Journal of Engineering Science and Technology
Vol. 14, No. 2 (2019) 797 - 809

HYBRID ARTIFICIAL INTELLIGENCE BASED ABC-PSO SYSTEM FOR GROUND WATER LEVEL FORECASTING IN UDUPI REGION

SUPREETHA B. S.[1,*], PRABHAKARA NAYAK K.[1], NARAYAN SHENOY K.[2]

[1]Department of Electronics and Communication,
[2]Department of Civil Engineering,
Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India
*Corresponding Author: supreetha.bs@manipal.edu

Abstract

The groundwater level modelling and forecasting have wide application for effective groundwater resources management. The traditional numerical groundwater level forecasting requires various hydrogeological parameters. The alternative approach for groundwater level forecasting is data-driven models. The ANN hybrid models are found to be more effective for predicting ground-water levels at different time domains. Soft computing based model is developed by considering historical groundwater level and rainfall data. We developed an innovative hybrid ABC algorithm based on PSO searching mechanism to carry out forecasts of future groundwater levels with the aid of earlier recorded groundwater levels and rainfall**.** The evaluation metrics of parameters such as RMSE, Error Variation Regression coefficient, and MAE have been used**.** The results obtained prove that hybrid soft computing technique is able to forecast the groundwater level over several years effectively**.** The model predicted trend followed the observed data closely (RMSE = 0.3928, R^2 = 0.90029). The Mean Absolute Error and relative error of predicted results are 0.574 and 2.11% respectively. The ABC-PSO technique has shown promising results in accurate monthly groundwater level prediction vis-à-vis ANN methods.

Keywords: Artificial bee colony, Artificial neural network forecasting, Groundwater level, Hybrid models, Particle swarm optimisation.

1. Introduction

The World Health Organisation (WHO) had announced that by 2025 the future war would be on water resources due to the scarcity of drinking water [1]. Forecasting groundwater resources with an appropriate model using advanced algorithms is essential. The hydrogeological models are probabilistic, deterministic and stochastic approaches for the assessment of groundwater systems. The traditional groundwater flow models are partial differential equations, which are embedded with simplifying assumptions about the aquifer properties and boundary conditions [2].

Numerical method of ground-water level forecasting was found less efficient for forecasting ground-water level. These numerical models are found to be accurate in the calculation but less efficient to predict irregularly varying patterns of data. The recent ground-water level forecasting models using a data-driven approach are adopted for collecting quantitative historical data to forecasting future trends. ANN's provide an alternative to conventional numerical modelling and can be used for exact patterns and forecast trends.

Backpropagation (BP) are extensively used for ANN training but the results obtained by using BP for ANN training are found to be less consistent and unstable [3]. Thus, data-driven models are used for predicting real-time groundwater flow analysis. For the administration of ground-water level, the advanced model is needed for predicting the ground-water level, in the days to come with the modern accessible data [4].

Taormina et al. [5] explained that, there has been an incredible pressure on natural resources primarily due to a rapid increase in population and industrialisation. This has led to an augmentation in the demand for irrigation needs to satisfy the surging food production requisites. It is true that there has been an amazing growth in agricultural technology, but it is unfortunate that in several areas substandard irrigation administration has paved the way for substantial exhaustion of the groundwater table, dented soils and decline in the water quality, entailing the accessibility of water highly doubtful in the days to come [6]. Taking into consideration the dearth of accessible water resources and the consequent challenges, the accessible water sources are effectively estimated by experts in the field and the planners to put them for clever utilisation.

Amutha and Porchelvan [7] have astoundingly propounded an innovative method by employing Adaptive Neuro-Fuzzy Inference System for forecasting ground-water levels rooted on historical seasonal ground-water levels and rainfall. The convincing outcomes illustrate the forecasting of the ground-water levels with reasonable precision. Topoglou et al. [8] used swarm intelligence based Particle Swarm Optimization(PSO) technique to train Artificial Neural Network for predicting changes in the hydraulic head for an identified individual well of Agia, Greece.

