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Ground Water Level Prediction using Adaptive Neuro-Fuzzy Inference Systems and Simulated Annealing

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Abstract: In Indian subcontinent the source of ground water is mainly from rainfall and partially due to the river flow, lakes, and reservoirs, which is highly nonlinear and dynamic. In this paper, the seasonal ground water levels will be predicted using the simulated Annealing (SA) based on previous seasonal rainfall and ground water levels. The study will be carried out in Lucknow district, India. The main objective of this paper is to develop a reliable groundwater level fluctuation forecasting system to generate trend forecasts. The forecasts, based on SA techniques, are then compared to actual measurements recorded during a subsequent monitoring period, for this MATLAB platform will be used for generating the SA codes.
Keywords: AI, ANFIS, BCM, GWL, and SA.

I. INTRODUCTION

The importance of groundwater for the existence of human society cannot be overemphasized. Groundwater is the major source of drinking water in both urban and rural India. Besides, it is an important source of water for the agricultural and the industrial sector. Being an important and integral 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 exploitation 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) [3].

In a watershed basin, the seasonal modeling of ground water fluctuations is very useful in planning and management of both the surface water and ground water resources. This is important in regions where there is depleting surface water resources and increase in water demand due to industrialization and urbanization. Further change in climatic trends results in the variation of rainfall quantities. Thus, ground water resources are becoming an alternate solution to meet the increase in demands. In case of Indian subcontinent, where rainfall patterns are changing due to change in climatic conditions, the over exploitation of ground water has become inevitable. The major source of ground water in most of the watersheds in India is through recharge from rainfall. The physical interaction between the hydrological variables (such as rainfall, evapotranspiration) with ground water is highly nonlinear, stochastic, and complex. The groundwater prediction models can be divided into two groups, namely, i) physical and ii) system theoretic. The main drawback of the physical model is the complexity of the models, which increases with increase in model parameters. Further, the development of these models is based on understanding of the physical processes in the system. On the other hand, the system theoretic model is based on data driven techniques, where the mapping or learning of the models is done through data itself. Here, the understanding of the physical process in model building is avoided to a large extent (Srivastav et al., 2007). For this ANN and ANFIS, both Artificial Intelligence techniques are used to a great extent.

II. RELATED WORK

Holger R. Maier, Graeme C. Dandy, [1] illustrated Artificial Neural Networks (ANNs) are being used increasingly to predict and forecast water resources variables. Hence in this paper, the steps that should be used in the development of such models are given. These are the choice of performance criteria, the division and pre-processing of the available data, the determination of appropriate model inputs and network architecture, optimisation of the connection weights (training) and model validation. The choices available to scientists at each of these steps are discussed and the issues that should be considered are discussed. A review of 43 papers dealing with the use of neural network models for the prediction and forecasting of water resources variables is undertaken in terms of the modelling process adopted. The vast majority of these networks are trained using the back-propagation algorithm.

Purna C. Nayak, Y. R. Satyaji Rao and K. P. Sudheer, (2006) illustrated a research study that investigates the potential of artificial neural network technique in forecasting the groundwater level fluctuations in an unconfined coastal aquifer in India. The most appropriate set of input variables to the model are selected through a combination of domain knowledge and statistical analysis of the available data series. Several ANN models are developed that forecasts the water level of two observation wells. The results suggest that the model predictions are reasonably accurate as evaluated by various statistical indices. In general, the results suggest that the ANN models are able to forecast the water levels up to 4 months in advance reasonably well. Such forecasts may be useful in conjunctive use planning of ground water and surface water in the coastal areas that help maintain the natural water table gradient to protect seawater intrusion or water logging condition.

Shaoyuan Feng, Shaozhong Kang, Zailin Huo, Shaojun Chen, and Xiaomin Mao, [3] illustrated artificial neural networks (ANNs) and applied to investigate the effects of these factors on ground water levels in the Minqin oasis, located in the lower reach of Shiyang River Basin, in Northwest China. Using data spanning 1980 through 1997, two ANNs were developed to model and simulate dynamic ground water levels for the two sub-regions of Xinhe and Xiqu. The ANN models achieved high predictive accuracy. Sensitivity analyses were conducted with the models demonstrating that agricultural ground water extraction for irrigation is the predominant factor responsible for declining ground water levels exacerbated by a reduction in regional surface water inflows.

