Groundwater Level Simulation by An Adaptive Neuro Fuzzy and Simulated Aniline Approach

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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 industry also shows an overall increase. Intense competition among users — 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 optimization techniques for the development of groundwater level prediction models in order to overcome groundwater related problems mentioned earlier. For this Sarojininagar Block of Lucknow district has been taken up as a case study. MATLAB platform will be used for the development of the model.**

Keywords: ANFIS, Groundwater level, GWL, RMSE

1 Introduction

Great emphasis is being laid on the importance of ground water for the survival of human society. In rural and urban India it is the vital source for drinking water as well as for industrial and agricultural use. It depends upon rainfall and the amount of recharge to the subsurface for its survival. Still it can be thought of as the uncontaminated water source.

With the increase in the population and the change in the life style there is more demand of drinking water which has led to its scarcity, together with the increase in contamination of the source. Further there is gradual increase in its industrial use. All this has led to the fall in the groundwater level. Thus there is need for continuous need for monitoring of the ground water levels. The water levels if properly predicted well in advance can help the administration to plan better ground water utilization.

Total replenishable ground water resource of Uttar Pradesh is 84 BCM, with present total extraction being about 40.95 BCM and the net exploitation 27 BCM (65.9% of total extraction). Thus 43.95 BCM is net available ground water resource for future exploitation, which is haphazardly distributed, leading to regional groundwater imbalance. The projected use of groundwater is that it will increase from 27 BCM to 64 BCM by 2025, which is almost double to its present level. This will lead to the increase in the increase of overexploited blocks in the future.

2 Literature Survey

Holger R. Maier, Graeme C. Dandy, (2000)[3] showed that ANN is very much used in solving water resources problems. They showed the steps involved in the development of the the models. The steps involved are performance criteria, preprocessing of data, model input parameters, network architecture, weights optimization and validation of the model. They have further discussed about the modelling process involved with the help of 43 paper reviews.

Purna C. Nayak, Y. R. Satyaji Rao and K. P. Sudheer, (2006) [4] used ANN techniques for prediction of groundwater level fluctuation in unconfined coastal aquifers of India. They considered local knowledge and statistical analysis of the available data for the selection of input variables. They considered two observation wells as a case study and developed a number of models. The results so obtained were almost good, being able to predict for almost 4 months in advance. They further analysed that such analysis is very helpful in groundwater and surface water planning in coastal areas and thus be able to maintain natural water gradient so as to protect saline water intrusion.

Shaoyuan Feng, Shaozhong Kang, ZailinHuo, Shaojun Chen, and Xiaomin Mao, (2008)[5] applied ANN techniques in Minquin oasis, located in the lower reach of ShiyangRiver Basin, in Northwest China. They used data between the period 1980 to 1997 and developed two ANN models for two area of Xinhe and Xiqu. The developed models were very accurate. They also carried out sensitivity analysis and showed that agriculture was the main factor responsible for lowering the water table in the area.

Edvin Aldrianand Yudha Setiawan Djamil, (2008) [6] used different surface weather input variables for the development of ANFIS prediction model for daily rainfall. They concluded that relative humidity is the best predictor variable for a better performance irrespective of teh data size. On the other hand other input variables showed poor results and were not very accurate as far as data size is concerned.

Fernando Castellanos, Nickel James, (2009)[7] used ANFIS approach for the prediction of average hourly wind flow speed. For this they trained and tested many ANFIS models so as to get the best performance vales. Various combinations of input variables, data size, membership function types, learning and momentum ratios and Fussy Inference System (FIS) were analysed. On the whole it was seen that the 4 input and 6 input models using grid and subtractive clustering learning algorithms respectively were the best models having very low error value. For this they used wind speed and air pressure as input variables.

3 Methodology

Simulated annealing (SA) is a versatile technique. It is used for solving combinatorial problems. Since a lot of real problems can be formulated in such form, hence this technique finds great scope in its use [8]. It is analogous to annealing of solids. In order to understand the process of SA it is required to convert a solid in low energy state, which is a highly ordered state, like crystal lattice. For this a solid is first heated to a particular temperature such that there are atomic re-arrangements. Next, it is allowed to cool slowly such that good crystals are formed. Similarly, in SA controlled operations are used for non-physical optimization problems. These could be solved in a short time. SA technique is capable of escaping from local maxima since it is based on local search problem. It has the properties of implementation ease, convergence properties and hill climbing moves. All this makes it a well accepted technique. It deals with continuous and discrete optimization problems. Unlike conventional optimization problems, SA can be used to tackle large problems irrespective of differentiality conditions, convexity, continuity. 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].