The optimal weights were identified by training the network using PSO algorithm. The initial populations of the synaptic weights of the network were initialised randomly, which causes a fluctuation in the result. Therefore, there was a need for an algorithm to search for the best positions before updating particles using PSO. Shah et al. [9] investigated the use of the ABC algorithm to train MLP to learn the complex behaviour of earthquake time series data prediction. They used real-time series data of seismic event earthquake from Southern California Earthquake Data Centre (SCEC) for 2011 were selected. The results show accuracy in prediction of the magnitude of earthquakes using the ABC algorithm and demonstrates the limitation of the ABC algorithm with respect to exploitation.

Kiran and Gunduz [10] investigated the improved hybrid ABC-PSO algorithm for time series finding global optima for time series data prediction task. They used different benchmark problems to test the efficiency of the learning algorithms. The hybrid ABC-PSO proved accurate results, which shows that the hybrid ABC-PSO approach outperforms the traditional Back Propagation/Levenberg-Marquardt algorithm for time series data prediction task.

We used swarm intelligence as an alternative optimisation methodology for training ANN to achieve a more stable and efficient result. In our work, soft computing based technique is employed for groundwater level forecasting with hybrid ABC-PSO system for training Artificial Neural Network.

2. Groundwater Level Forecasting using Hybrid Artificial Intelligence Approach

The system encompasses three important techniques, neural network based weighting scheme, a training phase and testing phase. At the outset, rainfall data and ground-water level of an open well identified at Manipal from Udupi, Karnataka, India were chosen. We used hybrid ABC-PSO for training MLP by balancing exploration and exploitation mechanisms.

However, the exploitation procedure of the ABC algorithm was poor at exploitation procedure. Therefore, to resolve the above problem, a new hybrid ABC approach guided by the Particle Swarm Optimisation search mechanism was used. In order to enhance the exploitability, ABC utilizes the search mechanism of the Particle Swarm Optimisation algorithm to compute new candidate solutions.

2.1. ANN-based weighting scheme modelling

The artificial neural network consists of rainfall data as an individual neuron furnishes one output. The solution cannot be gathered with one neuron so we try for the next likelihood. The data is guided by means of weather conditions like past ground-water level. The neural network training is intended to reduce an error function that is furnished by the weighting function given by Eq. (1).

$$\varpi = -\alpha_i \left[\!\left[\left[\frac{\exp\left(1-\sum_{j-0}^{N-1} \beta_{jk}\right)}{1-\exp 2(1-\sum_{j-0}^{N-1} \beta_{jk})} \right] - \left[\frac{1}{1-exp\ \ 2(\sum_{j=0}^{N-1} \beta_{jk})} \right] \right]\!\right] \tag{1}$$

where,

ϖ - Weighting factor

$\alpha_i\ \beta_{jk}$- The initial weight to be optimised.

2.2. Finding best solution using ABC

The PSO guided ABC approach was used to develop the groundwater level forecasting model. In ABC algorithm, the 50 percent of colony comprises of employed artificial bees and the remaining half comprises of onlookers. One employed bee is recommended for every food source; therefore, the number of employed bees is identical to the number of food sources around the hive [11].

The ABC algorithm consists of employed bee phase, onlooker bee phase, followed by the scout bee phase. In each cycle, the probe embraces four stages: In the first phase, the employed bees are sent out to find the food sources and then by analysing the amount of nectar to be obtained, gives input signal to onlooker bees.

In the onlooker phase, the selected food sources are identified based on the input signal from the employed bees, which enhances advanced solution. If the identified nectar of the food source is rejected, the scout bees arbitrarily decide the new food sources [12].

An onlooker bee chooses a food source depending on the probability value associated with that food source (P_i) given by Eq. (2).

$$P_i = \frac{F_i}{\sum_{K=1}^{N_P} F_n} \tag{2}$$

where, F_i - The fitness value of the solution, and N_p - The number of food sources, which is equal to the number of employed bees.

