European Water 57: 345-352, 2017.

Artificial neural networks and particle swarm optimization based model for the solution of groundwater management problem

S. Gaur*, A. Dave, A. Gupta, A. Ohri, P.K.S. Dikshit and S.B. Dwivedi
Department of Civil Engineering, Indian Institute of Technology (BHU), Varanasi, India
* *e-mail: shishir.gaur@gmail.com*

Abstract: Fulfilling the growing water demand, at domestic, industrial and agriculture level, is the most challenging task and groundwater plays the most important role for achieving this demand. In this scenario, proper management of groundwater resources is the most required act, as unmanaged groundwater extraction may cause shrinking of aquifer, sea water intrusion and water quality problems. The simulation-optimization approach is the most efficient way to solve any ground management problem where complex numerical models simulate the groundwater flow and/or contamination transport. The optimization model employs simulation for achieving the values of the groundwater head, velocity, concentration etc. This repeated use of the flow model increases the computational burden extensively and takes several hours to converge the final solution. In this study, Artificial Neural Network (ANN), Bagged Decision Trees (BDT) and Particle Swarm Optimization (PSO) models were developed and coupled for the management of groundwater resources. The Analytic Element Method (AEM) based flow model was developed and used to generate the dataset for the training and testing of the ANN model. These developed ANN-PSO & BDT-PSO models were applied to minimize the pumping cost of the wells. The results show that the ANN model can reduce the computational burden significantly and it is able to analyze different scenarios as well.

Key words: Groundwater Modeling, Groundwater management, Artificial Neural Network, Analytic Element Method, Particle Swarm Optimization

1. INTRODUCTION

The groundwater management problems are addressed by simulation-optimization approach. In the simulation-optimization process, simulation model is repetitively called by optimization model for generating head values of groundwater along with the velocity, concentration etc. The repetitive use of simulation models increases the computational burden extensively and it requires several hours to get the final solution. Different researchers (Rogers and Dowla, 1992; Johnson and Roger, 1995; Coppola et al., 2003; Singh et al., 2004) applied ANN modeling to substitute the numerical models. They applied ANN and optimization algorithm to solve different hydrological management problems and found this combination to be more fast and robust. ANN has been applied in the different areas of hydrology such as rainfall-runoff modeling, groundwater management, stream flow forecasting, ground-water modeling, water quality, water management policy, precipitation forecasting, hydrologic time series and reservoir operations, it was found that ANN based optimization model needs very less computational time and it is more flexible in comparison of mathematical programming methods. Arndt et al. (2005) approximated the results of finite-element based simulation model through ANN-computed predictions. The Study concluded 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) performed the study, by coupled ANN and differential evolution algorithm, to substitute the finite-element numerical model for water resource management problems. The study also concluded that the use of ANN as an approximation model could significantly reduce the computational burden and provide solutions very close to the optimal ones.

This paper examines the applicability of ANN-PSO & BDT-PSO based models to minimize the pumping cost of the wells, where the ANN & BDT model have been developed as a substitute of

AEM based groundwater simulation model. Both ANN & BDT models were trained and tested through dataset generated by AEM model. The results of ANN-PSO & BDT-PSO model have been compared with AEM-PSO model by applying both models on real field data for the aquifer of Dore river basin, France.

2. METHODOLOGY AND STUDY AREA

The presented study incorporates the strength of both the artificial neural networks and the optimization algorithms to solve the well field management problems. Initially, the groundwater flow model has been developed using analytic element method. Further, three scenarios have been taken by considering the set of four, five and six wells and AEM model has been used to compute the groundwater head with the given random discharges and co-ordinates for those set of wells. The random discharges of the wells have been generated for each scenario by using a random number generator that generates uniform random pumping rates within the range from 120 m^3/hr to 280 m^3/hr. Co-ordinates of the pumping wells have also been generated within the limit of study area by random number generator. Finally, the dataset for the training of ANN & BDT has been developed. The location and discharges of the wells have been taken as input and the groundwater head at the periphery of the well has been taken as output for ANN & BDT model. The database so generated is employed in training and testing the ANN's for all possible input ranges. Thus, the developed ANN & BDT models are integrated with PSO and used as a proxy simulator to AEM-PSO model for evaluation of the cost function. A penalty function method is used to handle the constraints in the optimization function. The optimal number of wells is determined by comparing the total cost of the system for all the 3 scenarios. Finally, the recommended management solution is validated using the AEM-PSO model. The major steps involved in the above procedure are explained in the following sections.