SA copies the physical process of annealing. It was initially used in statistical mechanics so as to study the natural process of solidification and crystal formations. In the process of cooling the material reaches an equilibrium state wherein the material has minimum energy and thus forms a perfect crystal. The two main features of the simulated annealing process are: (1) the transition mechanism between states and (2) the cooling schedule. SA during optimization problem solution tries to find the optimal solution of any configuration of a complex problem.

Here the free energy corresponds with the objective function of the problem. This is like formation of a perfect crystal. As in case of annealing, SA also has temperature known as control parameters which has to be determined for finding the solution of any optimization problem. The algorithm involved in SA is the Metropolis algorithm, which models the mocroscopic behaviour of a set of large particles. This is done by Monte Carlo simulation.

A. Metropolis Algorithm

Particles in any material have different levels of energy. The lowest level is the fundamental level. Here the number of particles are the maximum and the they stand still and have temperature 00K. Above this temperature the particles will have different energy level but eh number of particles will decrease. Thus there is variation in particle distribution with respect to temperature. Following the above algorithm a solid generates a chain of patterns. Giving a solid in state Si, with energy Ei, the next state Sj is generated by a transition mechanism that consists of a small perturbation 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, in case the difference is greater than zero, the new state is accepted with probability.

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].

Solving combinatorial optimization problem using SA, let G be a very large but finite set of configuration. Let v be the cost associated with it. The solution lies in finding the search space for pair G and v with lowest cost. The SA algorithm starts with an initial configuration G0 and an initial temperature T0 and generates a sequence of configurations N =N0. Next the temperature is lowered and the process is again repeated. The next configuration is accepted if its cost is less than the previous one. This repeated process allows the SA to escape the local configuration. The whole process is guarded by a cooling schedule that determines how the temperature is decreased during the optimization process.

B Simulated Annealing Algorithm

For combinatorial optimization problems evolutionary algorithm (EA), SA and Tabu search are widely used algorithms. EA is a probabilistic algorithm whose design is influenced by the biological science [9]. On the other hand SA is a metal cooling analogy, where a metal is cooled to a lowest energy state in order to form crystals, along with finding a local minima [8].

For solving the optimization problem, SA is used as an NLP problem, where the objective function and constraint functions are expressed in term of the specified independent variables. The objective function is expressed as

Optimize f(x)

Such that ‘x’ exists within the n-dimensional feasible region D:

X ıD, where

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

Here f(x), gi(x) are real valued scalar functions.

Vector x includes 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). 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)

C. 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

4. Result and Discussion:

In this section we are going to present our results obtained by combining simulated annealing optimization search with the previous section based ANFIS algorithm to accomplish our objective of getting lower prediction error by hybrid of SA and ANFIS. The initial FIS inference system is developed by SA algorithm using the environmental data records as used in Table 4.6. The SA algorithm generates different FIS structures at different value of cluster range of influence radii and finally we achieveradii for input vectors at which we get least prediction error in training data set. The lower bound for radii is considered near the vicinity of 0.9 because we are getting least error in prediction at radii of 0.9 (see table 4.6) and on applying SA at the lower bound 0.9 and upper bound of 1 the results shows minimum prediction error at radii= 0. 9741.The FIS structure obtained at these radii is described in upcoming section.

A. FIS Model Generation by SA Optimization

The FIS structure that uses M-I data generates optimized radii of 0.9741 at which the SA algorithm achieves minimum error. This FIS structure has 4 inputs and the respective optimized membership functions for all four inputs are shown in figure 1.