An artificial onlooker bee probabilistically generates a variation on the solution for locating a new food source and assesses the fitness value of the new solution, which is characterised by the following Eq. (3).

$$Z_i = Y_i + \varphi_i (Y_i - Y_j) \tag{3}$$

$Z_i = Y_i + \varphi_i (Y_i - Y_j)$ It manages the generation of a neighbour food source position around yi and the alteration characterises the assessment of the neighbour food positions visually by the bee. The position update equation illustrates that as the divergence between the constraints of the Y_i and Y_j comes down, the perturbation on the position Y_j also reduces. Thus, as the probe reaches the optimum solution in the search space, the step length is adaptively decreased.

$$Z_i = Y_i + \varphi_i (Y_i - Y_j) \tag{4}$$

Re-organizing the position updating stage is given by Eq. (4). The left side Z_{t+1} is the discrete version of the derivative of order $\beta = 1$ is given by:

$$D^\beta [Z_{t+1}] = \varphi_i(\gamma_i - y_j) \tag{5}$$

In the scout bee phase, with an eye on locating the best solution, the scout bee phase is substituted by the PSO technique. Thus, by launching the PSO, we set out to locate the pbest and gbest, which ushers in the best solution.

2.3. Finding pbest and gbest for scout bee phase using particle swarm optimisation algorithm

The i[th] particle is represented as $Xi = (X_1, X_2 \ldots. X_{iD})$. The particles are updated at each iteration by updating the two best values called *pb* and the *gb*. Thus, the velocity is adjusted based on these two components and the value of the updated position [13].

The velocity and position update equations are given by Eqs. (6) and (7).

$$V_i^{(it+1)} = V_i^{(it)} + l_1 * r_1 * \left(pb_i - \rho_i^{(it)}\right) + l_2 * r_2 * (gb_i - \rho_i^{(it)}) \quad (6)$$

$$\chi_i^{(it+1)} = \chi_i^{(it)} + V_i^{(it+1)} \quad (7)$$

where $V_i^{(it+1)}$ -The velocity of i[th] particle at iteration i_t, l_1 and l_2 -Learning factors, r_1, r_2- Random numbers produced lies between [0, 1], pb_i- Current best position, gb -global best position, $\chi_i^{(it)}$-Current position at iteration $i_{t.}$

The particles update their position and the velocity until it arrives at its termination benchmark. In the termination stage, the procedure gets replicated till the termination criteria is satisfied, then the process gets completed. Now, the final solution is the global best particle and it is chosen as the best solution.

3. Forecasting using Hybrid ABC-PSO

At the outset, rainfall data and groundwater level of earlier months are employed as the input constraint and then processed by means of the training scheme of hybrid ABC-PSO as shown in Fig. 1. The models were built using Matlab and Software Weka, developed by Waikato University, New Zealand.

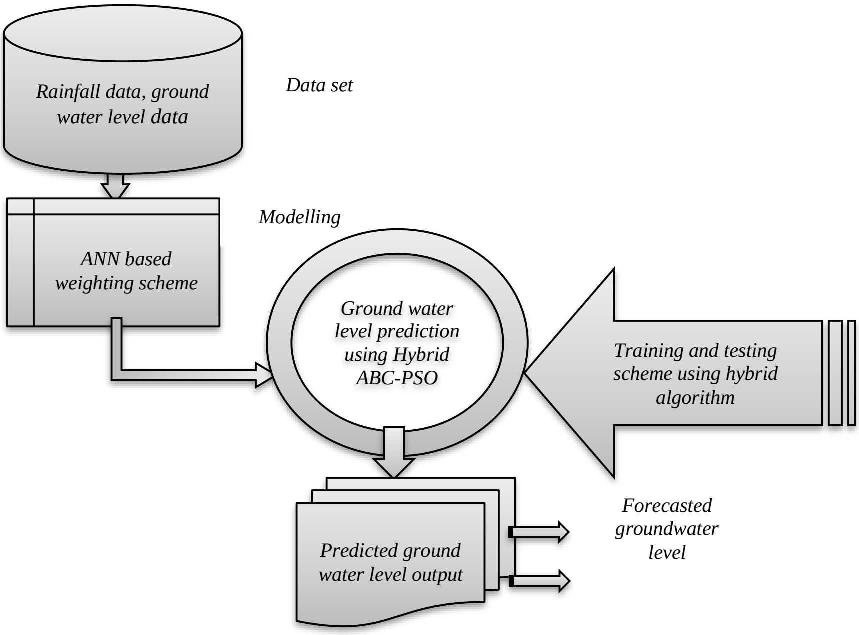

Fig. 1. Block diagram for proposed method.

