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Application of artificial neural network and genetic algorithm to modelling the groundwater inflow to an advancing open pit mine

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Abstract

In this study, a hybrid intelligent model was designed to predict groundwater inflow to a mine pit during its advance. The novel hybrid method coupling artificial neural network (ANN) with genetic algorithm (GA) called ANN-GA, was utilised. Ratios of pit depth to aquifer thickness, pit bottom radius to its top radius, inverse of pit advance time and the hydraulic head (HH) in the observation wells to the distance of observation wells from the centre of pit were used as inputs to the network. An ANN-GA with 4-5-3-1 arrangement was found capable of predicting the groundwater inflow to mine pit. The accuracy and reliability of the model was verified by field data. The predicted results were very close to the field data. The correlation coefficient (R) value was 0.998 for the training set, and in testing stage it was 0.99.

Keywords: *Groundwater Inflow, Mine Pit, Genetic Algorithm, Artificial Neural Network, Hybrid Model.*

1. Introduction

Groundwater is a natural resource that seriously affects any mining operations [1]. In mines where excavation is carried out below the water table, water flows from the surrounding strata toward the mining works. In particular, in the case of a confined aquifer, as the overburden materials and the mineral deposit are extracted during the mining operation, the impervious bed(s) may break and water under high-pressure may flow into the mining excavation. Investigations have revealed that the unexpected inflows in large quantities may impede production, delay in the project and may cause many safety and environmental problems [2]. Undesirable effects of this contain loss of access to all or part of the working mine area, greater use of explosives, increased explosive failures due to wet blast holes, or the need to use special explosives, increased wear to equipment and tires, inefficient loading and hauling, and unsafe working conditions [3].

Many analytical solutions have been used to estimate the groundwater inflow into mining excavations (e.g. [1, 4-9]). Analytical models are based on some assumptions and specific boundary conditions that limit their applicability in different mining situations. Hence, analytical solutions are not appropriate for all hydrogeological situations.

Numerical models are routinely used for simulation of the groundwater flow in a complex aquifer system. The finite element method incorporating the Galerkin approach ([10]) has been recognised as a strong and powerful numerical technique for this purpose [11]. Previously, several numerical models have been developed to predict the groundwater inflow to open pit mines (e.g. [12-16]).

Although numerical methods have been widely used for groundwater flow modelling and mine water related problems, these models require many parameters including hydraulic conductivity of the aquifer, transmissivity, pre-dewatering initial hydraulic head, rainfall data, saturated thickness of the aquifer, specific storage, porosity and other specific initial and boundary conditions. Determining all of these highly nonlinear characteristics is very difficult and requires a lot of time and cost. In addition, the multiplicity of the factors required to develop the model increases the probability of errors in the model's final results. In other words, since a miscalculation of any parameter causes an inaccuracy in model output, an increase in the number of parameters can increase the discrepancy between simulated and the observed outcomes.

On the other hand, approximation models such as artificial neural networks (ANNs) provide a powerful and reliable alternative with fewer required inputs to predict the nonlinear behaviour of groundwater inflow to open pit during its advance. An ANN is an empirical modelling tool that is based on the behaviour of biological neural structures [17, 18]. The use of such networks is rapidly growing, especially in process modelling, simulation and predictions [18-22].

Doulati Ardejani et al. ([18]) presented a neural network model to predict the groundwater rebound process after cessation of dewatering at a restored open cut coal site in the East Midlands area of the UK. Time (days after dewatering), water table levels in the aquifer and the backfilled site, hydraulic conductivity of the aquifer and backfilled site, and precipitation were used as inputs. The output of the network was the water table height (residual drawdowns). A feed-forward artificial neural network incorporating batch gradient descent with a momentum-learning algorithm and 6-1-6-1 arrangement was used to achieve this goal.

Sadeghiamirshahidi et al. ([22]) presented a feed-forward multi-layer ANN with back-propagation learning algorithm, with 4-7-4-1 arrangement to predict pyrite oxidation process in the spoils of the Anjir Tangeh coal washing plant, northern Iran. The spoil depth, annual precipitation, effective diffusion coefficient of oxygen transport and the initial amount of pyrite in the spoil particles were the inputs and the fraction of pyrite remaining in the spoil was the output of the model.

The performance of an artificial neural network depends upon the selection of proper weight connections and network topology during network training. Due to the complex nature of neural network training, even simple functions results in very complex error surfaces. Since the nature of neural network learning algorithms is local convergence, it can be demonstrated that solutions are highly dependent upon the initial random drawing of connection weights. If these initial weights are located on a local grade, which is probable, the learning algorithm will likely become trapped in a local solution that may or may not be the global solution [23]. Global search techniques are known to obtain the optimal solution more consistently [24]. Recently, genetic algorithm is frequently combined with neural network methods to avoid drawbacks of local minimization methods. Many other global minimization methods are suitable for that purpose, although they are used rather rarely in this context [25]. The coupled ANN-GA algorithm has a great potential to handle problems such as optimisation in complicated nonlinear systems. This method has also been used by many researchers (e.g. [26-30]).

Karimi and Yousefi ([26]) used a hybrid model including back-propagation network (BPN) and genetic algorithm (GA) to estimate the nano-fluids density. GA was coupled with BPN to optimise the BPN's parameters and improve the accuracy of the proposed model.

An effective method based on ANNs and GA has been suggested by Hao et al. ([27]) to model the carbon burnout behaviour in a tangentially fired utility boiler and optimise the operating conditions to achieve the highest boiler heat efficiency consecutively.

Benyelloul and Aourag ([28]) developed a hybrid model based on GA and ANNs to synthesise the optimal concentration of manganese (Mn). The main aim was to achieve the optimal bulk modulus of FeCrNiMn austenitic stainless steel alloy.