In the present study Dore river catchment, France has been taken as the study area. The developed models have been applied to fulfill the water demand of the city Thiers which is one of the major city of Loire region, France. The study area lies between $45^0 54'$ N to 46^0 N latitude and $3^0 25'$ E to $3^0 29' 10''$ E longitude. The average annual rainfall recorded at the rain gauge station of the basin is 780 mm. The major part of the area is covered by fluvial quaternary sediments underlain by marls and clay. The elevation of the bottom impervious layer of aquifer varies from 254 to 258 m from Mean Sea level (MSL). The location of the different hydrological features and other required data has been extracted from the geological maps 1/50,000 provided by BRGM (National Service for Geological Survey). Total 12 piezometric measurements are available in the study area, which shows the hydraulic gradient in the North direction.

3. OBJECTIVE FUNCTION AND CONSTRAINTS

The objective of the study is to minimize the total cost for the new pumping wells. The different parts of the cost function have been defined below.

(a) Well Installation Cost: the well construction have five separate steps. These include drilling, installing the casing, installing the well screen, installing the filter pack, grouting and well development. In the simplest form the well installation cost can be expressed as,

$$C_{wi} = A_1 N_w \tag{1}$$

where A_1 is the total cost for single well installation which includes the cost of drilling, casing, well screen, filter pack, sealing and well development; N_w*is* the total number of wells. In the above equation all the wells have been considered of the same depth and diameter. Therefore the cost of each well has been taken constant and the total cost can be calculated by multiplying the installation cost of one well by number of wells.

(b) Piping Cost: In this study, piping length has been considered from wells to reference location only and all pipes have been considered with the same diameter and material. The piping cost can be given as

$$C_{pn} = A_2 \sum_{i=1}^{N_w} L_i \tag{2}$$

where L_i = pipe length for i^{th} well and A_2 = total cost for the development of per meter pipe network which includes the cost of earthwork, cost of pipes, joining separate pipe sections together by welding, applying an outer insulation, and lowering the pipeline into the trench.

(c) Pumping Cost: The major factors that influence the pumping cost depends upon the volume of the water to be pumped, weight density of the water, hydraulic head, efficiency of the pump and energy cost (Sharma and Swamee, 2006; Moradi et al., 2003). Total cost of pumping ($C_p$in euros) consists of the cost of pump units (C_{pu} in euros) and the capitalized electricity cost (pumping cost) (C_{pE} in euros) including the annual repair and maintenance cost and hence can be expressed (Swamee and Sharma, 1990a; Swamee, 1996) for a single well as

$$C_{pi} = C_{pu} + C_{pE} = k_P \frac{\gamma QH}{\eta} + \frac{8.76 R_E \gamma Q H r_T}{\eta} \tag{3}$$

where, $r_T = \dfrac{(1+r)^T - 1}{r(1+r)^T}$ (4)

γ = weight density of the fluid (N/m^3); H = pumping head (m), which is equal to the head from water table in aquifer to the height of storage tank including head losses in pipes; η= combined efficiency of the pump and the prime mover; R_E = the cost of the electricity per kilowatt-hour (euros/kwh); r = the rate of interest expressed as "euros per euros per year" (euros/euros/year), T= life of the project in years. For the long life of the project (T→∞) Equation (4) gives r_T=*1/r*. The same pump unit was adopted for each well, therefore it was not included in the optimization function. Thus the total pumping cost can be expressed as

$$C_p = \sum_{i=1}^{N_w} \left(\frac{8.76 R_E \gamma Q_i H_i r_T}{\eta} \right) \tag{5}$$

where Q_i is the potential discharge from i^{th} well. i = 1, 2…….. N_w. As the well installation cost is constant for all the wells, it is not included in optimization process but is used to calculate the overall cost of the pumping system. Thus, the objective function for this problem is as follows,

$$Minimize \left\{ \sum_{i=1}^{N_w} \left(A_2 L_i + \frac{8.76 R_E \gamma Q_i H_i r_T}{\eta} \right) \right\} \tag{6}$$

subject to

$$Q_{i,\min} < Q_i < Q_{i,\max} \tag{6a}$$

$$\sum_{i=1}^{N_w} Q_i > Q_{total} \tag{6b}$$

$$h_i > h_{i,\min} \tag{6c}$$

$$(x_i, y_i) \neq A_i \tag{6d}$$

$$\sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \geq S_{w,\min} \tag{6e}$$

where $Q_{i,min}$ 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. $i \neq j$.