Steps in hybrid ABC-PSO

The artificial neural network was trained using hybrid ABC-PSO algorithm. The ABC algorithm is good in exploration and PSO algorithm is good in exploitation. Therefore in order to balance between exploration and exploitation capabilities hybrid training was employed. The steps of hybrid ABC-PSO were as below:

- Initialize the constraint and compute the fitness value.
- Allocate employed bee phase for locating the top best solution based on probabilities.
- Allocate the onlooker bee phase to locate the best onlooker.
- Locate best feasible onlooker, substitute with the best solution,
- In the place of the scout bee phase, PSO is employed to locate the best solution efficiently.
- If the fitness value is better than *pb*, fix the current value as the new p best.
- Compute velocity based on the velocity equation.
- Execute the velocity constraint.
- Locate the global best gb with the best fitness and carry on the procedure until the incidence of stoppage benchmark.

4. Results and Discussion

The ANN-based ABC-PSO system is trained for a time series data of 10 years duration (2000-2009). The data incorporates rainfall data and monthly-recorded groundwater level.

The first 80% of the data was adopted for training the network and the remaining 20% for evaluating the trained network.

The groundwater level predicted results for a small dataset of two years is as shown in Fig. 2. It is observed that in monsoon season we observe a large difference between the expected and the predicted data.

Therefore, we infer that a large dataset is required to train artificial neural network based models.

Figure 3 shown below gives the groundwater level predicted for the year 2017. The system is trained with 10 years of training data. From the graph shown below, it is observed that hybrid PSO guided ABC algorithm gives satisfactory results, while the PSO trained ANN observed graphical results give a large error.

The seasonal groundwater level is forecasted using the same data set with different lead-time is as shown in Figs. 4 and 5. It is observed that sudden change in groundwater level with respect to time in 2004, whereas the trend remains the same up to 2002.

The yearly forecasted groundwater level is as shown below and it is observed as shown in Fig. 6, that the groundwater level almost follows the same trend in which, after 2009, the groundwater level started decreasing.

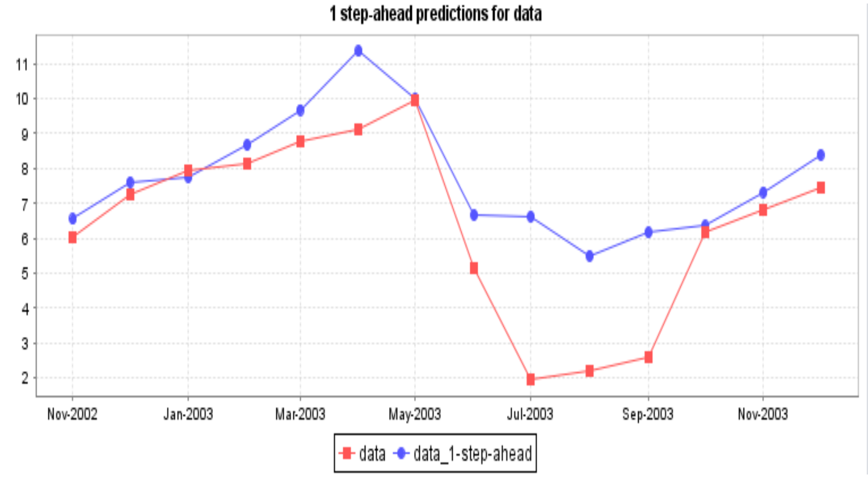

Fig. 2. Groundwater level prediction of 1 step ahead.

