as rural India. Besides, it being an important source of water for the agricultural it is also an importance source for industrial sector. Being an important and essential part of the hydrological cycle, its availability depends on the rainfall and recharge conditions. Till recently it had been considered as a dependable source of uncontaminated water.Total replenishable ground water resource of Uttar Pradesh is 84 BCM, out of which present total extraction is about 40.95 BCM and the net exploitation is 27 BCM which is 65.9% of total extraction. Thus, the ground water resource available for future utilization is about 43.95 BCM. However, this resource is unevenly distributed in space and the present state of exploitation has resulted in regional ground water imbalances. It is estimated that for domestic, industrial and irrigation needs of growing population, the level of ground water exploitation will increase from 27 BCM to 64 BCM by 2025 i.e. requirement of ground water will be more than double the present level. Due to this the number of over-exploited blocks may increase from 14 to 177 by the year 2025. (These represent the blocks where the drawls are more than recharge).

The ever-increasing demand for water has led to water scarcity in many parts of the world. The situation is antagonized by the problem of water pollution or contamination. India is moving towards a crisis of freshwater mainly due to improper management of water resources and environmental degradation, which has led to a lack of access to safe water supply to millions of people. This freshwater crisis is already noticeable in many parts of India, varying in scale and intensity depending mainly on the time of the year [1][2].

Groundwater crisis is not the result of natural factors; it is an effect of human actions. During the past two decades, the water level in several parts of the country has been declining rapidly due to an increase in extraction. The number of wells drilled for irrigation of both food and cash crops have expeditiously and indiscriminately increased. India's rapidly increasing population and changing lifestyles has also increased the domestic need for water. The requirement of water for the industry also shows an overall increase. Intense competition among users of agriculture, industry, and domestic sectors is driving the groundwater table lower. Thus, constant monitoring of the ground water levels is extremely important. The water levels if properly predicted well in advance can help the administration to plan better ground water utilization. Also, for an overall development of the basin, a continuous forecast of the ground water levels is required to effectively use any simulation model for water management. These models based on observed data or theoretical principles provide a framework for decision making for water users and water regulators.

II. RELATED WORK

Jignesh Patel, Dr.Falguni Parekh, (2014) [20] illustrated the development of an efficient model to forecast monthly monsoon rainfall for Gandhinagar station using Adaptive Neuro Fuzzy Inference System (ANFIS). Eight models were developed using various membership functions and climatic parameters as inputs. In this study, the generalized bell-shaped built-in membership function has been used as a membership function in both Hybrid and Back propagation method for ANFIS. The four evaluation parameters Root mean square error, Correlation Coefficient, Coefficient of Determination and Discrepancy ratio were used to evaluate the developed model. The study revealed that hybrid Model with seven membership functions and using three inputs, temperature, relative humidity and wind speed gives best result to forecast rainfall for study area.

FaramarzKeshvari and Seyed Amir Shamsnia, (2014) [21] illustrated evaluation of the system for predicting the flow of the QAREAGHAJ river has been given. For this purpose,

gauging, rainfall, temperature, evaporation and monthly discharge of the BANDE BAHMAN station on QAREAGHAJ River in 30-year period (October 1982 to October 2012) were used for the model. The results showed that the artificial neural network can predict monthly discharge of the river with solidarity coefficient of 75.0.

Samarjit Kara, Sujit Dasb, PijushKanti Ghosh, (2014) [22] illustrated neuro fuzzy systems (NFS) development using classification and literature review of articles for the last decade (2002–2012) to explore how various NFS methodologies have been developed during this period. Based on the selected journals of different NFS applications and different online database of NFS, this article surveys and classifies NFS applications into ten different categories such as student modeling system, medical system, economic system, electrical and electronics system, traffic control, image processing and feature extraction, manufacturing and system modeling, forecasting and predictions, NFS enhancements and social sciences. For each of these categories, this paper mentions a brief future outline. This review work indicates mainly three types of future development directions for NFS methodologies, domains and article types: (1) NFS methodologies are tending to be developed toward expertise orientation. (2) It is suggested that different social science methodologies could be implemented using NFS as another kind of expert methodology. (3) The ability to continually change and learning capability is the driving power of NFS methodologies and will be the key for future intelligent applications.