Edvin Aldrian and Yudha Setiawan Djamil, [4] illustrated the use of multi variable Adaptive Neuro Fuzzy Inference System (ANFIS) in predicting daily rainfall using several surface weather parameters as predictors. It was seen that relative humidity is the best predictor with a stable performance regardless of training data size and low RMSE amount especially in comparison to those from other predictors. Other predictors showed no consistent performances with different training data size. Performances of ANFIS reach a slightly above 0.6 in correlation values for daily rainfall data without any filtering for up to 100 data in a time series.

Fernando Castellanos, Nickel James, [5] adopts a new approach using Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to forecast the average hourly wind speed. To determine the characteristics of ANFIS that best suited the target wind speed forecasting system, several ANFIS models were trained, tested and compared. Different types and number of inputs, training and checking sizes, type and number of membership functions and techniques to generate the initial Fuzzy Inference Systems (FIS) were analyzed. Comparisons of the different models were performed and the results showed that the 4 inputs models generated by grid partitioning and the 6 inputs models generated by subtractive clustering provided the smallest errors with the models using wind speed and air pressure as inputs having the best forecasting accuracy.

III. METHODOLOGY

Evolutionary algorithms, simulated annealing and tabu search are widely used heuristic algorithms for combinatorial optimization. The term evolutionary algorithm is used to refer to any probabilistic algorithm whose design is inspired by evolutionary mechanisms found in biological species [9]. One of the most widely known 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 (the annealing process) and the search for a minimum in a more general system [8]. In the optimization process, the solution randomly walks in its neighbourhood with a probability determined by Metropolis principle while the system temperature decreases slowly; when the annealing temperature is closing 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)

Such that '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)

A. Proposed Work

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

IV. 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. The SA algorithm generates different FIS structures at different value of cluster range of influence radii and finally we achieves a radii 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 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 this 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.

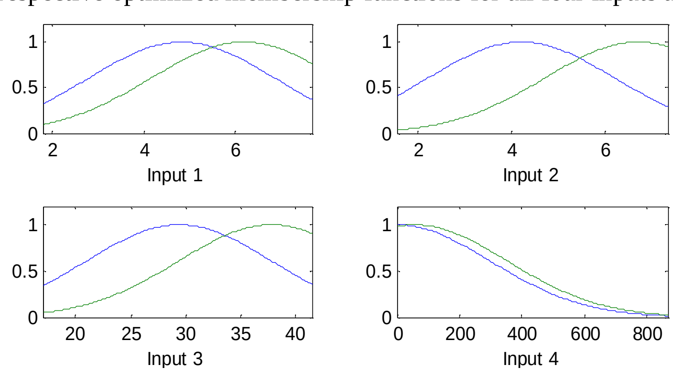


Fig. 1: Initial Input Membership function curves for all the input variables at radii =0.9741.

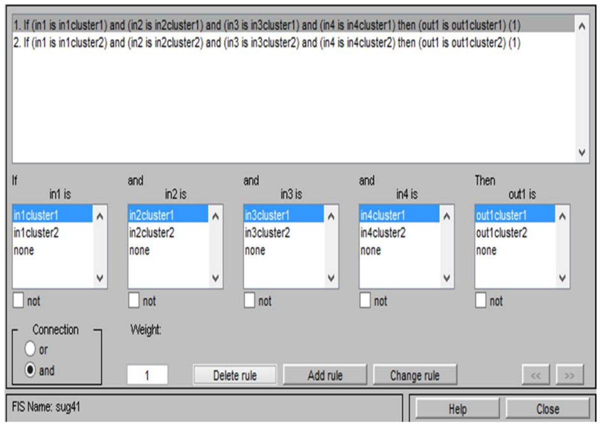


Fig. 2: The fuzzy rules at optimized cluster radii of influence are shown for input of figure 1.

B. *Generation of Modified Fuzzy Logic Predictor by ANFIS using 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 1 & 3 respectively.