The first constraint has been taken as to limit the drawdown of the groundwater under permissible limit.

$$h_i > 253 \text{ m} \tag{7}$$

where $h_i$is the minimum water head on the periphery of the i^{th} well and i = 1, 2…., N_w.

The second constraint is related to the minimum water discharge from all the wells. This constraint has been fixed on the basis of minimum water demand of the area and taken as 820 m^3/hr, and hence

$$Q_{tot} > 820 \text{ m}^3\text{/hr} \tag{8}$$

The third constraint prescribes the maximum and minimum discharge limits of the single well. On the basis of aquifer properties and availability of pumps, the discharge limit has been selected as follows

$$120 \text{ m}^3\text{/hr} < Q_i < 280 \text{ m}^3\text{/hr} \tag{9}$$

The fourth constraint incorporates the minimum distance between the wells. By considering the local practices and to provide the protective zone around the wells a minimum distance of 100 m between any two wells has been considered.

4. MODEL DEVELOPMENT

AEM is a computational method based upon the superposition of analytical expression to represent the two dimensional vector fields. Each type of analytic element can simulate different types of geohydrological features (extraction wells, rivers, infiltration areas, aquifer inhomogeneities and other features). In this study, groundwater flow model based on Analytic element theory is developed by MATLAB 7.0 and applied on the case study (Gaur et al., 2011).

The ANN structures are generally capable of identifying complex nonlinear relationship between input and output data sets (Maier and Dandy, 2000; ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000a). It can be considered as a universal function approximator. To design the architecture of ANN, a trial-and-error procedure suggested by various researchers (Atiya and Ji, 1997; Morshed and Kaluarachchi, 1998) have been used in this study. The back-propagation with Levenberg-Marquardt (L-M) technique was used to train the ANN model. The sigmoid transfer functions 'tansig', log-sigmoid 'logsig' and linear 'purelin' have been chosen for transfer functions of both the hidden layer and the output layer.

Only one hidden layer has been used. Similar to the neural networks, the decision trees are 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, but they are sensitive to overfitting thus, lead to low bias, but very high variance. Rather than taking output from just a single tree, the output from multiple trees can be taken. But training multiple trees from same dataset could give strongly correlated trees or may even give the same tree. To avoid this problem Bagging Technique is used.

Bagging or Bootstrap aggregating (proposed in 1994 by Leo Beriman) 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. Now $\mathcal{M}$ decision trees are trained for these new $\mathcal{M}$ datasets and output is decided by the average of all the trees. This same concept of sample bagging can be extended on the features also thus rather than selecting all the features at the same time only a fraction of features can be selected to further avoid correlation. The performance of both the models has been measured by calculating the value of the coefficient of correlation (R) and Normalized Root Mean Squared Error (NRMSE). The plots of all wells are similar therefore graph of only well 1 has been shown here. Figure 1 shows the plot between NRMSE and number of neurons. The optimum number of neurons was taken as 39 for 15 input features in ANN model. Whereas, Figure 2 shows plot between NRMSE and number of trees. The optimum number of trees was found out to be 105, in BDT model, for the 15 input features model. In this model, fraction of data used by each tree (considering replacement) from the data present in the training set was also varied.