Naser Almanaseer, A. Sankarasubramanian, M. Jerad Bales, (2014) [23] illustrated and analyses the potential in developing 6-month-ahead groundwater-level forecasts based on the precipitation forecasts from ECHAM 4.5 General Circulation Model Forced with Sea Surface Temperature forecasts. Ten groundwater wells and nine stream gauges from the USGS Groundwater Climate Response Network and Hydro-Climatic Data Network were selected to represent groundwater and surface water flows, respectively, having minimal anthropogenic influences within the Flint River Basin in Georgia, United States. Two low-dimensional models [principle component regression (PCR) and canonical correlation analysis (CCA)] for predicting groundwater and stream flow at both seasonal and monthly timescales were employed. Results from the work showed that using precipitation forecasts in climate models improves the ability to predict the inter annual variability of winter and spring stream flow and groundwater levels over the basin.

ShahaboddinShamshirband, Member IEEE et al. (2015) [24] illustrated an investigation of the accuracy of soft-computing techniques in precipitation estimation. The monthly precipitation data from 29 synoptic stations in Serbia from 1946 to 2012 are used as a case study. Despite a number of mathematical functions having been proposed for modeling precipitation estimation, the models still have disadvantages such as being very demanding in terms of calculation time. Soft computing can be used as an alternative to the analytical approach, as it offers advantages such as no required knowledge of internal system parameters, compact solutions for multivariable problems, and fast calculation. Because precipitation prediction is a crucial problem, a process which simulates precipitation with two soft-computing techniques was constructed and presented in this paper, namely, Adaptive Neuro-fuzzy Inference (ANFIS) and support vector regression (SVR). In the current study, polynomial, linear, and radial basis function (RBF) are applied as the kernel function of the SVR to estimate the probability of precipitation. The performance of the proposed optimizers is confirmed with the simulation results. The SVR results are also compared with the ANFIS results. According to the experimental results, enhanced predictive accuracy and capability of generalization can be achieved with the ANFIS approach compared to SVR estimation. The simulation results verify the effectiveness of the proposed optimization strategies.

III. METHODOLOGY

Simulated annealing (SA) is a generic probabilistic meta-algorithm for the global optimization problem, namely locating a good approximation to the global optimum of a given function in a large search space. It is often used when the search space is discrete.

a. The Technique of Simulated Annealing

Simulated annealing [8] is a method for optimisation based on a controlled random walk on the *error surface* (the multidimensional generalisation of the error curve shown in Figure. 1). Starting at some random point (1) on this surface, the error, *E*1, is evaluated from the model and data. A nearby point (2) is chosen at random and the error, *E*2, evaluated (see Figure 1). If the new point has a lower error, the search moves there and the process is repeated. However, if it has a higher error (as shown), there is still a chance of moving there. The probability for this is chosen to be $p = e^{(-\Delta E/k T)}$, as the analogy to statistical mechanics suggests [9]. This probability for moving to the next state ranges between 1 and 0 for very small and very large error differences respectively. In other words, 'uphill' moves are permitted, albeit with decreasing probability for larger differences. This has the effect of managing to 'escape' local minima, and hence permits a more comprehensive search of the parameter space. The quantity *kT* in the equation determines exactly how probable an uphill move of a certain size is: a large *kT* makes comparatively large uphill moves more likely. The idea behind simulated annealing is to reduce *T* slowly (for a fixed *k*) as the search

proceeds. This initially permits a large region to be searched. As time proceeds (and *T* is reduced), large uphill moves become increasingly prohibited, thereby focusing attention on finding what is hopefully the global minimum of the parameter space.