Gueguim et al. ([29]) reported the modelling and optimisation of biogas production on mixed substrates of saw dust, cow dung, banana stem, rice bran and paper waste using coupled ANNs and GA.

In another study ([30]), a theoretical model based on ANNs and GA was developed to optimise the magnetic softness in nanocrystalline Fe-Si powders prepared by mechanical alloying (MA).

In this paper, novel hybrid intelligent model (ANN-GA) is utilised to predict groundwater inflow to a mine pit during mining operation. For this purpose, MATLAB multi-purpose software was modified by providing extra codes. The accuracy of this hybrid intelligent model was verified by field data.

It is noted that the field data include the quantity of groundwater inflow from a confined aquifer to a mine pit (Kolahdarvazeh pit, Central Iran) and the hydraulic heads at four observation wells around the pit during its advance over 19 weeks [31].

2. Study area

2.1. Geographical Situation and the Climate

The Irankuh district comprises several Zn-Pb deposits including the Goushfil pit (sulphide ore), the Kolahdarvazeh pit (non-sulphide ore) and the Tappeh-Sorkh pit. They are located in the Irankuh Mountain Range, 20 km south of Esfahan and 1 km north-east of Abnil in West-Central Iran. The elevation of the mines is approximately 1700 m above sea level. The minable ore reserve of these mines is estimated at approximately 10 million tones with 7.5% zinc and 2.4% lead. Mining operations in the Kolahdarvazeh mine started in 1962. The study area has a warm climate with an annual relative humidity of 30% [31-33]. The location of the study area and a schematic view of the Kolahdarvazeh open pit mine and observation wells are shown in Figure 1 OW1, OW2, OW3 and OW4 (four observation wells in the vicinity of the pit) are located at 750, 1050, 1260 and 1440 m distance from centre of the pit, respectively.

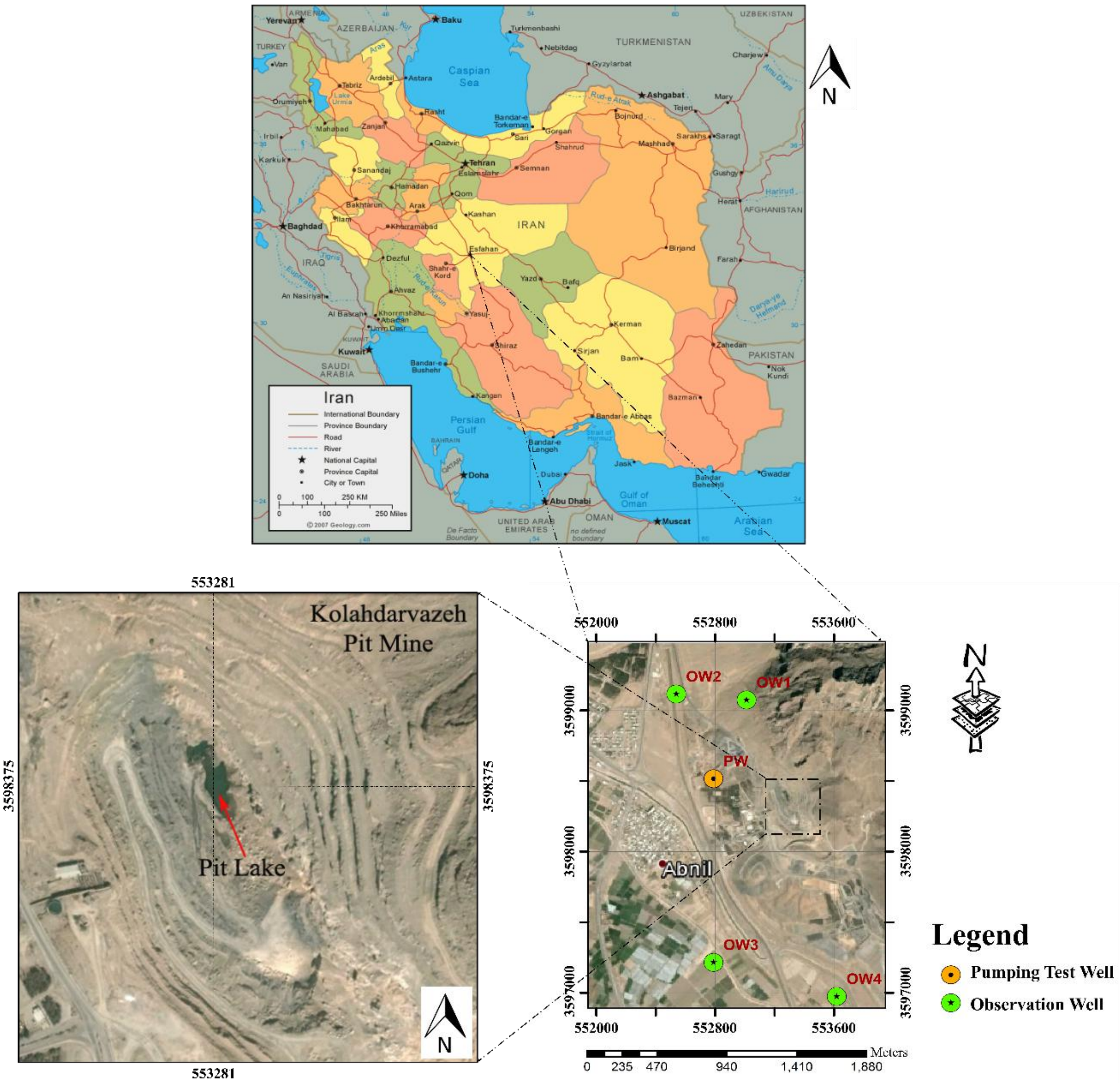

Figure 1. The location of the study area and a schematic view of the open pit, pumping well and observation wells.