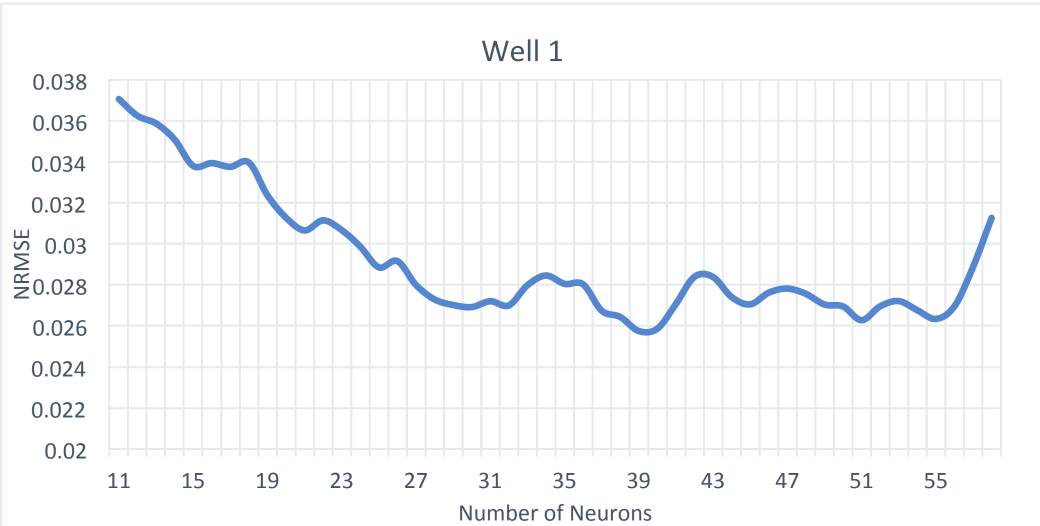


Figure 1. Shows plot of NRMSE v/s Number of Neurons.

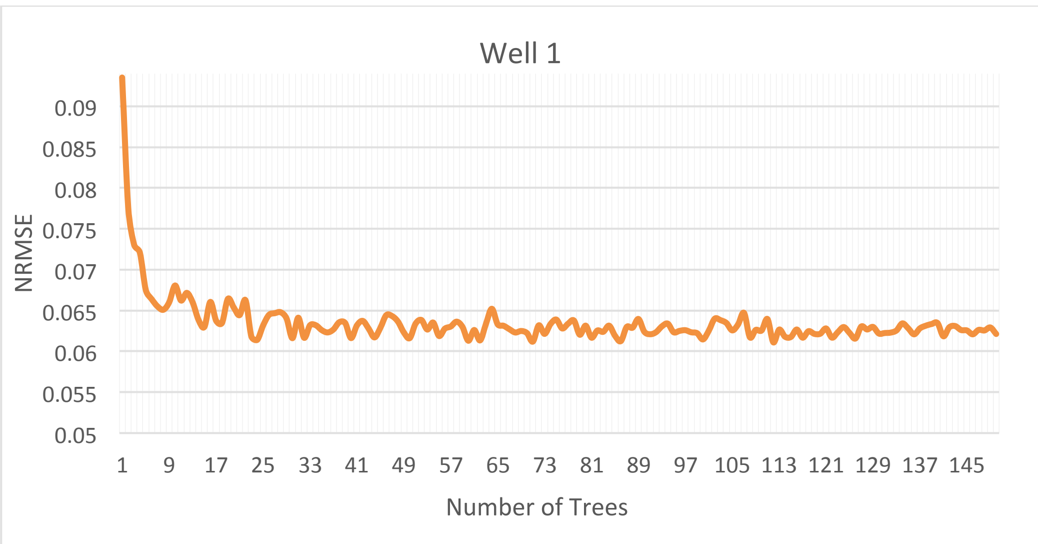


Figure 2. Shows plot of NRMSE v/s Number of Trees.