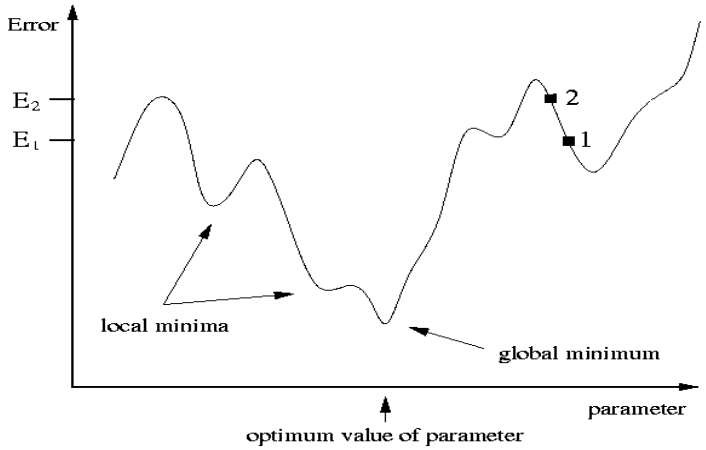


Fig.1: The Error of a Model's Predictions as a Function of Its One Free Parameter. [7]

b. Simulated Annealing Analogy:

Simulated annealing (SA) is one of the most versatile techniques applicable for solving combinatorial problems. Because many real world design problems can be cast in the form of such optimization problems, there is intense interest in general techniques for their solution. Simulated Annealing is one such technique, rather old, [8]. It is motivated to an analogy of annealing in solids. To understand such a situation, consider how to force a solid into a low energy state. A low energy state is a highly ordered state, such as crystal lattice. To achieve this, a material is annealed, heated to a temperature that permits many atomic arrangements, then cooled carefully, slowly, until the material freezes into a good crystal. SA uses an analogous set of controlled cooling operations for non-physical optimization problems. Interest in such technique is because some optimization problems could be solved in a reasonable time. Simulated annealing is a local search algorithm (metaheuristics) competent enough of escaping from local optima. Its ease of implementation, convergence properties and its use of hill-climbing moves to escape local optima have made it a well-accepted technique. It is normally used to deal with discrete, and to a lesser degree, continuous optimization problems. The main benefit of SA is that it can be useful to large problems regardless of the conditions of differentiability, continuity, and convexity that are normally necessary in conventional optimization methods. Annealing is the process of submitting a solid to high temperature, with successive cooling, so as to achieve high-quality crystals (i.e., crystals whose structure form perfect lattices) [7]. Simulated annealing emulates the physical process of annealing and was originally proposed in the domain of statistical mechanics as a means of modelling the natural process of solidification and formation of crystals. During the cooling process, it is assumed that thermal equilibrium (or quasi equilibrium) conditions are maintained. The cooling process ends when the material reaches a state of minimum energy, which, in principle, corresponds with a perfect crystal. It is known that defect-free crystals (i.e., solids with minimum energy) are more likely to be formed under a slow cooling process. The two main features of the simulated annealing process are: (1) the transition mechanism between states and (2) the cooling schedule. When applied to combinatorial optimization, simulated annealing aims to find an optimal configuration i.e. a state with minimum "energy", of a complex problem. The objective function of an optimization problem corresponds with the free energy of the material. An optimal solution is associated with a perfect crystal, whereas a crystal with defects corresponds with a local optimal solution. The analogy is not complete, however, because in the annealing process there is a physical variable that is the temperature, which under proper control leads to the formation of a perfect crystal. When simulated annealing is used as an optimization technique, the "temperature" becomes simply a control parameter that has to be properly determined in order to achieve the required results. The original idea behind the simulated annealing algorithm is the Metropolis algorithm that models the microscopic behaviour of sets of large numbers of particles, as in a solid, by means of Monte Carlo simulation. In a material, there are different levels of energy in the individual particles, according to a certain statistical distribution. The possible lowest level of energy, known as the fundamental level, corresponds with the state where all particles stand still and occurs at temperature 0^0 K. For temperatures above that level, the particles will occupy different levels of energy, such that the number of particles in each level decreases as the energy level increases (i.e., the maximum number of particles is found in the fundamental level). The distribution of the particles in the various levels varies with the temperature; for T = 0 K, for example, all particles are in the fundamental level; as the temperature increases, more particles are found in higher energy levels but always as a decreasing function of the energy level. The Metropolis algorithm generates a sequence of states of a solid as follows: giving a solid in state Si, with energy Ei, the next state Sj is generated by a transition mechanism that consists of a small tension with respect to the original state, obtained by moving one of the particles of a solid chosen by the Monte Carlo method. Let the energy of the resulting state, which also is found probabilistically, be Ej; if the difference [Ej-Ei] is less than or equal to zero, the new state Sj is accepted. Otherwise, if the difference is greater than zero, the new state is accepted with a probability of:

