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Application of Artificial Neural Networks for Identifying Optimal Groundwater Pumping and Piping Network Layout

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Abstract

The simulation-optimization approach is often used to solve water resource management problem although repeated use of the simulation model enhances the computational load. In this study, Artificial Neural Network (ANN) and Bagged Decision Trees (BDT) models were developed as an approximator for Analytic Element Method (AEM) based groundwater flow model. Developed ANN and BDT models were coupled with Particle Swarm Optimization (PSO) model to solve the well-field management problem. The groundwater flow model was developed for the study area and used to generate the dataset for the training and testing of the ANN & BDT models. These coupled ANN-PSO & BDT-PSO models were employed to find the optimal design and cost of the new well-field system by optimizing discharge & co-ordinate of wells along with the cost effective layout of piping network. The Minimum Spanning Tree (MST) based model was used to find out the optimal piping network layout and checking the hydraulic constraints in the piping network. The results show that the ANN & BDT models are good approximators of AEM model and they can reduce the computational burden significantly although ANN model performs better than BDT model. The results show that the coupling of piping network model with simulation-optimization model is very significant for finding the cost effective and realistic design of the new well-field system.

Keywords Groundwater modeling · Groundwater management · Artificial neural network · Bagged decision trees · Particle swarm optimization

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1 Introduction

The groundwater management problems are often solved by simulation-optimization approach (Lefkoff and Gorelick 1986; Zheng and Wang 2002; Finney and Samsuhadi 1992; Emch and Yeh 1998; Gaur et al. 2011; Ayvaz 2016; Karatzas 2017). In the simulation-optimization process, simulation model is repetitively called by optimization model for generating the groundwater levels along with the velocity, concentration etc. The use of the simulation models, in the each iteration of optimization model, increases the computational load extensively. Therefore, different researchers (Rogers and Dowla 1992; Johnson and Rogers 1995; Coppola et al. 2003; ASCE 2000; Singh et al. 2004; Nikolos et al. 2008; Christelis and Mantoglou 2016) used Artificial Neural Network (ANN) models as approximators of computationally expensive numerical models. They applied ANN and optimization algorithm to solve different hydrological management problems and found this combination to be more fast and robust. Arndt et al. (2005) approximated the results of Finite Element Method (FEM) based simulation model using predictions by ANN model. Results show that the value of the objective function at the simulation based optimal solution was only 1% better than the optimal solution obtained by the ANN. Nikolos et al. (2008) coupled ANN and differential evolution algorithm for substituting the FEM for water resource management problems. The study also concluded that the ANN can be used as a good approximation model to reduce the computational burden with optimal values close to simulation model. Christelis and Mantoglou (2016) applied the radial basis functions (RBF) as an approximator model to emulate the scalar response of a multivariate function. Results show that 96% of computational time was reduced by combined RBF and evolutionary annealing-simplex algorithm for the solution of pumping optimization.

Lots of work was also carried out for the optimal design of Water Distribution System (WDS). Wu and Simpson (2002) presented the application of fast messy Genetic Algorithm (GA) for the design of WDS. Nicklow (2010) concluded that GA is flexible and powerful technique to solve complex WDS network. Bieupoude et al. (2012) worked for the optimal design of water distribution network. The geometric and multi-scale optimization was used to analytically optimize T-shaped network architectures under the constraint related to water quality. The output of the study helped in the determination of an optimal geometry of the network that minimizes the head losses. Somaida et al. (2013) developed an analytical solution for determining the optimum pumping rate in a piping network supplied from the pumping wells. The gradient technique was used and examined on a predetermined optimal water distribution system.

To the best knowledge of the authors, the development of a new well-field system by the application of machine learning technique along with piping network model was not addressed by the researchers. Moreover, very few researchers have worked on the application of coupled groundwater and piping network models (Adams and Parkin 2002; Tsai et al. 2009). Mainly, the models were applied for the aquifer modelling in a karstic region and optimal scheduling and the design of the established piping networks. Tsai et al., (2009) developed a wells management model by integrating a water distribution system model (EPANET) and a groundwater model (MODFLOW) under an optimization framework. The management model considered multiple objectives which were solved by a parallel genetic algorithm (PGA) and were found to be effective. In the study, already established piping layout model was considered for the analysis. To the best knowledge of the authors, Bagged Decision Trees

(BDT) has not been used as an approximator of simulation model in the field of water resources.

The present research work is performed for the development of a new well-field system without considering any pre-defined layout of piping network, discharge and location of the wells which makes this work quite distinctive. Also the comparison of ANN and BDT models in the groundwater management problems is not addressed so far. In this regard, applicability of Particle Swarm Optimization (PSO) based ANN-PSO & BDT-PSO models were examined to minimize the pumping cost of the wells, where the ANN & BDT models were developed to approximate the Analytic Element Method (AEM) based groundwater simulation model. Both ANN & BDT models were trained and tested through dataset generated by AEM model. Piping layout network model was incorporated to design the optimal piping network. These coupled models were applied to find the optimal piping network by minimizing the pumping cost for the given water demand & maximum discharge limit of the wells. The results of ANN-PSO & BDT-PSO models were compared with AEM-PSO models. The study shows that combination of ANN & BDT models with piping layout design model is the efficient way for the design of new well-field system and can be applied on other areas.

