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Citation: AIP Conference Proceedings **1952**, 020021 (2018); doi: 10.1063/1.5031983
View online: https://doi.org/10.1063/1.5031983
View Table of Contents: http://aip.scitation.org/toc/apc/1952/1
Published by the American Institute of Physics

Particle Swarm Optimization Based Artificial Neural Network Model for Forecasting Groundwater Level in UDUPI District

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Abstract. The decline in groundwater is a global problem due to increase in population, industries, and environmental aspects such as increase in temperature, decrease in overall rainfall, loss of forests etc. In Udupi district, India, the water source fully depends on the River Swarna for drinking and agriculture purposes. Since the water storage in Bajae dam is declining day-by-day and the people of Udupi district are under immense pressure due to scarcity of drinking water, alternatively depend on ground water. As the groundwater is being heavily used for drinking and agricultural purposes, there is a decline in its water table. Therefore, the groundwater resources must be identified and preserved for human survival. This research proposes a data driven approach for forecasting the groundwater level. The monthly variations in groundwater level and rainfall data in three observation wells located in Brahmavar, Kundapur and Hebri were investigated and the scenarios were examined for 2000-2013. The focus of this research work is to develop an ANN based groundwater level forecasting model and compare with hybrid ANN-PSO forecasting model. The model parameters are tested using different combinations of the data. The results reveal that PSO-ANN based hybrid model gives a better prediction accuracy, than ANN alone**.**

INTRODUCTION

Groundwater is an important water resource for the economic and social progress. Currently there is a decline in the groundwater level because of the inconsistency in rainfall. Therefore, to avoid this groundwater level depletion and for the conjunctive use of water resource, a model for forecasting the groundwater level has to be developed. The prediction of a hydrogeological event is more complicated, because the parameters are unstable and vary with space and time. This nature of groundwater level limits the validity of mathematical or numerical forecasting models [1].

Monitoring of the status of groundwater levels from the observation wells is important for analyzing the depletion of water table and its influence over the sustainability of environment [2]. The most commonly used methods are numerical and statistical forecasting techniques. Although research in numerical method has taken place for a long time, there is a limited success in forecasting the applications. Success of these models is rare because they have found to be very accurate in calculation, but not in forecasting, as they cannot adapt to the irregularly varying patterns of data [3]. Nowadays the forecasting models of Ground Water Level are made by collecting the quantitative historical data and using the data driven techniques the future trends are predicted.

International Conference on Electrical, Electronics, Materials and Applied Science
AIP Conf. Proc. 1952, 020021-1–020021-8; https://doi.org/10.1063/1.5031983
Published by AIP Publishing. 978-0-7354-1647-5/$30.00

RELATED WORK

The Artificial Neural Network (ANN) models are data driven and have received much interest in the recent literature. Therefore, in groundwater studies the ANN models can be used with a high level of accuracy to improve the management strategies for a broad spectrum of groundwater problems, relating to both the quantitative and the qualitative aspects. The problem domain of the ANN is commonly formulated as an optimization problem over a very high dimensional space of possible weight configurations. Thus, learning can be considered a weight-updating rule of the ANN. The most cited learning algorithm in ANN literature is the gradient descent method [4]. These learning algorithms are iterative in nature, where in each iteration the current gradient information is used to update the weights of the ANN [5]. Another commonly used nonlinear optimization algorithm in ANN literature is Levenberg Marquardt algorithm. It is one of the efficient algorithms but it has a space requirement proportional to the square of the number of weights in the network [6].

The gradient descent algorithms are the local search methods, which are susceptible to being converted into local optima in which the initial weights are assumed randomly [7]. One of the learning techniques that attracted the researchers from the last one decade is the nature-inspired algorithm called Swarm Intelligence (SI). These algorithms have wide applications in the field of optimization where the complexity of the problems exists [8].