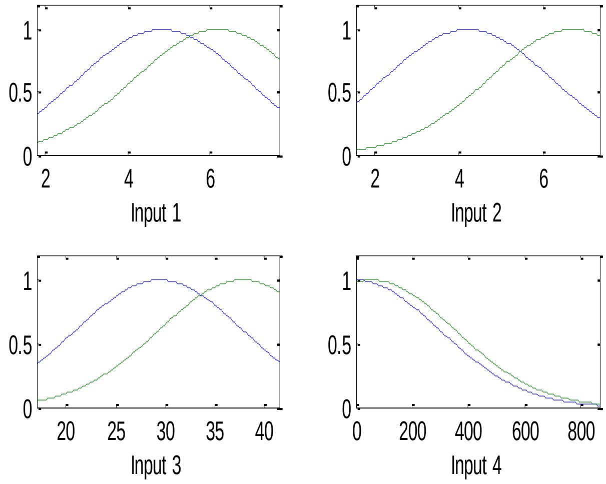


Fig. 1:Initial Input Membership Function Curves for all The Input Variables at Radii =0.9741.

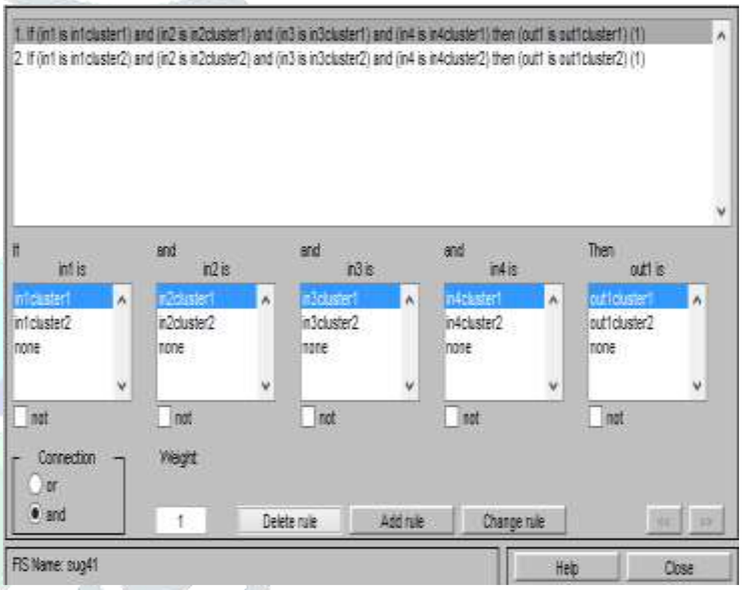


Fig. 2:TheFuzzy Rules at Optimized Cluster Radii Of Influence are Shown For Input of Figure 1.

B. Generation of Modified Fuzzy Logic Predictor by ANFISUsing SA FIS Structure

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 4.11&4.13respectively.

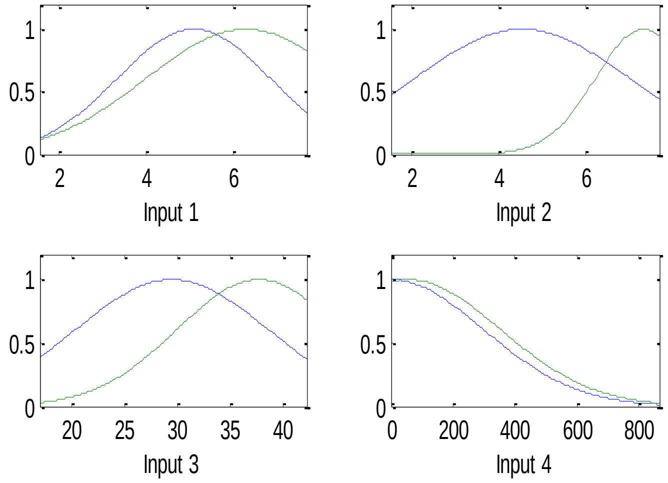
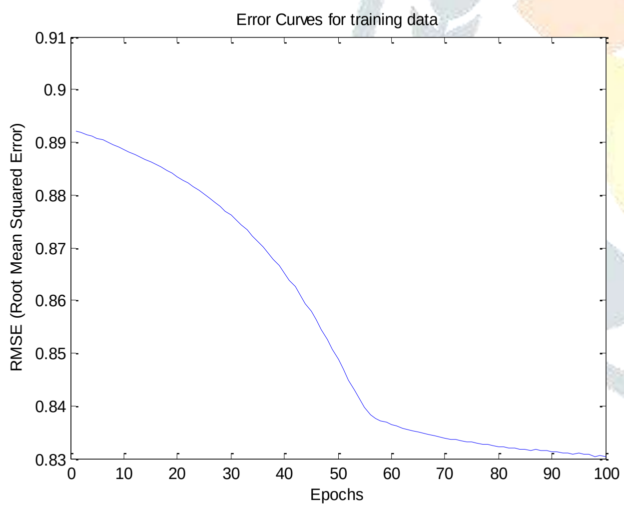
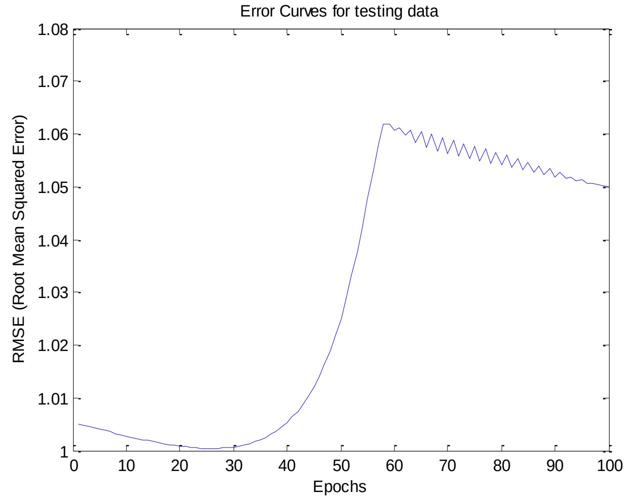