2 Methodology

The present study incorporates the strength of both machine learning techniques and optimization algorithm to solve the well-field management problem. AEM based groundwater flow model was developed in the first stage and was used to generate the groundwater head for the training and testing of ANN & BDT models. The co-ordinate and discharge of the wells were taken as inputs and the groundwater head at the periphery of the well was taken as output for the development of ANN & BDT models. The random discharge & co-ordinate of the wells were generated by random number generator. Further, developed ANN & BDT models are integrated with PSO and used as a proxy simulator to AEM-PSO models. Kruskal's algorithm based model was developed and coupled with ANN-PSO & BDT-PSO model to apply Minimum Spanning Tree (MST) method for generating the optimal piping layout network. The coupled models were applied for identifying the optimal layout of piping network, with minimum total length, in each iteration of the optimization model. Whereas, the hydraulic design of piping network was also checked in the each iteration by computing head losses at each segment of piping network and checking the continuity of flow in the network. A penalty function method was used to handle the constraints in the optimization function. The major steps involved in the above procedure are explained in the following sections.

3 Objective Function and Constraints

The objective function was to minimize the pumping and the piping network cost. The pumping cost consists of the cost of well installation, pump cost and electricity cost for the pumping. In this study, all the wells were considered to be of the same depth and diameter. Therefore the cost of each well was taken constant and the total cost was calculated by multiplying the installation cost of one well by number of wells. Detail description about the function is given below.

Piping Cost: In this study, the piping length was computed by MST algorithm which creates the network by joining all the nodal points and also gives the minimum length of that network. The piping cost is defined as

$$Minf_1 = \sum_{i=1}^{N_p} A_d L_i \tag{1}$$

where L_i = pipe length for i^{th} segment, A_d = total cost for the development of per meter pipe network of specific diameter d and N_p = total number of pipe segments. A_d consist of the cost of earthwork, pipes, connectors and platforms.

Pumping Cost is a major factor that influences the cost of WFS. The pumping cost is influenced by quantity of the water to be pumped Q, pumping head H along with specific weight of the water γ, efficiency η of pump and energy R_E (Sharma and Swamee 2006; Moradi et al. 2003). Total cost of pumping consists of the cost of pump units and the electricity cost (Swamee and Sharma 1990; Swamee 1996) which can be defined as,

$$Minf_2 = \sum_{i=1}^{N_w} k_p \frac{\gamma Q_i H_i}{\eta} + \frac{8.76 R_E \gamma Q_i H^n r_T}{\eta} \tag{2}$$

where,

$$r_T = \frac{(1+r)^T - 1}{r(1+r)^T} \tag{2a}$$

γ = 9810 N/m^3; η = 85%; R_E = 0.085 euros/kwh; r = the rate of interest in "euros per euros per year" (euros/euros/year) and taken as 6%, T = 25 project life, N_w = total number of wells, H^n = total required head at each well location/node to lift the water at storage tank and k_p = pump cost on the basis of required pump power. As the same pump unit was adopted for each well, therefore a constant value was adopted in the function. The well construction & installation cost was taken as 4000 Euros per well. The location of storage tank was taken as X = 687,000 and Y = 218,000.

Therefore final objective functions is defined as

$$Minf_{12} = (w_1 f_1 + w_2 f_2) + (\beta_1 P_1 + \beta_2 P_2 + \dots\dots + \beta_n P_n) \tag{3}$$

where P_n = penalty term which varies linearly with the magnitude of constraint violation and.

β_n = weighting factor which is selected on the basis of constraints within the range of 10^3 to 10^7. n is the number of constraints in the problem. Following constraints were taken in the model,

$$Q_{i,\min} < Q_i < Q_{i,\max} \tag{4a}$$

$$\sum_{i=1}^{N_w} Q_i > Q_{total} \tag{4b}$$

$$h_i > h_{i,\min} \tag{4c}$$

$$(\mathrm{x}_i, y_i) \neq Ar_i \tag{4d}$$

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \geq S_{w,\min} \tag{4e}$$

Hydraulic design constraints to maintain the flow in piping network are defined below.