The Genetic Algorithm, Simulated Annealing Algorithm and the Particle Swarm Optimization (PSO) algorithms are the popular and widely used algorithms in the Swarm Intelligence domain [9]. The PSO is a nature inspired technique developed by Eberhart and Kennedy in 1995 [10] inspired by the collective behavior of bird flocking. In PSO algorithm, the potential solution called particles is obtained by flowing through the problem space by following the current optimum particles. The rate of convergence can be increased by tuning the ideal parameters of PSO algorithm in order to find the global optimistic results [11]. The PSO was also used for the optimization of the connection weights for the prediction of monthly precipitation [12]. By combining the PSO with Back propagation (BP) hybrid algorithm, it is not only possible to make use of the strong global searching ability of PSO but also the strong local search ability of the back propagation algorithm [13].

The PSO is a computational method, which simulates the collective behavior of the flock of birds. The PSO uses the analogy of the flocking of birds, which is an unpredictable mechanism. This behavior is simulated graphically for solving the complexity of the problem. In PSO, each particle is treated as a point in the search space. The i^{th} particle is represented as $Xi = (X1, X2, \dots \dots \dots XiD)$. At each iteration, the particles are updated by the two best values called the cognition component pBest and the social component gBest. These two components combine together to adjust the velocity in each dimension. Based on this velocity, the updated position of the particle is calculated.

The velocity and the position update equations used in PSO algorithm are given by

$$V_t^{\,t+1} = WV_t^{\,t} + C1 * rand\left(Pbest_i - X_i^{\,t}\right) + C2 * rand(Gbest - X_i^{\,t}) \quad (1)$$

$$X_i^{\,t+1} = X_i^{\,t} + V_i^{\,t+1} \quad (2)$$

The C1 and the C2 are the acceleration coefficients with respect to social and cognitive components.

MATERIALS AND METHODS

The PSO technique is used for the weight optimization of feed forward neural network structure. The network was pre-trained using the PSO to arrive at the initial network weights. The searching process of PSO-BP algorithms is started from initializing the starting position and the velocity of particles. In this case, the particle is a group of the weights of the feed forward neural network structure. There are 13 weights for the 2-3-1 feed forward neural network structure node topology and thus the particle consists of 13 real numbers as shown in Fig1.

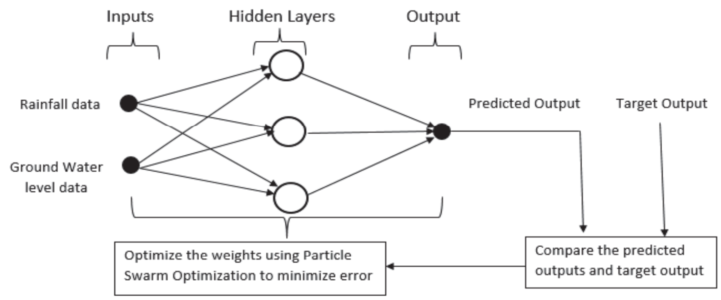

FIGURE1. Weight optimization process using PSO

The present work integrates the PSO with the Back Propagation algorithm to form a hybrid-learning algorithm for training the feed forward neural networks. In the proposed work for calculating the global optimum, the PSO and the ANN algorithms are integrated to increase the efficiency. The forecasting models were developed using the historical groundwater level and the rainfall data, which were recorded from three observation wells, located in Udupi district, India. The water level and the rainfall data of the observation wells located in Brahmavar, Kundapur, and Hebri taluks were used for the year 2000-2013. The groundwater in these regions mainly occurs in water table conditions. The PSO is used to evolve the neural network weights. The flowchart for ANN-PSO groundwater level forecasting is as given below in Fig2.