$$\exp\left\{\frac{Ei - Ej}{k_B T}\right\}$$

Where, T is the temperature of the solid and kB is the Boltzmann constant. This acceptance rule is also known as Metropolis criterion and the algorithm summarized above is the Metropolis algorithm [7]. The temperature is assumed to have a rate of variation such that thermodynamic equilibrium is reached for the current temperature level, before moving to the next level. This normally needs a large number of state transitions of the Metropolis algorithm. For a combinatorial optimization problem to get solved using simulated annealing, it is formulated as follows: let G be a finite, although perhaps very large, set of configurations and v the cost associated with each configuration of G. The solution to the combinatorial problem consists of searching the space of configurations for the pair (G, v) presenting the lowest cost. The SA algorithm starts with an initial configuration G0 and an initial "temperature" T0 and generates a sequence of configurations N =N0. Then the temperature is decreased; the new number of steps to be performed at the temperature level is determined, and the process is then repeated. A candidate configuration is accepted if cost of the configuration is less than that of the current configuration. If the cost of the candidate configuration is bigger than the cost of the current configuration, it still can be accepted with a certain probability. This ability to carry out uphill moves allows simulated annealing to escape from local optimal configurations. The entire process is controlled by a cooling schedule that determines how the temperature is decreased during the optimization process.

c. Simulated Annealing Algorithm

Evolutionary algorithms like simulated annealing and tabu search are widely accepted heuristic algorithms for combinatorial optimization. The term evolutionary algorithm is used to refer to any probabilistic algorithm whose prototype is inspired by evolutionary mechanisms found in biological species [9]. One of the most widely used of heuristic algorithms is simulated annealing (SA) algorithm. SA exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure i.e. the annealing process, and the search for a minimum in a more general system [8]. In the optimization process, the solution randomly moves in its neighbourhood with a probability calculated by Metropolis principle while the system temperature decreases slowly, When the annealing temperature is approaching zero, the solution stays at the global best solution in a high probability. [9]

The application of SA in optimization problem is formulated as an NLP problem, expressing the objective function and constraint functions in term of the specified independent variables. The objective function is expressed as :Optimize f(x), where 'x' exists within the n-dimensional feasible region D:

X ı D, where

D = {x | x >=0, gi(x) <=0, hi(x) = 0, i=1 to n}

In the above equations, f(x), gi(x) are real valued scalar functions and vector x comprises the n principal variables for which the optimization is to be performed. The function f(x) is called to be objective function, for which the optimal value of x result in the maximum value for f(x), and these optimal values satisfy the given constraints.

Algorithm: [10]

Simulated Annealing
Begin
Initialize (T0,N0);
K: = 0;
Initial configuration Si
Repeat procedure
Do L: =1 to Nk
Generate (Sj from Si);
If f(Si) ≤ f(Sj) do Si = Sj
Otherwise
If exp{(f(Si)-f(Sj)/Tk) >random [0,1] do Si = Sj;
End do;
K = K+1;
Calculation of the length (Nk);
Determine control parameter (Tk)
Stopping criterion
End;

From the current state Si with cost f(Si), a neighbour solution Sj, with cost f(Sj) is generated by the transition mechanism. The following probability is calculated in performing the acceptance test:

PT{Accept Sj} = 1 if f(Sj) ≤ f(Si), or
exp{(f(Si)-f(Sj)/Tk)}, if f(Sj) > f(Si)

Objectives of Proposed work

- To develop an optimum GWL prediction model using ANFIS and SA technique.
- To compare of various model structures using performance measurement criteria and selection of the best model.
- To justify how these models can be useful to solve the groundwater related problems.
- To apply Simulated Annealing technique for finding out the model having lowest error probability.