Law of conservation of mass at each node: total input will be equal to total output at junction

$$Q_{out} = \sum_{i=1}^{N_s} Q_i \tag{4f}$$

Conservation of energy at each node:

$$hd_i - hf_i = H^n \tag{4g}$$

where head of i^{th} inlet pipe at junction node – head loss in i^{th} inlet pipe = head at junction node. Q_i is the potential discharge from i^{th} well. $i = 1, 2.......Nw$. $Q_{i,min}$ and $Q_{i,max}$ are the minimum and maximum discharge limit for i^{th} well, $h_{i,min}$ = minimum allowable head of groundwater at i^{th} well, $S_{w,min}$ = minimum distance between any pair of wells; x_j and y_j are co-ordinates of remaining well i.e. $i \neq j$. where h_i is the water head at the i^{th} well and $i = 1, 2…., N_{w.}$ hd_i is the head at particular well node and hf_i is the head loss in the pipe connecting well node i to next well node.

The study area consists of two rivers Allier and Dore, where Dore river is an important tributary of Allier River. Dore river catchment is situated in the eastern part of the Massif-Central in France. The study area lies between 45054'N to 460 N latitude and 3025′E to 3029′ 10″E longitude. The developed model was applied on the part of the basin to identify the optimal location and discharge of the wells by satisfying the above said constraints. Depending on the rate of clay deposits, the hydraulic conductivity in the study area varies from 1×10^{-3} to 3×10^{-3} m/s. For the development of groundwater model, the rivers of the study area were represented by 39 head line-sink elements. Discharge wells were represented by well elements. A total of 12 piezometric measurements were available in the study area which were used for calibration of the model. The water level in the rivers was under observation at 11 different locations and were used to develop the AEM model (Gaur et al. 2011). Whereas, the constraint 4a was defined to insure the maximum and minimum discharge limit of the single well which was taken as 120 m^3/h to 280 m^3/h. The constraint 4b was taken to insure the minimum water discharge from all the wells and was fixed on the basis of minimum water demand of the area and taken as 980 m^3/h. The constraint 4c was taken to limit the drawdown of the groundwater i.e. 253 m. The constraint 4d was taken to keep the wells in specified zone for the development of well-field. The constraint 4e was taken to insure the minimum distance between the wells. To provide the protective zone around the wells a minimum distance of 300 m between any two wells was defined for protective zones. The constraint 4f & 4 g were taken as hydraulic constraints to maintain the continuity of flow and conservation of energy in the piping network (Tsai et al. 2009).

3.1 Model Development

AEM is a computational method based upon the superposition of analytical expression to represent the two dimensional vector fields. Ground water flow model was developed in MATLAB 7.0 (Strack 1989; Gaur et al. 2011; Math Works Inc 2001). The ANN and BDT models were developed and trained for a defined area which had the highest probability for occurrence of wells. This specific area was selected as potential alluvium aquifer between the two rivers and considering the output of AEM-PSO model (Gaur et al. 2011). 2000 sets of random discharge and location of wells were generated for the training and testing of both the models and AEM model was used to compute the groundwater head on the basis of this data. Total 21 input variables were used for the training and testing of ANN and BDT models which consists of co-ordinates (*x, y*) and the discharge (*Q*) of all the seven wells and corresponding groundwater head. Total seven ANN models were developed where each model gave the value of one selected well out of the seven wells. Therefore, all seven models were capable to give the head on the periphery of all the seven wells. Finally, to minimize the cost of all seven wells, PSO was combined with ANN and BDT models.

Architecture of ANN model was finalized on the basis of trial-and-error procedure (Atiya and Ji 1997; Morshed and Kaluarachchi 1998). The ANN model was trained using the back-propagation with Levenberg-Marquardt (L-M) technique and the sigmoid transfer functions 'tansig', log-sigmoid 'logsig' and linear 'purelin' were chosen for transfer functions of both the hidden layer and the output layer. The decision trees are also popularly used for various machine learning applications. The individual decision trees are highly sensitive to noise in its training dataset. The trees that grow very deep may learn a highly irregular pattern lead to low bias, but very high variance. The output from multiple trees can be taken instead of output from just a single tree. Although training multiple trees from same dataset could give strongly correlated trees or may even give the same tree. Bagging Technique was used to avoid this problem. Bagging or Bootstrap aggregating (Breiman 1994) is a machine learning technique used to improve accuracy and stability of machine learning algorithms. In order to improve the accuracy of decision trees, it combines results from different trees trained using randomly generated dataset. Thus, the trees get de-correlated. Given a training dataset of samples N, bagging generates $\mathcal{M}$ new datasets of size S, by taking samples from dataset uniformly with replacement. Further, $\mathcal{M}$ decision trees are trained for these new $\mathcal{M}$ datasets. Output is decided on the basis of average of all the trees. This concept of sample bagging can be extended on the features rather than selecting all the features at the same time only a fraction of features can be selected to further avoid correlation.