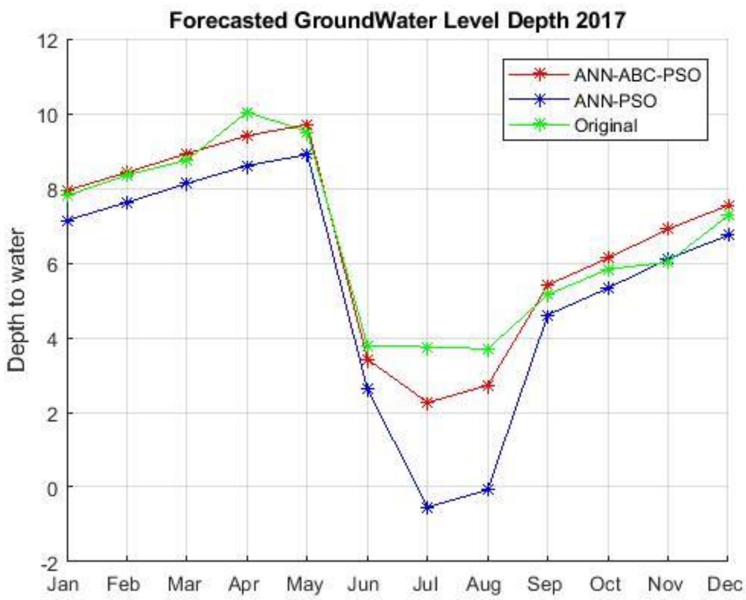

Fig. 3. Groundwater level prediction for 2017.

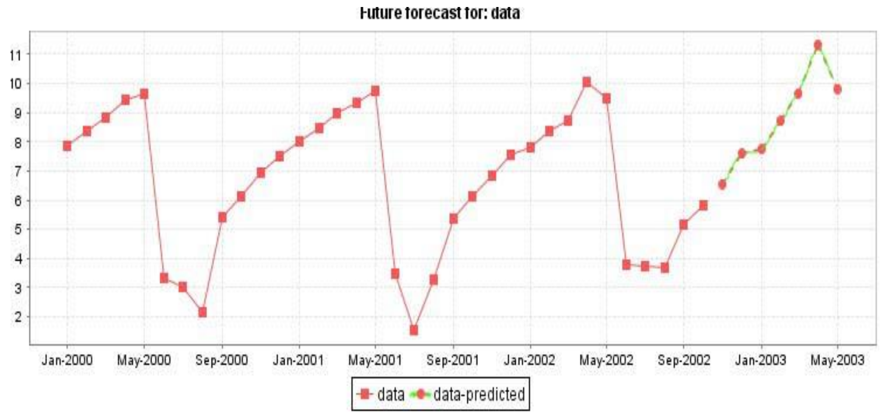

Fig. 4. Forecasted groundwater level for pre-monsoon period using hybrid technique.

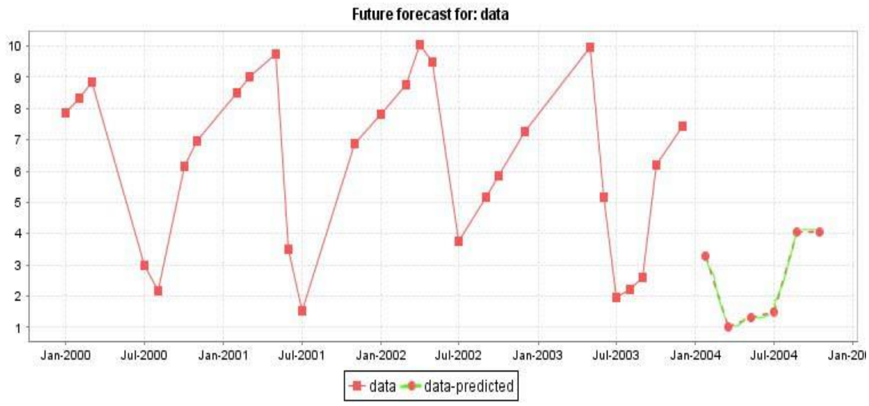

Fig. 5. Forecasted groundwater level for post-monsoon period using hybrid technique.