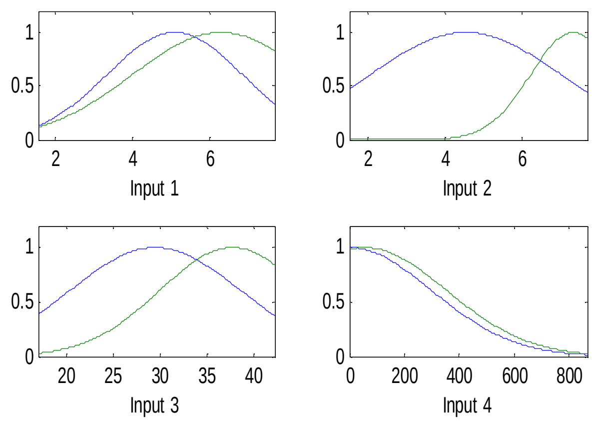
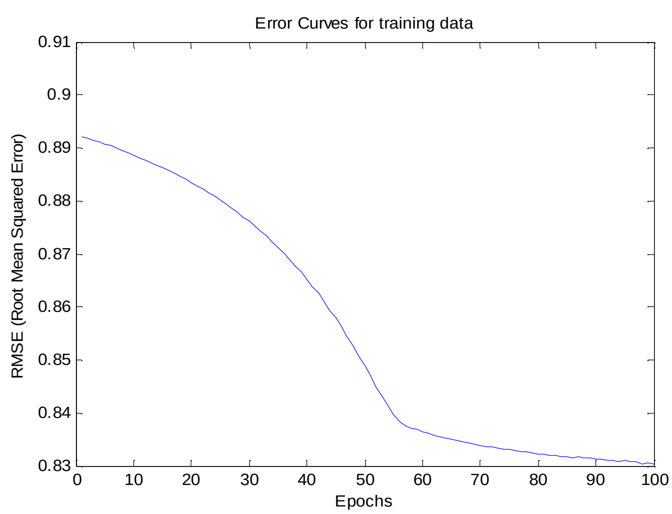
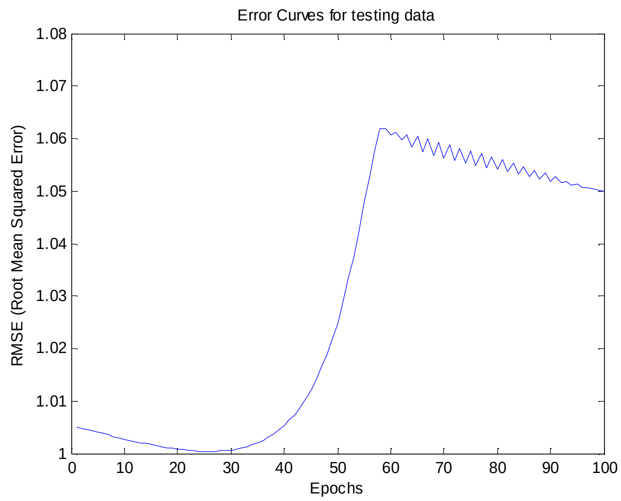
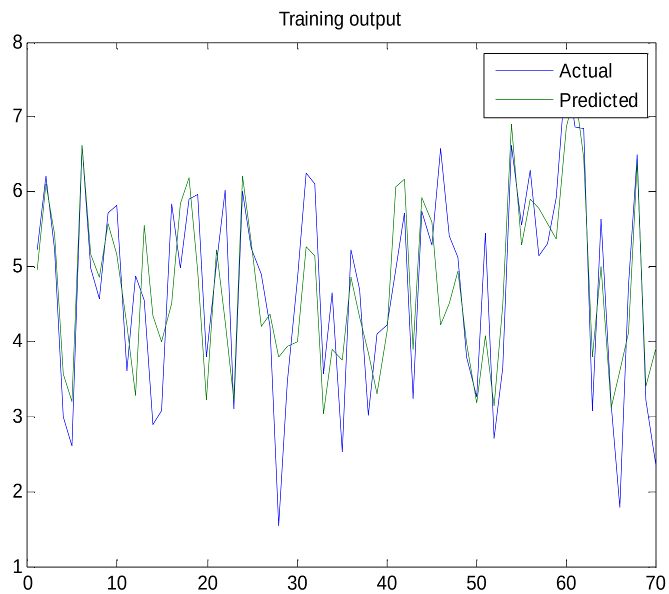


Fig. 3 Final Membership function curves for all the input variables by ANFIS using optimized SAFIS fuzzy structure.

Here the SA based generated FIS model has been trained and tested by ANFIS 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.