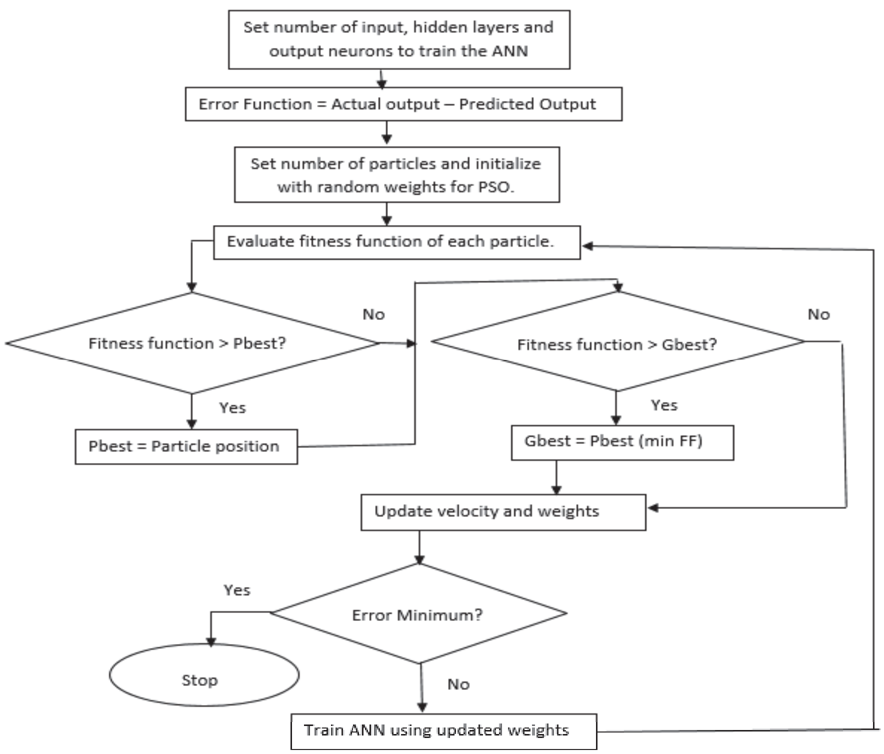

FIGURE 2. A flowchart for ANN-PSO groundwater level forecasting

The particles are evaluated and updated until a new generation set of particles are generated. The Root Mean Square Error (RMSE) is used as the fitness function. This searching procedure is repeated to search the global best position in the search space. If the fitness function is greater than the particle best, then the particle best is considered the particle position, otherwise the global best as the particle best which has the minimum value of fitness function. Based on the pBest, the gBest, and the current best values, the updated velocity is computed. The particle position is updated based on the updated velocity. The process is repeated for iterations until a minimum error is obtained. The PSO can be applied to train the ANN and this process is iterated until we get a minimum error. Thus, the PSO is integrated with the ANN in order to search the optimal weights for the network. Finally, the network is trained using the updated weights and finally the trained network is used to forecast the groundwater level of the testing set.

RESULTS AND DISCUSSION

The analysis is being performed for forecasting the groundwater levels for the different input combinations as identified by all the three well locations. Initially nine years (2000-2008) of data is considered as the training set and the ground water level is forecasted for 2009. It is observed that the forecasting results are not satisfactory, so the training period is increased to 13 years (2000-2012) and forecasted for 2013. Finally, a comparison was made between the values predicted using the BP and the Hybrid ANN-PSO algorithms. The forecasted groundwater level using ANN and ANN-PSO models during testing for the located wells of the study area are shown graphically from Fig. 3 to Fig. 8.

Study area 1. Observation Well at Brahmavar.

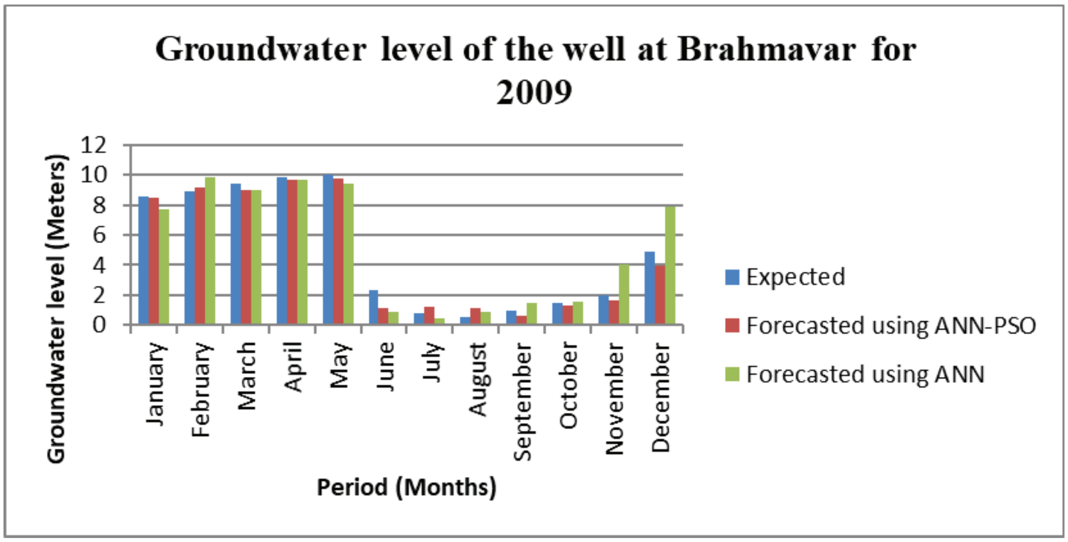

FIGURE 3. A comparative plot between the simulated and the actual groundwater levels of the well located at Brahmavar with 9-year training data