5. MODEL APPLICATION

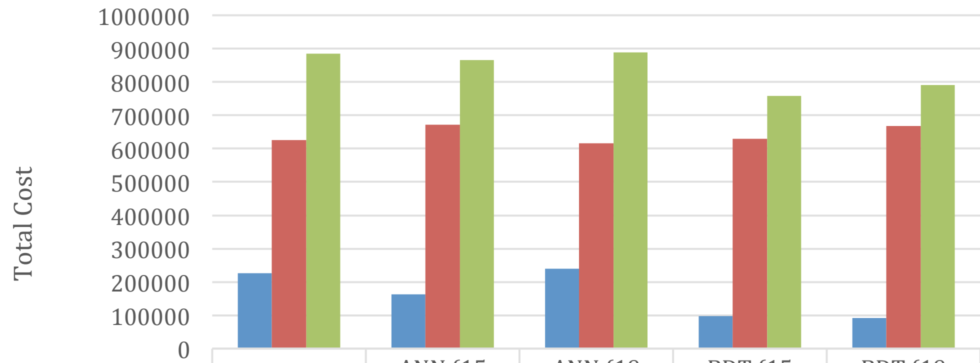
The ANN and BDT models were developed and trained for a specific area which had the highest probability for occurrence of well. This specific area was obtained from the results of the AEM-PSO model. The training and testing dataset for both the models have been generated with the help of AEM model. In this process, 2000 set of random discharge and location of wells, i.e. pumping patterns, were generated by random number generator. Further AEM model was used to compute the groundwater head for generated data set. Therefore, 15 input variables, which consist of coordinates (x, y) and the discharge (Q) of all the five wells, and corresponding groundwater head were used for the training and testing of ANN and BDT models. Finally, to minimize the cost of all five wells, PSO has been combined with ANN and BDT models. Two modifications have been done to overcome this problem and increase the efficiency & accuracy of these models.

Firstly, the velocity term of PSO models has been modified to deal with the decision variable of the well coordinate. The decimal number values generated by the velocity term generally increase the iteration of PSO models exceptionally, especially in the case of optimal location. To deal with this problem, restrictions have been put 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 significantly due to this modification. An examination has been done on a set of 5 wells. It was observed that the modified model got converged in less than 1000 iterations whereas the normal AEM-PSO took more than 2500 iterations to converge the model.

Secondly, modifications were done in ANN model to improve its accuracy and efficiencies. Additional input features were introduced in the models which consisted of the distances of the concerning well from the remaining wells. From the results obtained, significant improvements were seen in the model 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 15 to 19, the number of neurons in the hidden layer required for the ANN model reduced notably. It was observed that the optimum no. of neurons was 36 for 19 input features ANN model. 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 19 parameters, optimum number of trees was found out to be 85.

Three different scenarios have been developed for finding out the optimal well location and discharges. The increment in the number of wells has also been done in a systematic way from one scenario to the other. In each scenario, total 15 (4+5+6) neural networks are constructed, one ANN for each well. The coefficient of correlation (R) and NRMSEare used to measure the performance of the developed ANN and BDT. It is discovered that as the number of pumping patterns increase, the coefficient of correlation for both the ANN model and BDT model increases, however, after a certain limit the accuracy remains almost constant. It is observed that even though the pumping patterns increase beyond a certain value, the coefficient of correlation does not further increase. Thus, 1400 and 1150 pumping patterns have been found suitable for the 15 input features and 19 input features model, respectively .The integration of these developed models is done with PSO model to further determine the optimal pumping cost for the considered problem. In the first stage, Models have been operated for 1000 iterations, but they converged after 842, 935 and 984 iterations for the set of 4, 5 and 6 wells respectively. The PSO models are said to converge if its objective function value does not change for 50 iterations. The models have been operated for 1000 iterations in the second stage but it converged after 753, 793 and 923 iterations for the set of 4, 5 and 6 wells respectively.

A total of fifteen runs have been done for each set of wells. Out of these runs the value that comes out to be minimum, has been considered as the optimal solution. It is further found that the set of five wells is likely to get more optimal rates in comparison of the set of four and six wells. The optimal cost by AEM-PSO, ANN-PSO and BDT-PSO models is shown in Figure 3.



	AEM	ANN (15 features)	ANN (19 features)	BDT (15 features)	BDT (19 features)
Piping Cost (in €)	227148	162441	240002	96866	91180
Pumping Cost (in €)	625221	671974	616568	628974	668078
Total Cost (in €)	884369	866414	888570	757840	791257

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

Final optimal cost by ANN-PSO model for the set of five wells is 888570 Euros for 19 input features model comprising of 616,568 Euros for pumping, 240,002 Euros for piping, 20,000 Euros for well installation and 12,000 Euros for pumping unit and that for BDT-PSO model is 791,257 Euros for 19 input features model comprising of 668,078 Euros for pumping, 91,180 Euros for piping, 20,000 Euros for well installation and 12,000 Euros for pumping unit. It has been found that the total length of all pipes, from reference location by ANN-PSO (19 input features) is 5% more than the total length found by AEM-PSO model. It can be concluded from the results that the 19 input features ANN-PSO model is capable to produce the results near to AEM-PSO model whereas the results from other three models are inferior to the result of AEM-PSO model.