IV. RESULT AND DISCUSSION

The initial and the final membership function curves for the input variables for the best fit model based on performance criteria are shown in figure 2.

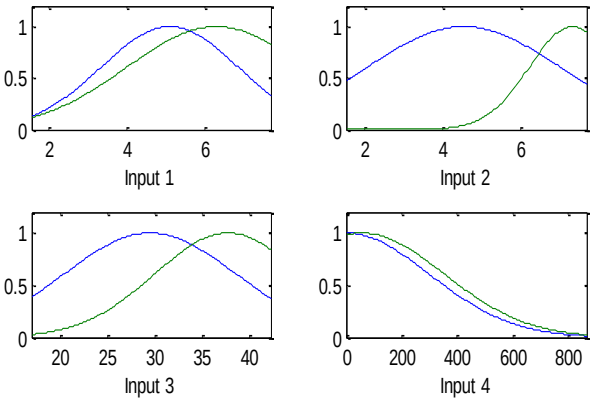
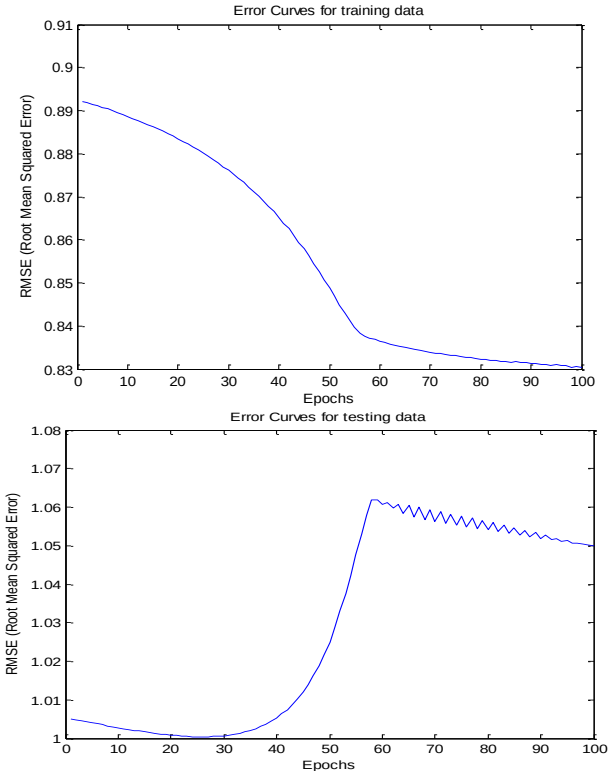


Fig.2: Final Membership Function Curves for all The Input Variables by ANFIS Using Optimized SA FIS Fuzzy Structure.

Here the SA based generated FIS model has been trained and tested by ANFIS method and their performance for the best prediction model M-I for clustering radius r=0.9741 are evaluated and compared for separately for training and testing data sets. The RMSE performances of the ANFIS model both for training and testing datasets have been plotted separately and their corresponding range of values for all the four models are summarized. The comparative plot of all the four models M-I to M-IV is plotted.