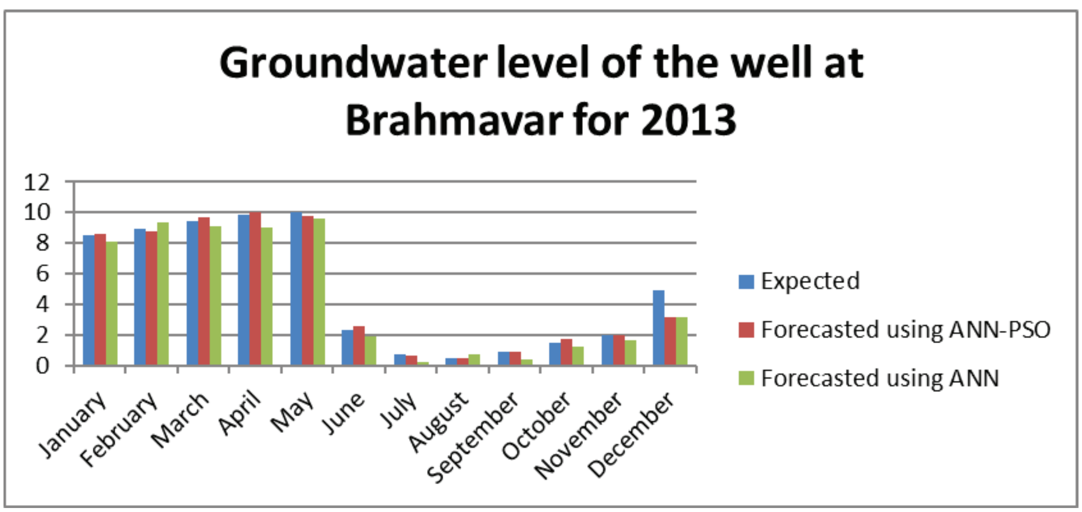

FIGURE 4. A comparative plot between the simulated and the actual groundwater levels of the well located at Brahmavar with 13-year training data

Study area 2. Observation Well at Kundapur.

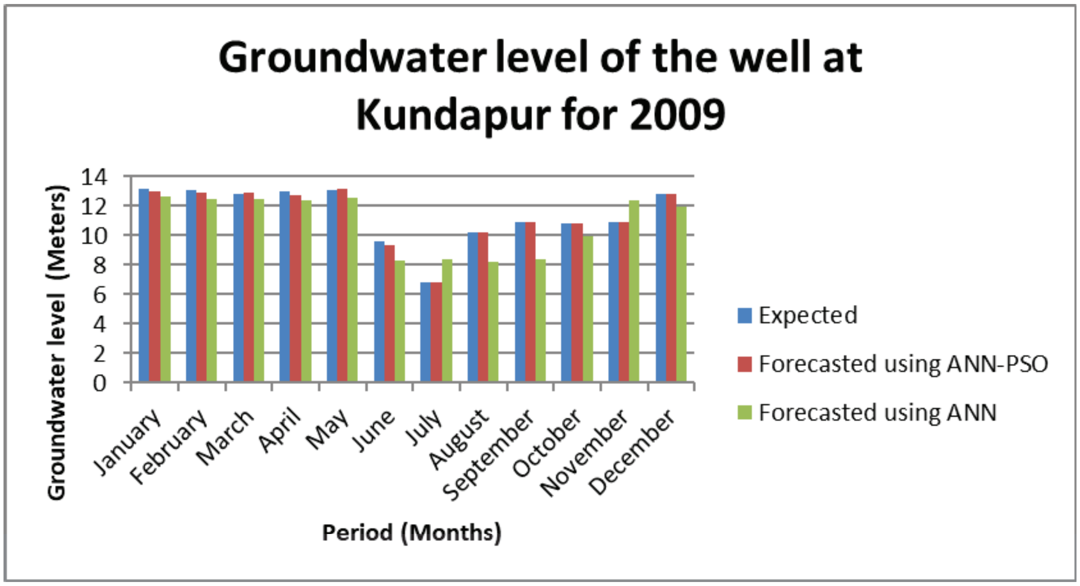

FIGURE 5. A comparative plot between the simulated and the actual groundwater levels of the well located at Kundapur with 9-year training data