The efficiency & accuracy of the models were increased by two modifications. In this regard, the velocity term of PSO models were modified to deal with the wells coordinate. The decimal number values generated by the velocity term generally increase the iteration of PSO models exceptionally. To handle this, restrictions were applied on velocity term for integer number and 'units position' rounded up to 5 or 10 accordingly. This implies that from each previous location, new search location will be at least 5 m away. The number of iterations got reduced by 11% due to this modification. It was observed that the modified model converged in less than 1000 iterations whereas more than 1000 iterations were required to converge the model without this modification. In the second modification, additional input features were introduced in the ANN and BDT models which consisted of the distances of the concerning well, for which model was developed, from the remaining wells. These inputs helped to account the impact on the groundwater head due to distances between the wells. Significant improvements were observed as the NRMSE value was found to be lower than the previous case. It was also observed that with the increase in the number of input features from 21 to 27, the number of neurons in the hidden layer required for the ANN model reduced notably which was found 36 for 27 input features. The similar trends were observed in case of BDT model. The number of trees required for the model decreased with the increase in the number of input features. For BDT model with 27 parameters, optimum number of trees was found out to be 39.

In the present study, the performance of both ANN-PSO and BDT-PSO models were measured on the basis of coefficient of correlation (R) and Normalized Root Mean Squared Error (NRMSE). Figure 1 shows the plot between NRMSE and number of neurons for the well-1. Figure 2 shows plot between NRMSE and number of trees. The optimum number of trees in BDT model was found 39 through training of model up to 50 trees. In this model, fraction of data used by each tree (considering replacement) from the data present in the training set was also varied.

4 Model Application

Three scenarios were considered to find out the optimal cost of WFS. In the first two scenarios, the model was run by considering single diameters of all pipes in the piping network and an optimal cost was obtained for those diameters of pipes. The piping diameters were taken as 200 mm and 250 mm in the first two scenarios respectively. In the third scenario, diameter of the pipes, in the network system, was also considered as one of the decision variables. As the diameter with a continuous value is not practically feasible, discrete values were taken in the optimization process i.e. 200 and 250 mm.