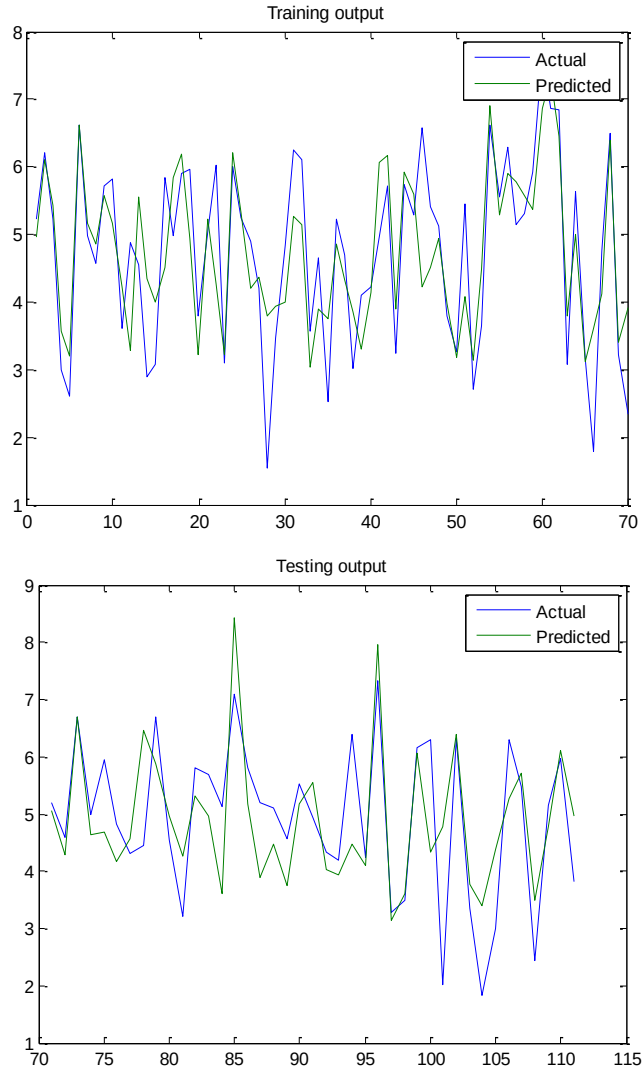


Fig.3: Comparative Plots of all The Four Models M-I to M-IV

V. CONCLUSION

SA guarantees a statistically optimal solution for arbitrary problems is more than other optimization techniques can claim. Simulated annealing can easily deal with arbitrary systems and cost functions, statistically guarantees finding an optimal solution. It is relatively easy to code, and even for complex problems generally gives a "good" solution. This makes annealing an attractive approach for optimization problems where heuristic (specialized or problem specific) methods are not available.

VI. REFERENCES

[1]. "Groundwater Resources of India", (1995), CGWB, Government of India.
[2]. "Groundwater" available at www.edugreen.teri.res.in/explore/water/ground.htm.