2.2. Geology

The main zone of the mine is covered with carbonate sediments, which is located on lower Jurrassic sediments as unconformity. The sediments consist of continuous periodic age (low Cretaceous). The total thickness of these rocks is above 800 m, which comprise limestone and dolomite with less shale and marl. The carbonate sediments are identified as a source rock for Kolahdarvazeh mine deposit [32].

2.3. Hydrogeological Investigation and Precipitation

Investigations ([33, 34]) showed a fully saturated confined aquifer with an average thickness of 30 m in the Irankuh district in the dolomite rocks, which extends toward the Kolahdarvazeh mine throughout the study area. It is an artesian aquifer type with a 60 m initial head and a porous medium flow domain is dominant. The hydraulic conductivity and storage coefficient of the confined aquifer were 3.5×10^{-4} m/s and 0.2, respectively.

2.4. Pit Geometry

Information about the ore body comprising thickness, dip, depth, lateral extension and the proposed mining boundaries can help to define the pit geometry [8]. Topmost and bottommost benches of the study pit were 1670 m and 1565 m and the periphery extended about 1100 m NW-SE and 600 m NE-SW (Figure 1). The confined aquifer upper layer is located at 1593 m, above sea level. The parameters considered in the open pit design were bench height of 10 m, individual bench slope about 70°, overall pit slope of 45°. In the final stage of mine development, the pit had penetrated 30 m into the confined aquifer [33].

3. Materials and Methods

3.1. Measuring Field Data

The water levels were monitored at the observation wells using a tape measure equipped with a device that is designed to make a noise when it touches the water surface. The pit inflow rate from the confined aquifer was obtained by measuring the pump-out rate from the pit sump at a constant water level equal to the height of pit floor. In all wells, the aquifer thickness was approximately 30 m.

3.2. Artificial Neural Networks (ANNs)

The literature review shows that since the 1940s, ANNs have been used in several requests in engineering and science [35]. ANN is a hugely parallel distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain [36]. The advantage of using ANNs is their parsimonious data requirements, rapid implementation time and capability to yield models, where the relationship between inputs and outputs are not fully understood [37]. Different types of ANNs have been previously used in hydrological modelling (e.g. [38-42]). Most popular ANN model is the multilayer perceptron (MLP). MLP includes a feed-forward and layered network of neurons. It can provide a nonlinear mapping between the input and output. The general relationship between input and output in an ANN model can be expressed as [43]:

$$y_k = f_o\left(\sum_j w_{kj} F_h\left(\sum_i W_{ji} X_i + b_j\right) + b_k\right) \qquad (1)$$

where, x,y are input and output vectors, respectively; w_{ji} denotes the connection weight from the ith neuron in the input layer to the jth neuron in the hidden layer; b_j represents the threshold value or bias of jth hidden neuron; w_{kj} stands for the connection weight from the jth neuron in the hidden layer to the kth neuron in the output layer; b_k refers to bias of kth output neuron and f_h and f_0 are the transfer function for hidden and output neuron, respectively.

Sigmoidal-type transfer functions and linear transfer functions are recommended for the hidden and output layers, respectively [44]. The objective is to find the value of the weight that minimises differences between the real output and the predicted output in the output layer in order to minimise the mean square errors (MSEs), the average squared error between the network predictions and the target outputs [22]. In order to find the optimal weight (w) and the bias (b), training or learning processes must be implemented to minimise the error [43]. In recent years, several optimisation algorithms have been presented and extensively investigated in the related literature. Most of them were based on deterministic or stochastic methods, in order to solve optimisation problems with multiple objectives that conflict with each other. Some multi-objective stochastic optimisers have been developed based on local or global search methods to solve optimal design problems. Most local optimisation algorithms are gradient-based. As indicated by the name, gradient-based optimisation techniques utilise gradient information to find the optimum solution. Gradient-based algorithms are widely used to solve a variety of optimisation problems in engineering. These techniques are popular because they are efficient in terms of the number of function evaluations required to find the optimum. In addition, they can solve problems with large numbers of design variables and they typically need light problem-specific parameter tuning. However, these algorithms can only locate a local minimum point and they encounter difficulty to solve discrete optimisation problems. Moreover, they are so complex that are difficult to be implemented efficiently, and they may be susceptible to numerical noise. Global optimisation algorithms offer a much better chance of finding global or near global optimum than the local algorithms [45]. Genetic algorithm is one of the best global search methods ([24, 25, 46]).

3.3. Genetic Algorithm (GA)

The GA is a global search technique that searches from one population of points to another. As the algorithm continuously samples the parameter space, the search is directed towards the area of the best solution so far. This algorithm has been shown to perform extremely well in gaining global solutions for difficult non-linear functions [47]. Basically, a GA is categorised to four main steps [48]:

(1) Creating population, to generate the numbers of the initial populations. (2) Selection, to choose the solution for creating the offspring. (3) Crossover, this section is devoted to create new solutions by considering the solutions from the selection step. (4) Mutation as a sudden change in a step of the solution's feature.

3.4. Hybrid ANN-GA Method

Important task of ANNs is to adjust or update the weight factors and thresholds iteratively such that a pre-specified effectiveness function (performance function) can be minimised by decreasing the differences between the ANNs estimations and the target values. This iterative process is known as training or learning process. The sum-squared error (SSE) was employed as performance function in optimisation algorithm which can be expressed by the following Equation:

$$SSE = \sum_{i=1}^{n} (\mathrm{x}_{experimantal\,(i)} - \mathrm{x}_{calculated\,(i)})^2 \qquad (2)$$

where, $\mathrm{x}_{experimantal\,(i)}$ and $\mathrm{x}_{calculated\,(i)}$ are the ith experimental and ANNs predicted value respectively.