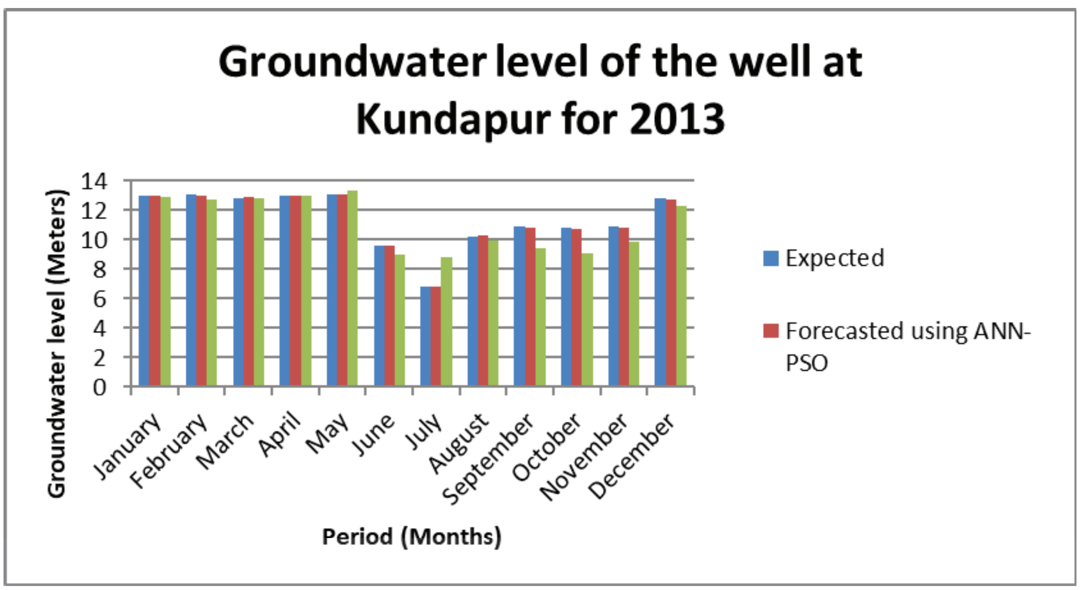

FIGURE 6. A comparative plot between the simulated and the actual groundwater levels of the well located at Kundapur with 13-year training data

Study area 3. Observation Well at Hebri.