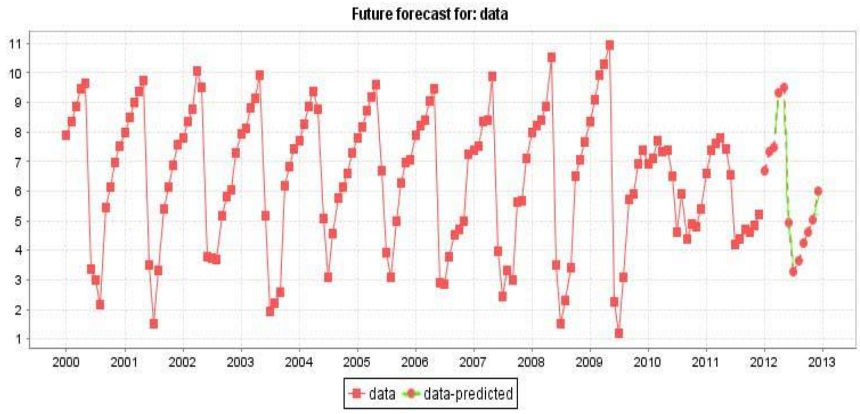

Fig. 6. Yearly forecasted groundwater level using hybrid technique.

5. Performance Evaluation

In the current study for evaluating the prediction accuracy of the RMSE, regression coefficient and error variation were used. The statistical indices utilised in the study can be characterised as given from Eqs. (8) to (10).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{y_i - \overline{y_i}}{n}} \tag{8}$$

where,

y_i - Observed Data

$\overline{y_i}$ - Calculated Data

n - the number of observations

$$Error\ Variation = \left(\frac{(y - \hat{y})}{y} * 100\right) \tag{9}$$

where,

$\hat{y}$- Calculated data

$$Regression\ Coefficient = 1 - \frac{\sum(y_i - \overline{y_i})^2}{\sum y_i{}^2 - \frac{\sum \overline{y_i}^2}{n}} \tag{10}$$

The evaluation metrics of parameters such as RMSE, Error Variation and Regression coefficient have been used for performance analysis as shown in Table 1**.** The results obtained proved to be efficient to forecast the groundwater level over several years**.**

To prove the system to be effective we have compared this hybrid method with the FFBN.The comparative plot for ANN and hybrid ABC-PSO with statistical parameters MAE and RMSE for ANN-PSO and ANN-ABC-PSO model is presented graphically in Fig. 7. The RMSE for hybrid ANN is small compared to other traditional methods such as FFBN, ANN-PSO.

The RMSE forecasting error variance varies across time, so absolute error is used for evaluating forecasting accuracy. Mean Absolute Error provides the average error across all predictions, and it is less sensitive to large deviations than the usual squared loss.

In Fig. 7, the RMSE and MAE values are smaller for hybrid ANN compared to other traditional approaches.The Normalised Mean Squared Error (NMSE) statistics for PSO trained ANN and ABC guided PSO trained ANN forecasting models is shown in Fig. 8. The smaller the NMSE value better the forecast.

We observed that the NMSE values of our hybrid trained ANN is stable and efficient compared to PSO trained ANN for prediction period of 2013 and 2014. The groundwater level is compared with different techniques such as artificial bee colony and FFBN for 2003 and 2004 respectively are as shown in Figs. 9 and 10.

The above plots show an improved correlation between forecasted outputs using the ANN-based ABC-PSO system and observed groundwater level graphically compared to other approaches. From this analysis, we can infer that hybrid soft computing ABC-PSO trained system was found to be more accurate compared with other traditional techniques such as ABC, FFBN.

Table 1. Performance measures of ABC-PSO, ABC and FFBN model.

Year	Performance measures		
	ABC-PSO	ANN-PSO	FFBN
RMSE	0.39284	0.98515	3.3453
Regression coefficient	0.90024	0.373572	0.68712
Error variation	2.24772	4.25039	6.92543
MAE	0.574	0.743	0.850
MAPE	5.6	8.4	10.2