[3]. Holger R. Maier, Graeme C. Dandy, (2000), "Neural Networks for The Prediction and Forecasting of WaterResources Variables: A Review of Modelling Issues and Applications", Environmental Modelling & Software, pp. 101–124.
[4]. Purna C. Nayak, Y. R. Satyaji Rao and K. P. Sudheer, (2006), "Groundwater Level Forecasting in a Shallow Aquifer Using Artificial Neural Network Approach", Water Resources Management pp. 77–90.
[5]. ShaoyuanFeng, Shaozhong Kang, ZailinHuo, Shaojun Chen and Xiaomin Mao, (2008), "Neural Networks to Simulate Regional Ground Water Levels Affected by Human Activities", Vol. 46, No. 1, pp. 80–90.
[6]. EdvinAldrian, and YudhaSetiawanDjamil, (2008), "Application of Multivariate ANFIS for Daily Rainfall Prediction: Influences of Training Data Size", Vol. 12, No. 1, pp. 7-14.
[7]. Fernando Castellanos1, Nickel James2, (2009), "Average Hourly Wind Speed Forecasting with ANFIS", 11th Americas Conference on Wind Engineering, pp.1-14.
[8]. Mehmet Tektaş, (2010), "Weather Forecasting Using ANFIS and ARIMA MODELS. A Case Study for Istanbul", Environmental Research, Engineering and Management, 2010. Vol. 1(51), pp. 5 – 10.
[9]. Amutha R and Porchelvan P, (2011), "Seasonal Prediction of Groundwater Levels Using ANFIS and Radial Basis Neural Network", International Journal of Geology, Earth and Environmental Sciences, Vol. 1 (1), pp. 98-108.
[10]. Jawad S. Alagha, MdAzlinMd Said, YunesMogheir, (2012), "Review - Artificial Intelligence Based Modelling of Hydrological Processes", The 4th International Engineering Conference towards engineering of 21st century, pp. 1-13.
[11]. HadiGalavi and Lee TeangShui, (2012), "Neuro-Fuzzy Modelling and Forecasting in Water Resources", Scientific Research and Essays Vol. 7(24), pp. 2112-2121.
[12]. Riccardo Taormina et al., (2012), "ANN Simulation of Hourly GWL in a Coastal Aquifer System of the Venice Lagoon", Engineering Applications of AI pp. 1670-1676.
[13]. Hong Ding, XianghuiLi,Wenkai Liao,(2012) , "A Prediction Model Base On Evolving Neural Network Using Genetic Algorithm Coupled With Simulated Annealing For Water-Level" , IEEE Fifth International Joint Conference on Computational Science and Optimization.
[14]. Sanjeev Kumar, Ajay Indian, Zubair Khan, (2013), "Neural Network Model for prediction of Ground Water Level in Metropolitan Considering Rainfall-Runoff as a Parameter", International Journal of Soft Computing and Engineering (IJSCE), Vol. 3, Issue-3, pp. 195-198.
[15]. MajidHeydari, EhsanOlyaie, Hamid Mohebzadeh and Ozgiir Kisi, (2013), "Development of a Neural Network Technique for Prediction of water Quality Parameters in the Delaware River, Pennsylvania", Middle-East Journal of Scientific Research 13 (10): pp. 1367-1376.
[16]. P. Abbasi Maedeh, N. Mehrdadi, G.R. NabiBidhendi and H. ZareAbyaneh, (2013), "Application of Artificial Neural Network to Predict Total Dissolved Solids Variations in Groundwater of Tehran Plain, Iran", International Journal of Environment and Sustainability, Vol. 2 No. 1, pp. 10-20.
[17]. Manouchehr Chitsazan, GholamrezaRahmani, Ahmad Neyamadpour, (2013), "Groundwater Level Simulation Using Artificial Neural Network: A Case Study from AghiliPlain, Urban Area of Gotvand, South-West Iran", JGeope 3 (1), pp. 35-46.
[18]. M. Rezaeianzadeh, et al. (2013), "Flood Flow Forecasting Using ANN, ANFIS and Regression Models", Neural Computing & Application, pp.14-45.
[19]. Vahid Nourani, (2014), "A Review on Applications of Artificial Intelligence-Based Models to Estimate Suspended Sediment Load", International Journal of Soft Computing and Engineering (IJSCE), Vol. 3, Issue-6, pp. 121-127.
[20]. Jignesh Patel, Dr.Falguni Parekh, (2014), "Forecasting Rainfall Using Adaptive Neuro-Fuzzy Inference System (ANFIS)", International Journal of Application or Innovation in Engineering & Management (IJAIEM), Vol. 3, Issue 6, pp 262-269.
[21]. FaramarzKeshvari and Seyed Amir Shamsnia, (2014), "Evaluation of Artificial Intelligence Models (Artificial Neural Networks) To Forecasting the Discharge of Monthly River Flow (Case Study: Bahman Section, Qareaghaj River)", Indian Journal of Fundamental and Applied Life Sciences, Vol. 4 (S3), pp. 8-13.
[22]. Samarjit Kara, SujitDasb, PijushKantiGhoshb, (2014), "Applications of Neuro- fuzzy systems: A brief review and future outline", Applied Soft Computing, pp. 243–259.
[23]. Naser Almanaseer, et al. (2014), "Improving Groundwater Predictions Utilizing Seasonal Precipitation Forecasts from General Circulation Models Forced with Sea Surface Temperature Forecasts", Journal of Hydrologic Engineering © ASCE, pp. 87-98.
[24]. ShahaboddinShamshirband, Member, IEEE, et al. (2015) March, "Soft-Computing Methodologies for Precipitation Estimation: A Case Study", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 8, No. 3.