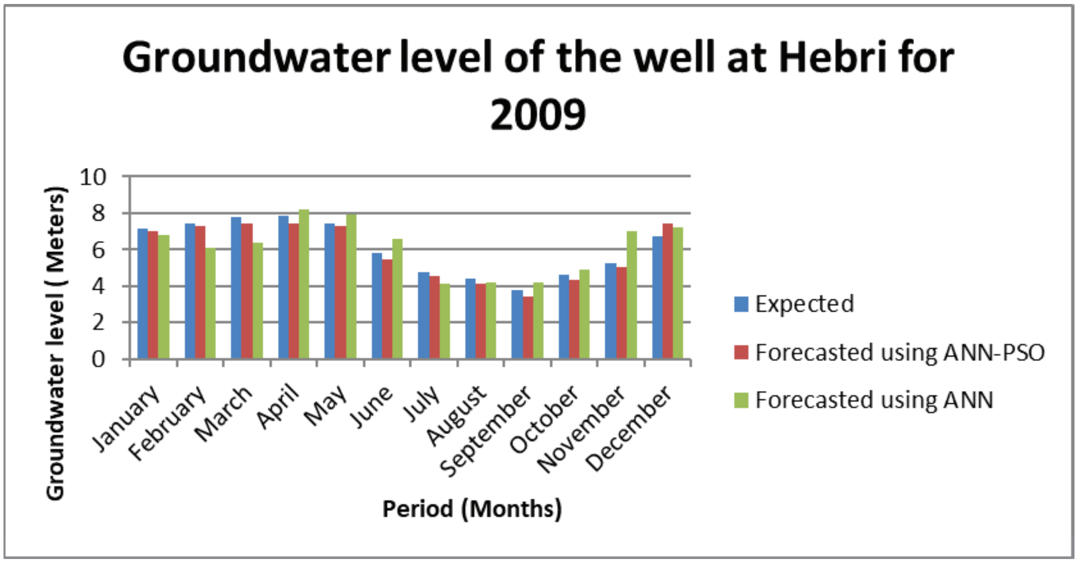

FIGURE 7. A comparative plot between the simulated and the actual groundwater level of the well located at Hebri with 9-year training data

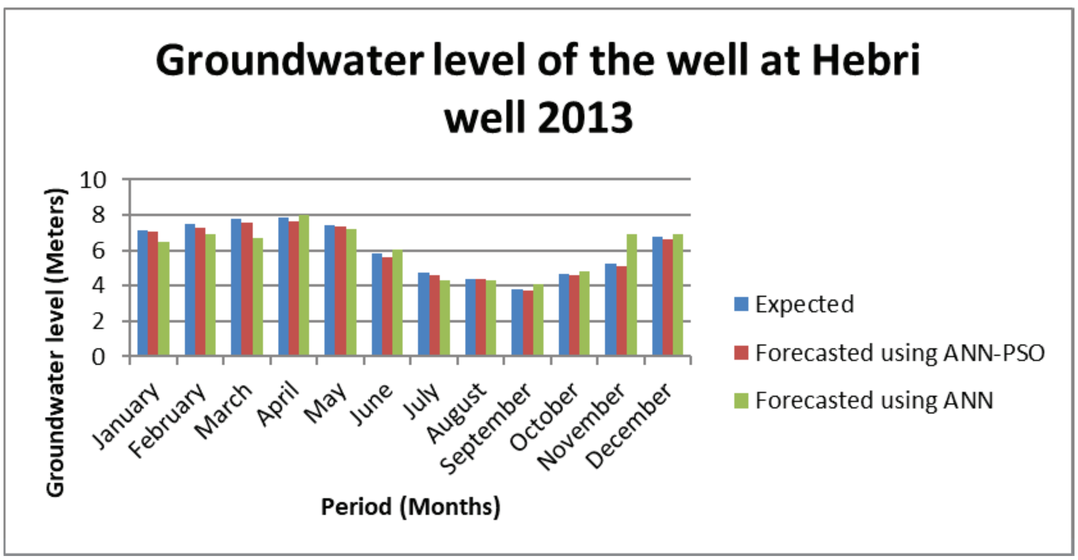

FIGURE 8. A comparative plot between the simulated and the actual groundwater level of the well located at Hebri with 13-year training data

From the time series graphs it is concluded that the ANN-PSO model gives the results that are more accurate compared to ANN closely following the trend with the expected time series. It is observed that the prediction accuracy of the ANN model is satisfactory for 9-year of data. Therefore, to improve the prediction accuracy, the network is trained with 13year data (2000-2012) and the groundwater level of 2013 was predicted.

CONCLUSION

The current work focuses on the development of hybrid ANN-PSO based groundwater level forecasting model to forecast the groundwater level of the three study wells located in Udupi district. The forecasted groundwater levels of all the three well locations using the ANN-PSO model were compared with the basic ANN-BP model. It is observed from the time series graphs that the ANN-PSO model outperforms the basic ANN-BP model for forecasting the groundwater levels of the selected regions of the Udupi district. Hence, the hybrid ANN-PSO algorithm predicts more accurately than the Error Back Propagation Algorithm. Thus, the PSO is powerful and the simple optimization algorithm based on swarm Intelligence, which can be easily hybridized with the other optimization algorithms for forecasting applications.

ACKNOWLEDGMENTS

We express our gratitude to the Department of Geology, District Commissioner office, Udupi, for providing us the valuable groundwater level and rainfall data for our study.

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