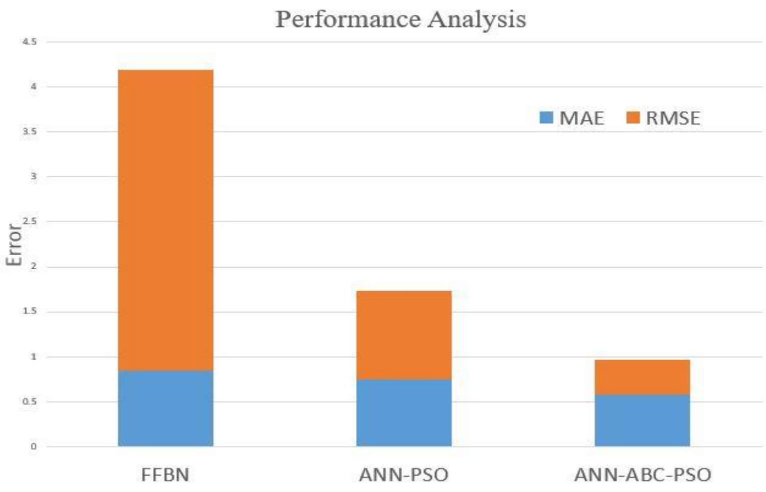

Fig. 7. Box plot for performance analysis.

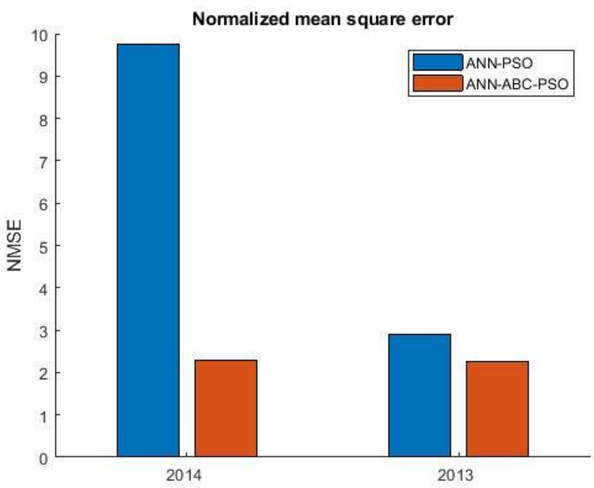

Fig. 8. NMSE plot for 2013 and 2014.

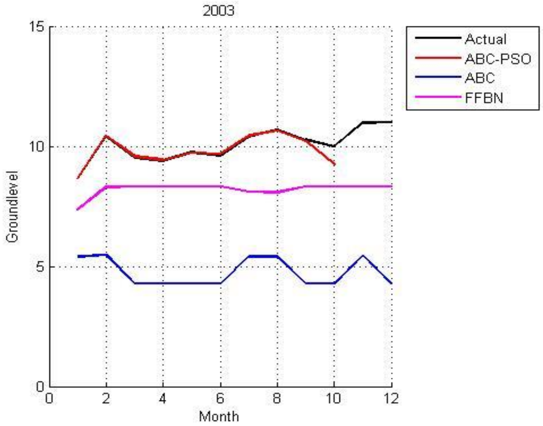

Fig .9. Comparative plot of forecasted groundwater depth for 2003 using hybrid technique and other existing techniques.

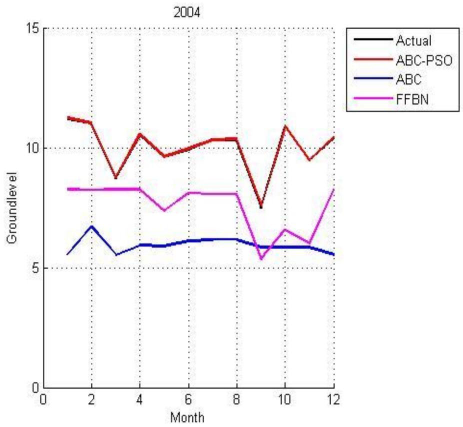

Fig 10. Comparative plot of forecasted groundwater depth for 2004 using our hybrid technique and other existing techniques.

6. Conclusion

In this work for forecasting groundwater levels, a hybrid ABC-PSO system was developed. The identified well for forecasting is from Udupi region of Karnataka state, India. The PSO was found to be poor at exploration but better in finding a global beast solution. Therefore, to overcome this problem ABC based PSO search mechanism was developed to enhance the exploration ability.