ANNs are usually trained by the use of local gradient-based methods. Such procedures frequently find suboptimal solutions being trapped in local minima. Global minimization methods which are applied to network cost functions have a strong effect on all aspects of network performance [25]. It has been shown that genetic algorithm has great capability to perform optimisation process for a wide variety of complex problems [49]. GA was used in this study to optimise the error function (SSE) of ANN.

3.5. Performance Measures

The performance of the presented network is evaluated by correlation coefficient (R) value as follows [44]:

$$R = \frac{\sum_{i=1}^{n} (\mathrm{h_i} - \mathrm{h'_i})(\mathrm{t_i} - \mathrm{t'_i})}{\sqrt{\sum_{i=1}^{n} (\mathrm{h_i} - \mathrm{h'_i})^2 \sum_{i=1}^{n} (\mathrm{t_i} - \mathrm{t'_i})^2}} \qquad (3)$$

where, $\mathrm{h_i}$ and $\mathrm{t_i}$ are the actual and predicted output values for the ith output respectively, $\mathrm{h'_i}$ and $\mathrm{t'_i}$ represent the average of the actual and predicted outputs, and n denotes the number of samples.

3.6. Model Development using the Hybrid ANN-GA Method

The available database was used to develop the ANN-GA prediction model considering ratios of (1) pit depth to aquifer thickness, (2) bottom base pit radius to top base pit radius, (3) inverse of time (weeks after pit penetration into aquifer) and (4) the hydraulic head in observation wells to distance of observation wells from the centre of pit as inputs to the network.

Several runs were performed to provide an efficient parameterisation for this hybrid method. The best results were obtained by the Levenberg-Marquardt ([50, 51]) method. In addition, the transfer function between the input, first and second hidden layers were hyperbolic tangent. A linear transfer function (purelin) was adopted between the second hidden layer and output layer.

To perform modelling, MATLAB software was modified by providing extra codes. Figure 2 shows the optimal architecture (4-5-3-1) of ANN-GA network that was found capable to predict groundwater inflow to the mine pit.

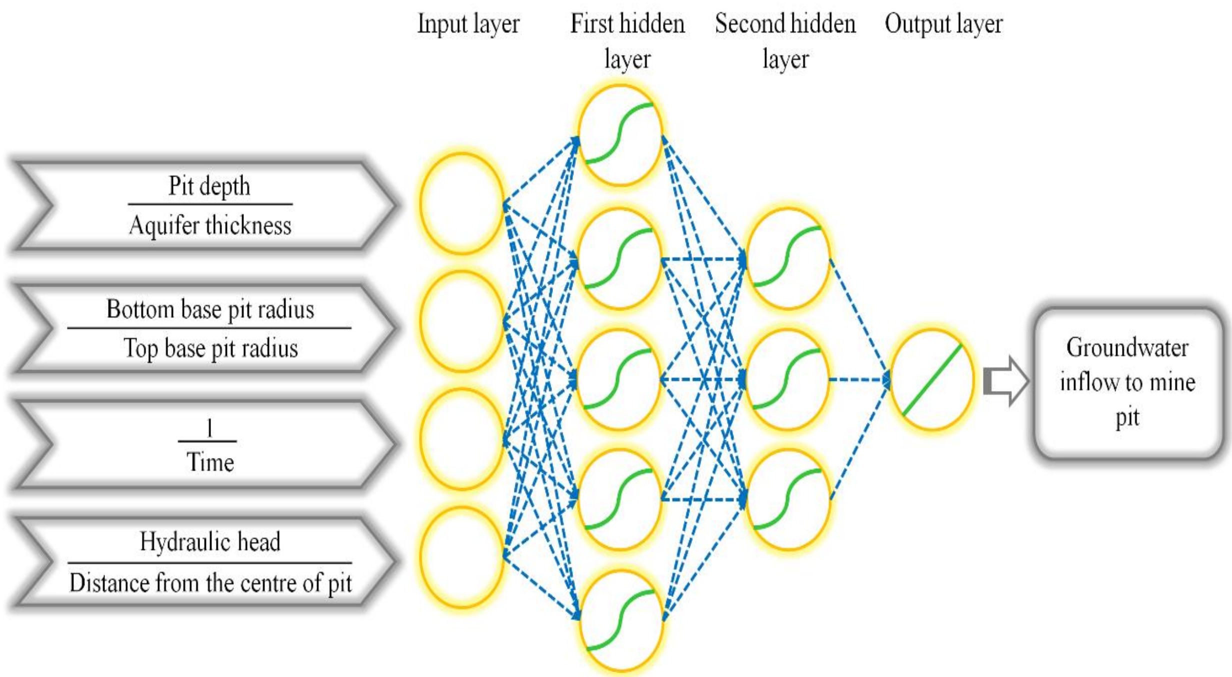

Figure 2. ANN-GA architecture with 4-5-3-1 arrangement comprising hyperbolic tangent and linear transfer functions.

4. Results and Discussion

4.1. Results of Groundwater Inflow Simulation to Mine Pit

A total of 65 data sets were used for training and testing the network for predicting the rate of groundwater inflow to the mine pit (46 sets for training and 19 sets for testing the network). Table 1 gives the correlation Matrix between the ratios of (A) pit depth to aquifer thickness, (B) bottom base pit radius to top base pit radius, (C) inverse of time, (D) the hydraulic head in observation wells to distance of observation wells from the centre of pit (as input parameters) and (E) groundwater inflow to mine pit (output of the network). According to this table, the absolute correlation values between E and the parameters of input layer vary between 0.04 and 0.33. It is noted that these values are smaller than 0.5; hence, the use of ANNs approach is justified.