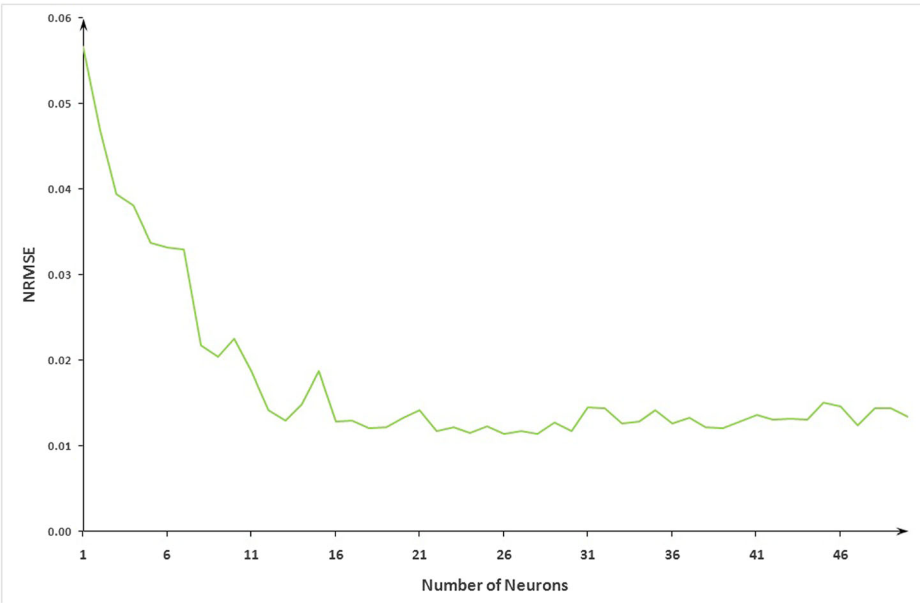

Fig. 1 Shows plot of NRMSE v/s Number of Neurons

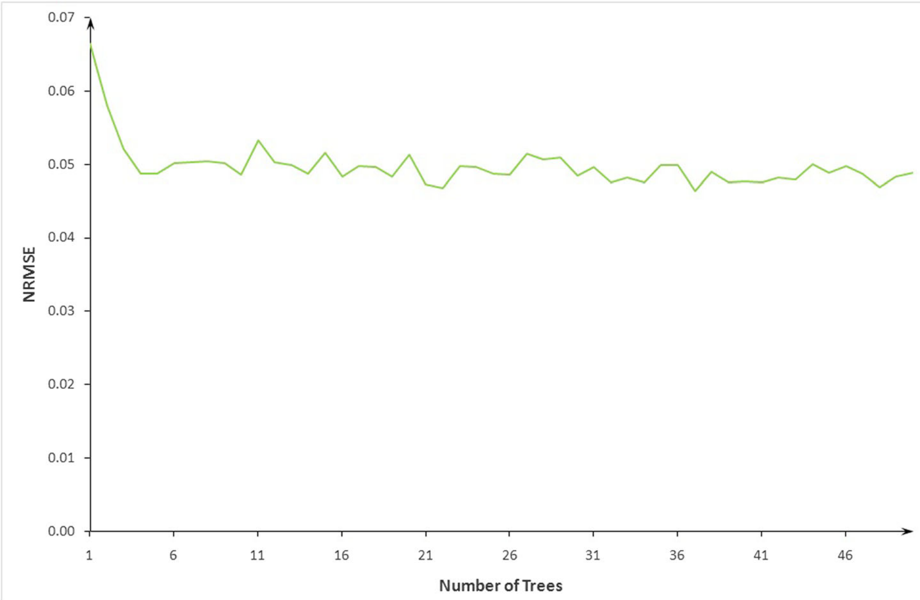

Fig. 2 Shows plot of NRMSE v/s Number of Trees

A spanning tree of a network connects all the vertices of that network together (wells in this case), and MST is a spanning tree with minimum possible total weight, where the weights are measured as the distances between the edges/wells. In every iteration of ANN-PSO & BDT-PSO models, the piping network model first developed the five optimal piping network layouts through minimum spanning tree method. Once the piping network layouts were finalized on the basis of total minimum lengths, total discharge at each junction node from all input pipe segments and discharge of well at that node was considered as total discharge of that node. Once the network layout was finalized, the hydraulic design model was applied to calculate the total discharge through connected pipes, at each junction node. A single well was considered at each node of piping network layout. The discharge value at node, which has only one output pipe segment and no input pipe segment, was assigned to the discharge value corresponding to the discharge of that well only. Whereas, discharge at junction nodes, which had one or more input pipes, was computed by hydraulic design model. Once all the discharge values were known at each single & multi pipe nodes, the hydraulic design model computed the head losses in each pipe segment on the basis of the discharge value and the length of the corresponding pipe segment. The model started adjusting the head losses by adding it in the head 'H^n' at each well. At the same time, the hydraulic design model also adjusted the final value of 'H^n' at wells in such a way that all connected pipes started having same head at nodes i.e. junctions. This helped to satisfy the constraints 4 f. The model started the adjustment from the storage tank and moved along the network till it reached the starting point(s) of the network. The corresponding, pumping and pump cost was computed on the basis of final "H^n" computed by the piping network model. Total 21 decision variables were taken for S-1 & S-2 which accounted the discharge and co-ordinates of the wells. Whereas, 28 decision variables were taken for S-3 by accounting the discharge, co-ordinates of the wells and diameter of the pipes. In the optimization process, a population of PSO particles was initialized with random values of decision variables i.e. X & Y co-ordinates, discharge of wells and diameter of pipes, in the problem space. In each iteration of the PSO optimisation, the pumping cost was calculated by using groundwater head values. The coupled ANN & BDT model computed the head values at given locations and discharges of wells for each PSO particle at each iteration. Meanwhile, the layout of the piping network model also identified the optimal layout in each iteration of PSO model & the hydraulic design model was used for computing head values at junctions of piping network. Finally, the PSO model converged to search the optimal location and discharge of wells along with optimal layout and diameters of piping network.

The coefficient of correlation (R) and NRMSE were used to measure the performance of the developed ANN and BDT models. It was observed that coefficient of correlation for both the ANN model and BDT model increased as the number of pumping patterns increase, however, after a certain limit the accuracy remained almost constant. Total 1400 pumping patterns were found suitable. The integration of these developed models was done with PSO model to further determine the optimal pumping cost for the considered problem. The PSO models were converged if their objective function value did not change for 50 iterations. Maximum 1000 iterations were used in the model but it was converged after 791. Total of fifteen runs were done and the value that came out to be minimum was considered as the optimal solution. The optimal cost by AEM-PSO, ANN-PSO and BDT-PSO models is shown in Fig. 3.

The total minimum cost of the system by AEM-PSO model was found 1,378,758 euros 1,438,732 euros and 1,607,746 euros for the scenario S-3, S-2 & S-1 which shows that S-3 is the most economical in comparison to other scenarios. Optimal values were selected from fifteen runs of model where values vary within the range of 0.18% to 0.26%. The results show that the total cost in ANN-PSO model is increased by 1.26%, 1.08% & 1.48% in S-3, S-2 & S-1. The total cost in BDT-PSO is increased by 8.69%, 7.90% & 8.74% in S-3, S-2 & S-1 with comparison to AEM-PSO. As the total cost of the system in S-3 was found to be minimum in comparison to other two scenarios which shows that ANN-PSO model is capable to handle the diameter of pipes as a decision variable along with discharges and location of wells. In S-3, 4 pipe segments with 250 mm diameter and 2 pipe segments with 200 mm diameters were found optimal (Figure 4). Figures 5 and 6 show the graph for the cost of piping & pumping in all the three scenarios. Table 1 shows the discharge and co-ordinates of optimal wells in all three scenarios. The results show that piping cost & pumping cost increases in S-1 with comparison