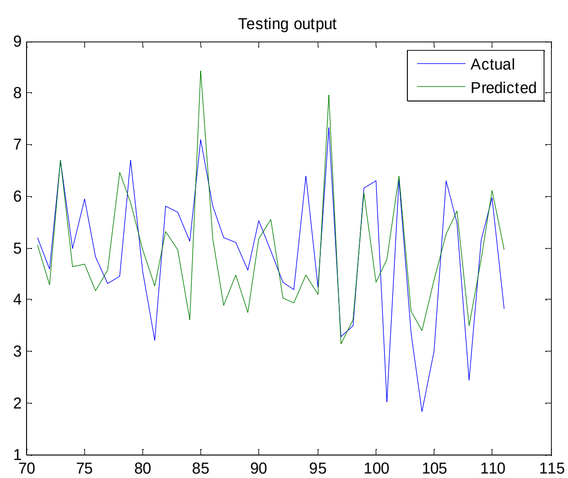


Fig. 4 Comparative plots of all the four models M-I to M-IV

V. CONCLUSION

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

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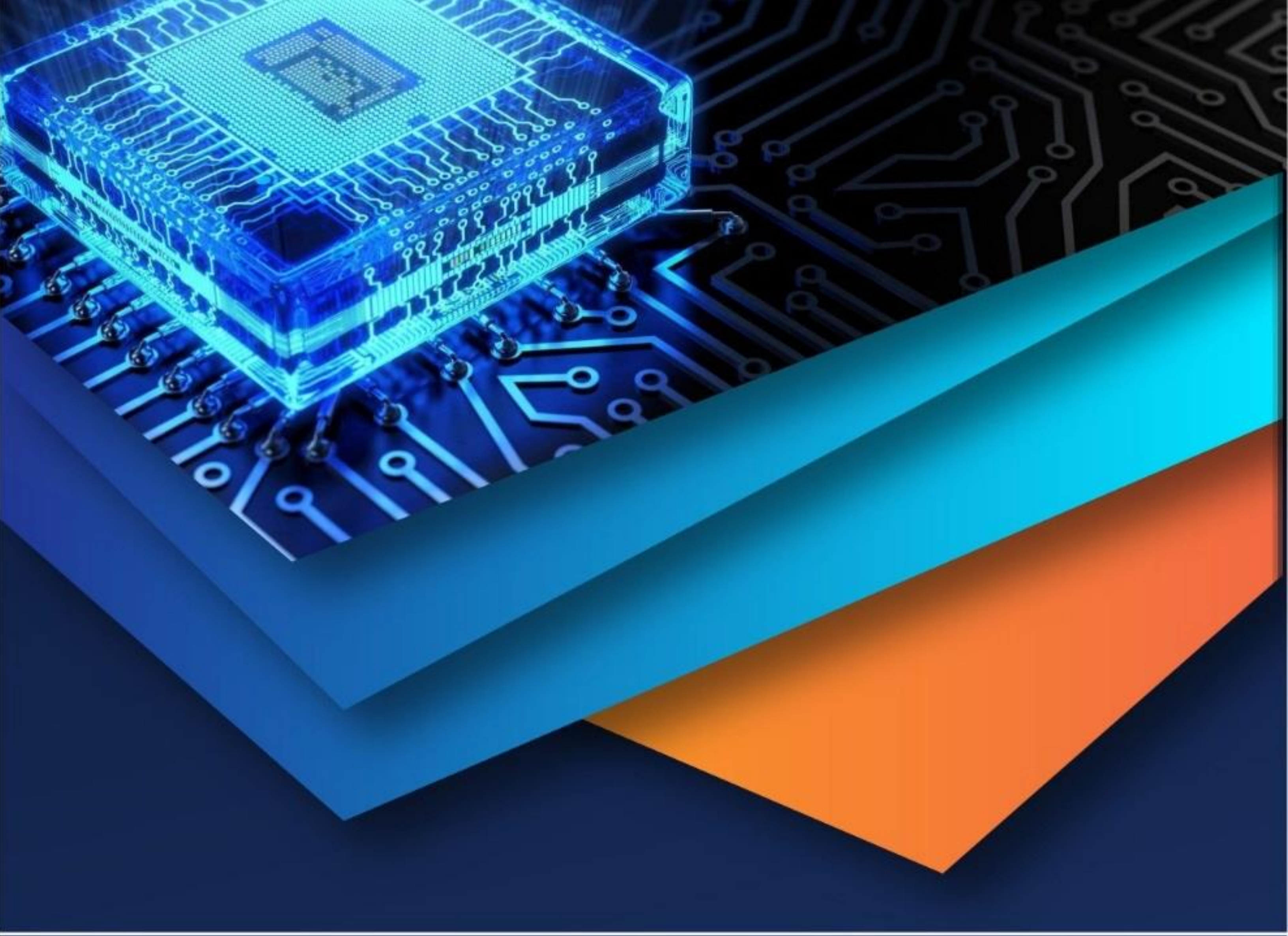

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