For improving the accuracy, the initial population is generated by using Artificial Bee Colony algorithm without adopting random selection. The result obtained concludes that hybrid ABC-PSO trained ANN system was more effective and accurate for forecasting groundwater level comparing to error backpropagation and PSO trained ANN mechanisms. Thus, our hybrid ANN based ABC-PSO system is efficient in forecasting future trends of groundwater level.

Nomenclatures

F_i	Fitness value
l_1, l_2	Learning factors
N_p	Number of food sources
P_i	Probability of food source
pb, gb	Public and global best
r_1, r_2	Random numbers in the range [0,1]
$V_i^{(it)}$	Velocity of i^{th} particle at iteration i_t, m/s
$\mathcal{W}$	Inertia factor
Z_i, Y_i	Old and new positions, m

Greek Symbols

α_i	Initial weight to be optimized
β_{jk}	Inertia weights
ω	Weighting factor

Abbreviations

ABC	Artificial Bee Colony
ANN	Artificial Neural Networks
FFBN	Feed Forward Backpropagation Network
LM	Levenberg-Marquardt
MAE	Main Absolute Error
MLP	Multi-Layer Perceptron
PSO	Particle Swam Optimisation
RBF	Radial Basis Function
RMSE	Root Mean Squared Error
SCEC	Southern California Earthquake Data Centre
WHO	World Health Organisation

References

1. Charles, K.; Pond, K.; Pedley, S.; Hossain, R.; and Jacot-Guillarmod. (2015). Vision 2030 the reliance of water supply and sanitation in the face of climate change, *Technology Projection Study*. University of Surrey, 109 pages.
2. Satish, S.; and Elango, L. (2015). Numerical simulation and prediction of groundwater flow in coastal aquifer of Southern India. *Journal of Water Resources and Protection*, 7, 1483-1494.
3. Nourani, V.; Mogaddam, A.A.; and Nadiri, A.O. (2008). An ANN-based model for spatiotemporal groundwater level forecasting. *Hydrological Processes*, 22(26), 5054-5066.
4. Coulibaly, P., Anctil, F., Aravena, R., and Bobee, B. (2001). Artificial neural network modelling of water table depth fluctuation. *Water Resources Research*, 37(4), 885-896.
5. Taormina, R.; Chau, k.-W.; and Sethi, R. (2012). Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. *Engineering Applications of Artificial Intelligence*, 25(8), 1670-1676.

6. Adamowski, J.; and Chan, H.F. (2011). A wavelet neural network conjunction model for groundwater level forecasting. *Journal of Hydrology*, 407(1-4), 28-40.
7. 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*, 1(1), 98-108.
8. Tapoglou, E.; Trichakis, I.C.; Dokou, Z.; Nikolos, I.K.; and Karatzas, G.P. (2014). Groundwater-level forecasting under climate change scenarios using an artificial neural network trained with particle swarm optimization. *Hydrological Sciences Journal*, 59(6), 1225-1239.
9. Shah, H.; Ghazali, R.; Herawan, T.; Khan, N.; and Khan, M.S. (2015). Hybrid guided artificial bee colony algorithm for earthquake time series data prediction. *Communication Technologies, Information Security and Sustainable Development*, 204-215.
10. Kıran M.S.; and Gunduz, M. (2013). A recombination based hybridization of particle swarm optimization and artificial bee colony algorithm for continuous optimization problems. *Applied Soft Computing*, 13(4), 2188-2203.
11. Karaboga D.; Akay B.; and Ozturk, C. (2007). Artificial Bee Colony (ABC) optimization algorithm for training feed-forward neural networks. *Proceedings of the International Conference on Modeling Decisions for Artificial Intelligence.* Kitakyushu, Japan, 318-329.
12. Ozturk, C.; and Karaboga, D. (2011). Hybrid Artificial Bee Colony algorithm for neural network training. *Proceedings of the IEEE Congress Evolutionary Computation (CEC).* New Orleans, Los Angeles, United States of America, 84-88.
13. Umarani, R.; and Selvi, V. (2011). Particle swarm optimization evolution, overview and applications. *International Journal of Engineering Science and* Technology, 2(7), 2802-2806.