The major advantage of the ANN-PSO model that has been found is that it reduces the computational time. Where the AEM-PSO model approximately takes 5-6 hours for 700 iterations of model convergence, ANN-PSO model takes only 4-5 minutes and BDT-PSO takes 10-12 minutes (when run in intel core i7 processor) for the same number of iterations.

6. SUMMARY AND CONCLUSIONS

In this study, the AEM based simulation model was approximated to ANN & BDT models which were later combined with PSO algorithm to minimize the pumping well cost. The cost of ANN-PSO model is found to be 2% more and 0.5% less (in case of 15 & 19 input parameters respectively) than the cost obtained from AEM-PSO model. Whereas the cost of BDT-PSO model is found to be nearly 14% less and 10% less (in case of 15 & 19 input parameters respectively) from the cost of AEM-PSO model. Even though cost in case of BDT-PSO model is minimum, it is not in accordance with the AEM-PSO model as it fails to account interference. The result obtained from ANN-PSO models was found close to the result of AEM-PSO model with the error of 1%. Whereas, the results obtained by BDT-PSO models were found to be more inferior to the results of AEM-PSO model with error of 10%. It was found that number of iterations for the convergence of ANN-PSO models is less in comparison to the BDT-PSO. This ANN model for the area was successful in accounting well interference and also required fewer amounts of data for training.

REFERENCES

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000a. Artificial neural networks in hydrology. I: Preliminary concept. Journal of Hydrologic Engineering; 5(2), 115–123.

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

Coppola, E., Poulton, M., Charles, E., Dustman, J., 2003. Application of Artificial Neural Networks to complex groundwater management problems. International Association for Mathematical Geology; 12(4), 303–320.

Gaur, S., Chahar, B.R., Graillot, D., 2011. Analytic Elements Method and Particle Swarm Optimization based Simulation-Optimization Model for Groundwater Management. Journal of Hydrology; 402 (3-4), 217-227.

Johnson, V.M., Rogers, L.L., 1995. Location analysis in ground-water remediation using neural networks. Ground Water; 33(5), 749-758.

Maier, H.R., Dandy, G.C., Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environmental Modelling and Software; 15(1), 101-123.

Math Works Inc..2001. MATLAB V R2009a, Apple Hill Drive, Natick, Massachusetts, USA.MathWorks, Inc., 2001. MATLAB. 3 Apple Hill Drive, Natick, Massachusetts, USA.

Morshed, J., Kaluarachchi, J.J., 1998a. Application of artificial neural network and genetic algorithm in flow and transport simulations. Advances in Water Resources; 22(2), 145-158.

Moradi, J.M., Marino, M.A., Afshar, A., 2003. Optimal design and operation of irrigation pumping station. Journal of Irrigation and Drainage Engineering; 129(3), 149-154.

Nikolos, I.K., Stergiadi, M., Papadopoulou, M.P., Karatzas, G.P., 2008. Artificial neural networks as an alternative approach to groundwater numerical modelling and environmental design. Hydrological Processes; 22, 3337–3348.

Rogers, L.L., Dowla, F.U., 1992. Groundwater remediation optimization with artificial neural networks and the genetic algorithm (abstract). Eos. Trans. AGU, Fall Meeting; 73(43), 186.

Rogers, L.L., Dowla, F,U., 1994. Optimization of groundwater remediation using artificial neural networks with parallel solute transport modeling. Water Resources Research; 30(2), 457–481.

Sharma, A.K., Swamee, P.K., 2006. Cost Considerations and General Principles in the Optimal Design of Water Distribution Systems. ASCE Conference Proceeding; 247, 85.

Singh, R.M., Datta, B., Jain, A., 2004. Identification of unknown groundwater pollution sources using artificial neural networks. Journal of Water Resource Planning and Management; 130(6), 506-514.

Swamee, P.K., 1996. Design of multistage pumping mains. Journal of Transportation Engineering; 122(1), 1–4.

Swamee, P.K., Sharma, A.K., 1990a. Decomposition of large water distribution systems. Journal of Environmental Engineering; 116(2), 269–283.