The data sets used for training the network were from Esfahan province environmental office ([31]). Figure 3 shows the linear regression plot of field-measured inflow against the predicted inflow for training stage including the correlation coefficient (R) value. Based on Figure 3, the ANN-GA model can be generalised. Figure 4 displays the linear regression plot of measured inflows to the predicted inflows for testing stage including the R value. According to Figure 4, the ANN-GA model has the capability to be a good predictive tool. The mean percent error between the field data and ANN-GA simulation results was less than 0.1%.

Table 1. Correlation Matrix between the arguments of the input and output layers of the presented network.

Parameters	A	B	C	D	E
A	1	-0.61	-0.55	-0.14	-0.11
B	-	1	0.75	0.01	0.04
C	-	-	1	0.30	0.21
D	-	-	-	1	0.33
E	-	-	-	-	1

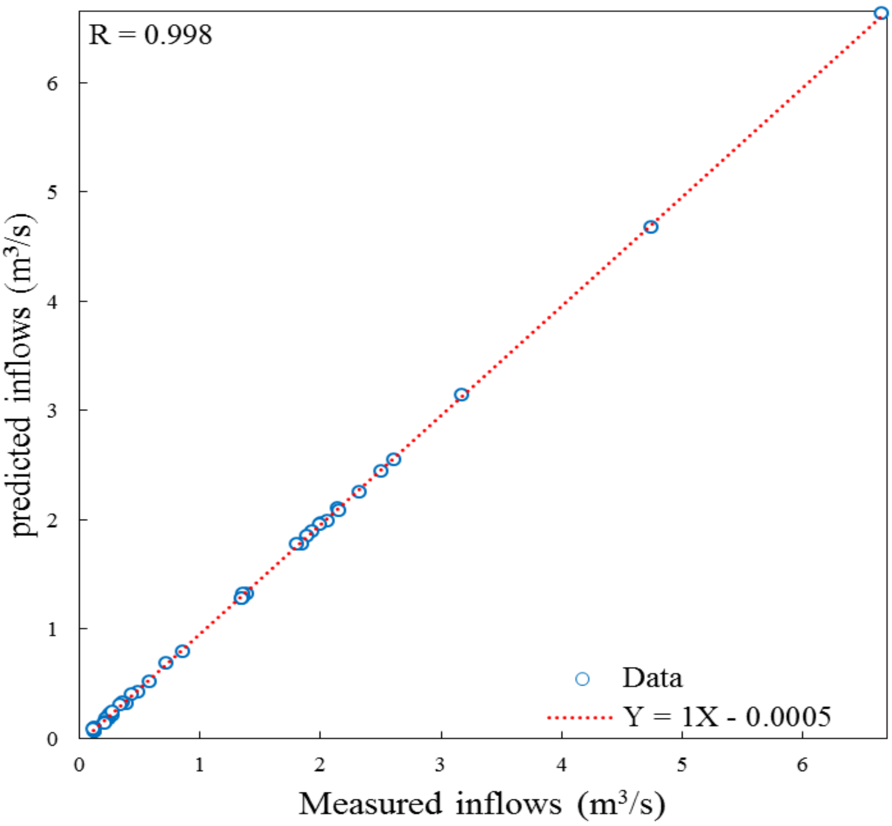

Figure 3. The linear regression plot of the field measured inflow versus the predicted inflow for the training stage including R value by ANN-GA.

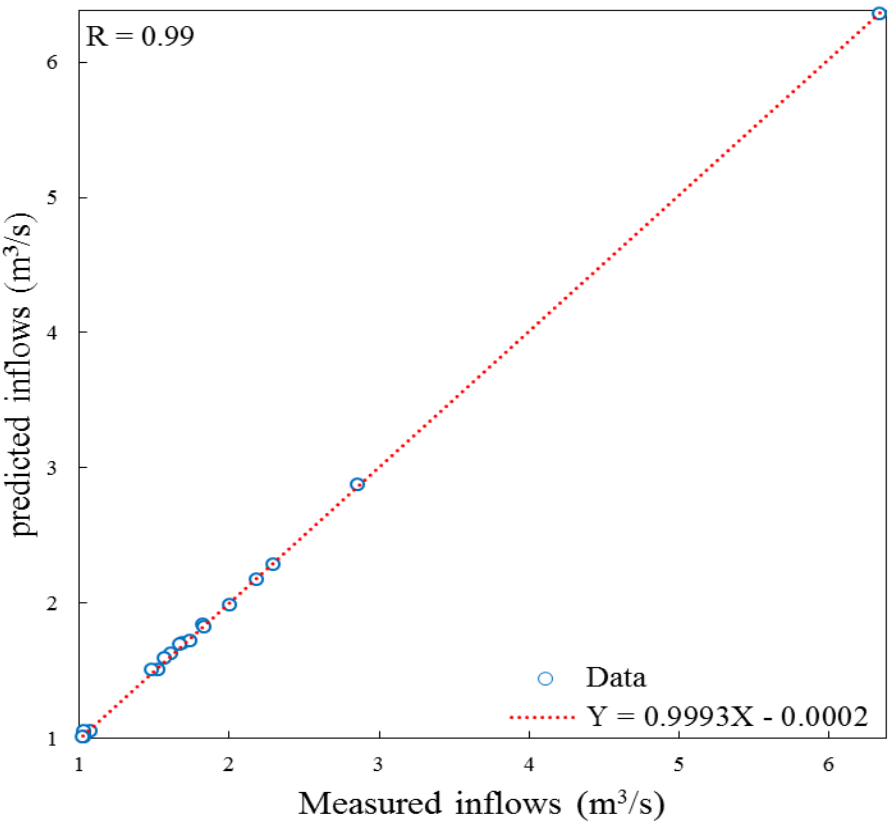

Figure 4. The linear regression plot of the field measured inflow versus the predicted inflow for the testing stage including R value by ANN-GA.