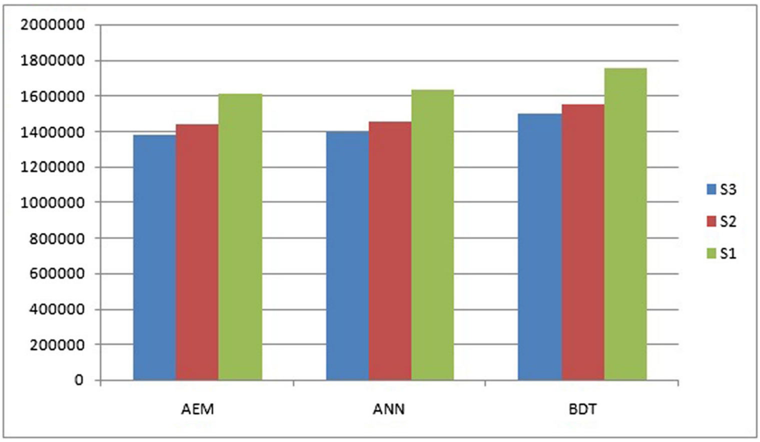

Fig. 3 Optimal cost by AEM-PSO, ANN-PSO and BDT-PSO Models

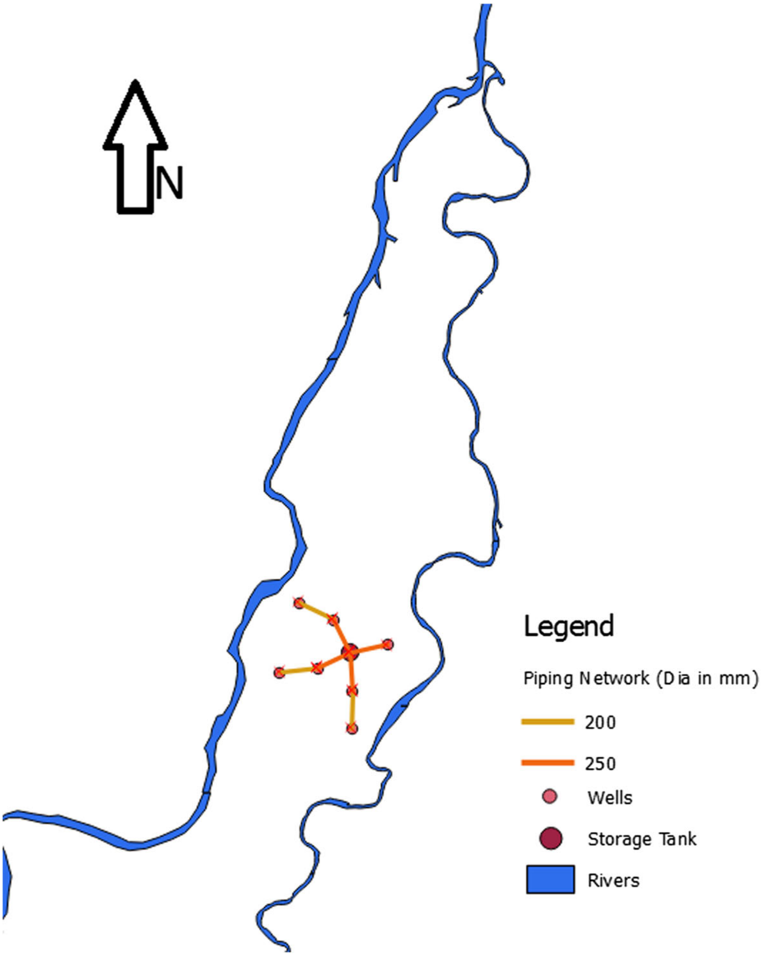

Fig. 4 Map of optimal location of wells and piping network in Scenario-3

to S-3. Whereas in S-2, piping cost increases & pumping cost decreases with comparison to S-3 in all 6, 7 & 8 set of the wells. The results of S-1 and S-2 show that piping diameter influences the total cost of the system where increasing the diameter of pipes becomes cause of the increased piping cost and the decreased pumping cost. Therefore, expenses on piping network increases due to increased diameter but at same time it reduces the head losses in pipes which helps to reduce the pump power to transport the water at storage tank. As the diameter of the pipes depends on the discharge in the pipes, the optimal diameter for pipe with single wells can be different from the pipes with accumulated discharge of different pipes.