Fig. 3:Final Membership Function Curves for all The Input Variables by ANFIS Using Optimized SAFIS Fuzzy Structure.

Here the SA based generated FIS model has been trained and tested byANFIS method and their performance for the best prediction model M-I for clustering radius r=0.9741 are evaluated and compared for training and testing data sets separately. 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.





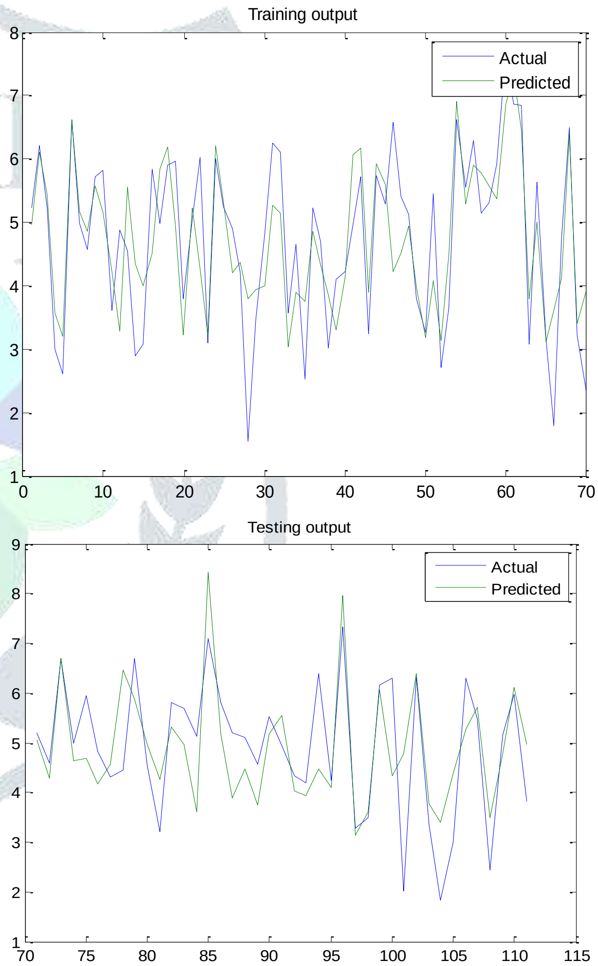


Fig. 4:Comparative Plots of all The Four Models M-I toM-IV

5. Conclusion:

The work carried out in the earlier section demonstrated that ANFIS and SA techniques have been successful enough for taking care of the objective of the study. The research demonstrates that ANFIS can be trained to accurately predict water levels in complicated groundwater systems under variable hydrological and climatic conditions. It was seen that a relatively shorter historical record of groundwater level and climatic information was sufficient for achievement of accurate water level predictions with

ANFIS. On the other hand, SA is better able to handle optimization problem using arbitrary solution and hence able to get the optimal solution of the problem at hand. SA is further seem to be easy in coding and in case of dealing with complex problems it gives an easy solution. Thus SA is better than heuristic methods, especially where problem specific methods are not available.

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