As Figure 5 shows, in the first phase of the mining operation below the water table, the inflow decreased sharply from 6.7 m^3/s to 3.04 m^3/s within two weeks of the beginning of the pit advance. From week 2 to week 6 (at the end of first phase), it decreased linearly from 3.04 m^3/s to 2.1 m^3/s. The inflow increased steadily from 2.1 m^3/s to 2.6 m^3/s at the beginning of phase 2 (between weeks 6 and 7). It then decreased at almost the same rate from 2.6 m^3/s to 2.3 m^3/s between times 7 and 8 weeks. At times between 8 and 14 weeks, the inflow decreased steadily at a lower rate from 2.3 m^3/s to 1.85 m^3/s. As time progressed (from week 14 to week 15), the inflow decreased linearly from 1.85 m^3/s to 1.55 m^3/s. In the third phase, the inflow decreased very slightly from 1.55 m^3/s to 1.4 m^3/s with a gradual rate of decline (from week 15 to week 19).

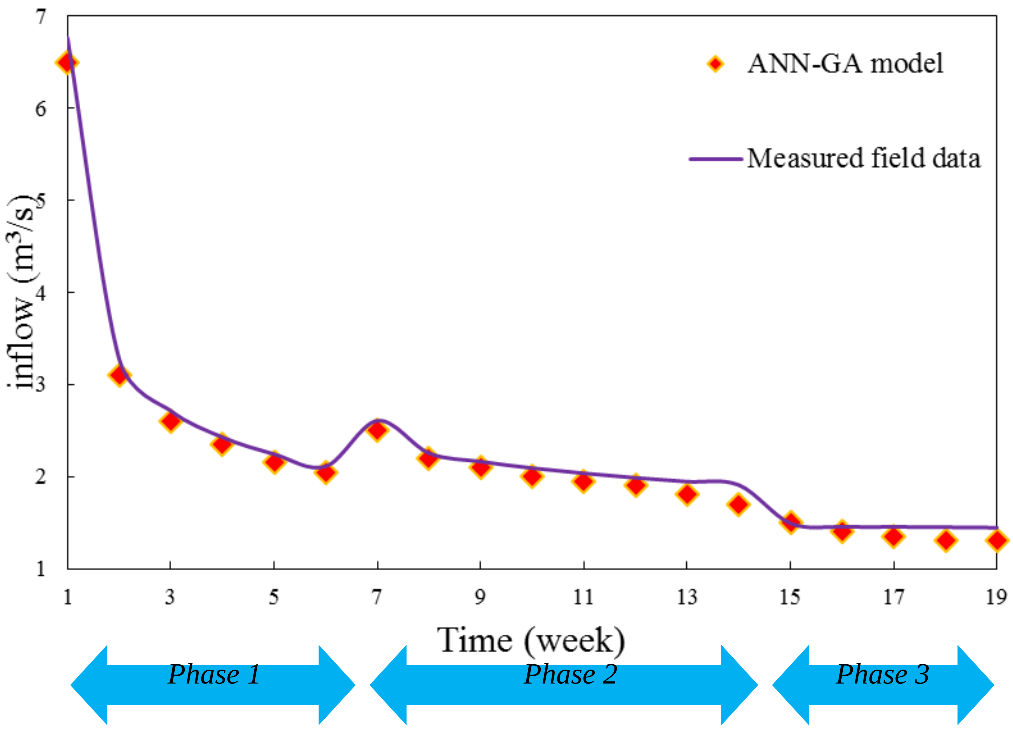

Figure 5. Comparison of filed data with ANN-GA model results for groundwater inflow to Kolahdarvazeh mine pit during its advance.

5. Conclusions

An intelligent model was designed to predict the groundwater inflow to a mine pit during its advance, utilising novel hybrid method coupling artificial neural network (ANN) and genetic algorithm (GA), called ANN-GA. Ratios of pit depth to aquifer thickness, pit bottom radius to its top radius, inverse of pit advance time and the hydraulic head in the observation wells to the distance of observation wells from the centre of pit were used as inputs to the network in order to predict groundwater inflow to mine pit. The accuracy and reliability of the hybrid model was verified by field data. The performance (correlation coefficient value) of the model on the training and testing data indicates that the hybrid intelligent model has both good predictive ability and generalisation performance. Results further show that despite using the fewer and elementary (in terms of cost and time for data collection) parameters for the intelligent hybrid model, this model has the ability to compete with the numerical models. The results of this paper can be used for developing an effective dewatering program.

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References

[1]. Bravner, C.O. (1986). Groundwater and coal mining. Mining Science and Technology. 3: 187-198.

[2]. Singh, R.N. and Atkins, A.S. (1985a). Application of idealized analytical techniques for prediction of mine water inflow. International Journal of Mining Engineering. 2: 131-138.

[3]. Morton, K.L. and Van Mekerk, F.A. (1993). A phased approach to mine dewatering. Mine Water and the Environment. 12: 27-33.

[4]. Singh, R.N. and Atkins, A.S. (1985a). Analytical techniques for the estimation of mine water inflow. International Journal of Mining Engineering. 3: 65-77.

[5]. Hofedank, R.H. (1979). Computation of and experience on lignite opencast mine drainage. Proceedings of the First International Mine Drainage Symposium. Denver, Colorado. 383-408.