To understand the importance of piping layout model, model was run and piping cost was computed without optimizing piping layout. In this run, each well was directly connected to the storage tank. The results show that optimal cost of WFS system is high in this condition. The total cost in this run is increased by 4.21% in comparison to the cost in S-3, which is 58,045 Euros higher. On the other side, this price is lower in comparison to S-1which shows that piping layout model is effective when optimal selection of diameter is also incorporated to compute the total cost. It is also found that decreasing the diameter of pipe becomes cause of

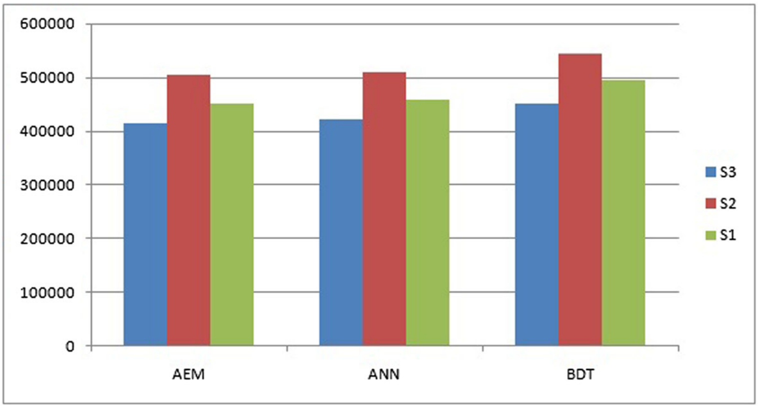

Fig. 5 Optimal piping cost by AEM-PSO, ANN-PSO and BDT-PSO Models

increased head losses and corresponding higher pumping cost, which highly dominates the piping cost of the system. The results also show that application of piping network model is effective and capable to reduce the cost of system & found the realistic network. The major advantage of the ANN-PSO model that was found is that it reduces the computational time. Where the AEM-PSO model approximately takes 6–7 h for 1000 iterations of model convergence, ANN-PSO model takes only 4–5 min and BDT-PSO takes 10–12 min (when run in intel core i7 processor) for the same number of iterations.

5 Summary and Conclusions

In this study, the AEM based simulation model was approximated to ANN & BDT models. Further these models were coupled with PSO algorithm to minimize the pumping cost of the wells. The optimal cost by ANN-PSO models was found more close to AEM-PSO models within the limit of 1.48% to 0.9% in S-1 & S-2. The cost by BDT-PSO model was found within the range of 7.9% to 8.7% of the cost obtained from AEM-PSO models. The result obtained from ANN-PSO models was found close to the result of AEM-PSO model with the

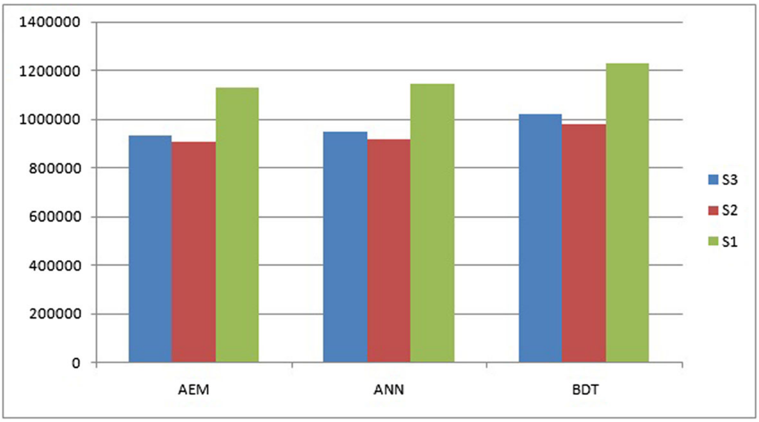

Fig. 6 Optimal pumping cost by AEM-PSO, ANN-PSO and BDT-PSO Models

Table 1 Optimal discharge and co-ordinates of wells in the Scenarios 1, 2 & 3

	Well discharges			Co-ordinate (X, Y)		
	S1	S2	S3	S1	S2	S3
1	137.7	135.1	162.3	(687,292, 2,108,072)	(686,768, 2,108,190)	(686,423, 2,107,839)
2	128.4	173.7	120.2	(686,700, 2,107,971)	(687,300, 2,108,002)	(687,006, 2,107,384)
3	123.6	131.7	139.6	(686,704, 2,108,290)	(687,119, 2,107,725)	(686,855, 2,108,270)
4	132.6	142.1	131.8	(687,007, 2,108,301)	(687,204, 2,107,436)	(686,727, 2,107,874)
5	167.0	132.0	129.3	(687,178, 2,107,758)	(686,439, 2,107,781)	(687,011, 2,107,690)
6	147.2	139.6	123.8	(686,429, 2,108,120)	(686,725, 2,107,873)	(686,575, 2,108,408)
7	143.6	125.8	173.1	(686,877, 2,107,721)	(686,483, 2,108,287)	(687,292, 2,108,068)

error of less than 2%. Whereas, BDT-PSO model was found to be more inferior in comparison of AEM-PSO model with error of less than10%.