[6]. McWhorter, D.B. (1981). Predicting groundwater response to disturbance by mining-selected problems. Symposium of Surface Mining, Hydrology, Sedimentology and Reclamation. University of Kentucky, Lexington, KY. 89-95.

[7]. Singh, R.N. and Atkins, A.S. (1984). Application of analytical solutions to simulate some mine inflow problems in underground coal mining. International Journal of Mine Water and the Environment. 3 (4): 1-27.

[8]. Singh, R.N., Ngah, S.A. and Atkins, A.S. (1985). Applicability of current groundwater theories for the prediction of water inflows to surface mining excavations. Proceedings of the Second International Congress of the International Mine Water Association. Granada, Spain. 553-571.

[9]. Marinelli, F. and Niccoli, W.L. (2000). Simple analytical equations for estimating ground water inflow to a mine pit. Ground Water. 38 (2): 311-314.

[10]. Gray, W.G. and Pinder, G.F. (1974). Galerkin approximation of the time derivative in the finite element analysis of groundwater flow. Water Resources Research. 10 (4): 821-828.

[11]. Rabbani, M.G. and Warner, J.W. (1994). Shortcomings of existing finite element formulations for subsurface water pollution modelling and its rectification: One-dimensional case. SIAM Journal on Applied Mathematics. 54 (3): 660-673.

[12]. Doulati Ardejani, F., Singh, R.N., Baafi, E. and Porter, I. (2003a). A finite element model to: 1. predict groundwater inflow to surface mining excavations. Mine Water and the Environment. 22 (1): 31-38.

[13]. Crowe, A.S., Shikaze, S.G. and Ptacek, C.J. (2004). Numerical modelling of groundwater flow and contaminant transport to Point Pelee marsh, Ontario, Canada. Hydrological Processes. 18: 293-314.

[14]. Hernández, J.H., Padilla, F., Juncosa, R., Vellando, P.R. and Fernández, A. (2012). A numerical solution to integrated water flows: Application to the flooding of an open pit mine at the Barcés river catchment – La Coruña, Spain. Journal of Hydrology. 328-339.

[15]. Aryafar, A., Doulati Ardejani, F. and Singh, R.N. (2009). Numerical modelling of groundwater inflow from a confined aquifer to sangan open pit mine, northeast of Iran. International Journal of Geomechanics and Geoengineering. 4 (3): 189-198.

[16]. Singh, R.N., Atkins, A.S. and Doulati Ardejani, F. (2012). Hydrogeological issues concerning the Thar Lignite prospect. International Journal of Miningand Geo-Engineering (IJMGE). 46 (1): 3-49.

[17]. Yao, H.M., Vuthaluru, H.B., Tade, M.O. and Djukanovic, D. (2005). Artificial neural network-based prediction of hydrogen content of coal in power station boilers. Fuel. 84: 1535-1542.

[18]. Doulati Ardejani, F., Sadeghiamirshahidi, M., Singh, R.N., Eslam Kish, T. and Reed, S.M. (2013). Prediction of the groundwater rebound process in a backfilled open cut mine using an artificial neural network. Mine Water and the Environment. 32 (4): 251-257.

[19]. Banerjee, P., Singh, V.S., Chatttopadhyay, K., Chandra, P.C. and Singh, B. (2011). Artificial neural network model as a potential alternative for groundwater salinity forecasting. Journal of Hydrology. 398: 212-220.

[20]. Yoon, H., Jun, S.C., Hyun, Y., Bae, G.O. and Lee, K.K. (2011). A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. Journal of Hydrology. 396: 128-138.

[21]. Khalil, B., Ouarda, T.B.M.J and St-Hilaire, A. (2011). Estimation of water quality characteristics at ungauged sites using artificial neural networks and canonical correlation analysis. Journal of Hydrology. 405: 277-287.

[22]. Sadeghiamirshahidi, M., Eslam Kish, T. and Doulati Ardejani, F. (2013). Application of artificial neural networks to predict pyrite oxidation in a coal washing refuse pile. Fuel. 104: 163-169.

[23]. Zanchettin, C. and Ludermir, T.B. (2007). Global optimisation methods for designing and training feed-forward artificial neural networks. Advances in Neural Networks. 14: 328-337.

[24]. Sexton, R.S., Dorsey, R.E. and Johnson, J.D. (1999). Beyond backpropagation: using simulated annealing for training neural networks. Journal of End User Computing. 11: 3-10.

[25]. Duch, W. and Korczak, J. (1998). Optimisation and global minimization methods suitable for neural networks. Neural Computing Surveys 2.

[26]. Karimi, H. and Yousefi, F. (2012). Application of artificial neural network-genetic algorithm (ANN-GA)

to correlation of density in nano-fluids. Fluid Phase Equilibria. 336: 79-83.

[27]. Hao, Z., Qian, X., Cen, K. and Fan, J. (2003). Optimising pulverized coal combustion performance based on ANN and GA. Fuel Processing Technology. 83: 113-124.

[28]. Benyelloul, K. and Aourag, H. (2013). Bulk modulus prediction of austenitic stainless steel using a hybrid GA-ANN as a data mining tools. Computational Materials Science. 77: 330-334.

[29]. Gueguim Kana, E.B., Oloke, J.K., Lateef, A. and Adesiyan, M.O. (2012). Modelling and optimisation of biogas production on saw dust and other co-substrates using artificial neural network and genetic algorithm. Renewable Energy. 46: 276-281.

[30]. Yazdanmehr, M., Mousavi Anijdan, S.H. and Bahrami, A. (2009). Using GA-ANN algorithm to optimise soft magnetic properties of nanocrystalline mechanically alloyed Fe-Si powders. Computational Materials Science. 44: 1218-1221.