Even though the cost in the case of the BDT-PSO models is quite low but it is not in accordance with the AEM-PSO models as it fails to account interference. Study concluded that number of iterations and computation time for the convergence of BDT-PSO model is more in comparison of ANN-PSO model. Developed ANN model was successful in accounting well interference and also required lesser data for training. The study concludes that use of piping network model is very important to identify realistic and cost effective piping network. The diameter of the pipe is found to be a very influencing parameter and can vary the location and arrangement of the wells significantly. The use of coupled models increases the computational time significantly, further which can be reduced by parallel processing.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

References

ASCE Task Committee (2000) Application of artificial neural networks in hydrology artificial neural networks in hydrology I: preliminary concept. J Hydrol Eng 5-2:115–123

Adams R, Parkin G (2002) Development of a coupled surface-groundwater-pipe network model for the sustainable management of karstic groundwater. Environ Geol 42:513–517

Arndt O, Barth T, Freisleben B, Grauer M (2005) Approximating a finite element model by neural network prediction for facility optimization in groundwater engineering. Eur J Oper Res 166:769–781

Atiya A, Ji C (1997) How initial conditions affect generalization performance in large networks. IEEE Trans on Neural Netw 8(2):448–451

Ayvaz MT (2016) A hybrid simulation–optimization approach for solving the areal groundwater pollution source identification problems. J Hydrol 538:161–176

Bieupoude P, Azoumah Y, Neveu P (2012) Optimization of drinking water distribution networks: computer-based methods and constructal design. Comput Environ Urban Syst 36:434–444

Breiman L (1994) Bagging predictors. Technical Report 421, Department of Statistics, University of California at Berkeley

Coppola E, Poulton M, Charles E, Dustman J (2003) Application of artificial neural networks to complex groundwater management problems. Int Assoc Math Geol 12(4):303–320

Christelis V, Mantoglou A (2016) Pumping optimization of coastal aquifers assisted by adaptive metamodelling methods and radial basis functions. Water Resour Manag 30:5845–5859

Emch PG, Yeh WG (1998) Management model for conjunctive use of coastal surface water and groundwater. J Water Resour Plan Manag 124:129–139

Finney BA, Samsuhadi WR (1992) Quasi-three-dimensional optimization model for Jakarta basin. J Water Resour Plan Manag 118:18–31

Gaur S, Chahar BR, Graillot D (2011) Analytic elements method and particle swarm optimization based simulation-optimization model for groundwater management. J Hydrol 402(3–4):217–227

Karatzas GP (2017) Developments on modeling of groundwater flow and contaminant transport. Water Resour Manag 31(10):3235–3244

Johnson VM, Rogers LL (1995) Location analysis in ground-water remediation using neural networks. Ground Water 33(5):749–758

Lefkoff LJ, Gorelick SM (1986) Design and cost analysis of rapid aquifer restoration systems using flow simulation and quadratic programming. Ground Water 24:777–790

Math Works Inc (2001) MATLAB V R2009a, Apple Hill drive, Natick, Massachusetts, USA

Morshed J, Kaluarachchi JJ (1998) Application of artificial neural network and genetic algorithm in flow and transport simulations. Adv Water Resour 22(2):145–158

Moradi JM, Marino MA, Afshar A (2003) Optimal design and operation of irrigation pumping station. J Irrig Drain Eng 129(3):149–154

Nikolos IK, Stergiadi M, Papadopoulou MP, Karatzas GP (2008) Artificial neural networks as an alternative approach to groundwater numerical modelling and environmental design. Hydrol Process 22:3337–3348

Nicklow J (2010) State of the art for genetic algorithms and beyond in water resources planning and management. J Water Resour Plann Manag 136:412–432

Rogers LL, Dowla FU (1992) Groundwater remediation optimization with artificial neural networks and the genetic algorithm. Eos Trans AGU Fall Meeting 73:186

Sharma AK, Swamee PK (2006) Cost considerations and general principles in the optimal Design of Water Distribution Systems. ASCE Conference Proceeding 247:85

Singh RM, Datta B, Jain A (2004) Identification of unknown groundwater pollution sources using artificial neural networks. J Water Resour Plan Manag 130(6):506–514

Somaida MM, El-ZaharMedhat MH, Yasser AH, Mahmoud SS (2013) Optimizing pumping rate in pipe networks supplied by groundwater sources. KSCE J Civ Eng 17(5):1179–1187

Swamee PK (1996) Design of multistage pumping mains. J Transp Eng 122(1):1–4

Strack ODL (1989) Groundwater mechanics. Prentice-Hall, Englewood Cliffs, NJ

Swamee PK, Sharma AK (1990) Decomposition of large water distribution systems. J Environ Eng 116(2): 269–283

Tsai FTC, Katiyar V, Toy D, Goff RA (2009) Conjunctive Management of Large-Scale Pressurized Water Distribution and Groundwater Systems in semi-arid area with parallel genetic algorithm. Water Res Manage 23:1497–1517

Wu ZY, Simpson A (2002) A self-adaptive boundary search genetic algorithm and its application to water distribution systems. J Hydraul Res 2:191–203

Zheng C, Wang PP (2002) A field demonstration of the simulation optimization approach for remediation system design. Ground Water 40(3):258–266