[31]. Esfahan province environmental office. (2013). Unpublished groundwater data of the Esfahan province.

[32]. Cheraghi Seifabad, M. and Beheshti Zavareh, S. (2013). Excavation methods in Goushfil mine. International Journal of Engineering and Technology. 2 (3): 225-229.

[33]. BAMA Mining Company. (2003). Detailed exploration of Irankuh district. Unpublished data of the Bama Mining.

[34]. Reichert, J. (2007). A metallogenetic model for carbonate-hosted non-sulphide zinc deposits based on observations of Mehdi Abad and Irankuh, Central and Southwestern Iran. PhD thesis, Martin-Luther-Universität Halle-Wittenberg. 157 p.

[35]. Jorjani, E., Chehreh Chelgani, S. and Mesroghli, S.H. (2008). Application of artificial neural networks to predict chemical desulfurization of Tabas coal. Fuel. 87: 2727-34.

[36]. He, Z., Wen, X., Liu, H. and Du, J. (2014). A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region. Journal of Hydrology. 509: 379-386.

[37]. Belayneh, A., Adamowski, J., Khalil, B. and Ozga Zielinski, B. (2014). Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models. Journal of Hydrology. 508: 418-429.

[38]. Sivakumar, B. and Jayawardena, A.W. (2002). River flow forecasting: use of phase-space reconstruction and artificial neural networks approaches. Journal of Hydrology. 265: 225-245.

[39]. Imrie, C.E., Durucan, S. and Korre, A. (2000). River flow prediction using artificial neural networks: generalisation beyond the calibration range. Journal of Hydrology. 233: 138-153.

[40]. Cannas, B., Fanni, A., Sias, G., Tronci, S. and Zedda, M.K. (2006). River flow forecasting using neural networks and wavelet analysis. Proceedings of the European Geosciences Union.

[41]. Chiang, Y.M., Chang, L.C. and Chnag, F.J. (2004). Comparison of static-feed forward and dynamic-feedback neural networks for rainfall-runoff modelling. Journal of Hydrology. 290: 297-311.

[42]. Adamowski, J. and Sun, K. (2010). Development of a coupled wavelet transform and neural network method for flow forecasting of non-perennial rivers in semi-arid watersheds. Journal of Hydrology. 390: 85-91.

[43]. Badrzadeh, H., Sarukkalige, R. and Jayawardena, A.W. (2013). Impact of multi-resolution analysis of artificial intelligence models inputs on multi-step ahead river flow forecasting. Journal of Hydrology. 507: 75-85.

[44]. Mekanik, F., Imteaz, M.A., Gato-Trinidad, S. and Elmahdi, A. (2013). Multiple regression and artificial neural network for long-term rainfall forecasting using large scale climate modes. Journal of Hydrology. 503: 11-21.

[45]. Venter, G. (2010). Review of optimisation techniques. Encyclopedia of Aerospace Engineering. John Wiley & Sons, Ltd.

[46]. Jiang, J. (2013). BP neural network algorithm optimised by genetic algorithm and its simulation. International Journal of Computer Science Issues. 10 (1): 516-519.

[47]. Sexton, R.S., Dorsey, R.E. and Johnson J. (2000). Toward a global optimum for neural networks: A comparison of the Genetic Algorithm and Backpropagation. Journal of End User Computing. 13: 10-17.

[48]. Enayatifar, R., Abdullah, A.H. and Isnin, I.F. (2014). Chaos-based image encryption using a hybrid genetic algorithmand a DNA sequence. Optics and Lasers in Engineering. 56: 83-93.

[49]. Goffe, W.L., Ferrier, G.D. and Rogers, J. (1994). Global optimisation of statistical functions with simulated annealing. Journal of Econometrics. 60: 65-99.

[50]. Levenberg, K. (1994). A method for the solution of certain non-linear problems in least squares. Quart. Applied Mathematics. 2: 164-168.

[51]. Marquardt, D. (1963). An algorithm for least-squares estimation of nonlinear parameters. SIAM J. Applied Mathematics. 11: 431-441.

کاربرد شبکه عصبی مصنوعی و الگوریتم ژنتیک برای مدل‌سازی ورود آب به داخل یک پیت روباز معدنی درحال‌توسعه

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چکیده:

در این مطالعه، یک مدل هوشمند ترکیبی برای پیش‌بینی ورود آب به یک پیت معدنی درحال‌توسعه طراحی شد. روش ترکیبی جدید شبکه عصبی مصنوعی (ANN) و الگوریتم ژنتیک (GA)، با نام ANN-GA مورد استفاده قرار گرفت. نسبت عمق پیت به ضخامت آبخوان، شعاع پایین پیت به شعاع بالای پیت، عکس زمان معدن‌کاری و هد هیدرولیکی (HH) در چاه‌های مشاهده‌ای به فاصله چاه مشاهده‌ای از مرکز پیت برای پارامترهای ورودی شبکه استفاده شد. شبکه ANN-GA با ساختار ۱-۳-۵-۴ توانست ورود آب به پیت معدنی را پیش‌بینی کند. دقت و صحت مدل با استفاده از اطلاعات صحرایی ارزیابی شد. نتایج پیش‌بینی مدل همبستگی خوبی با اطلاعات صحرایی داشت. مقدار ضریب همبستگی به ترتیب برای مرحله آموزش و امتحان شبکه برابر با ۰/۹۹۸ و ۰/۹۹ محاسبه شد.

کلمات کلیدی: ورود آب زیرزمینی، پیت معدن، الگوریتم ژنتیک، شبکه عصبی مصنوعی، مدل ترکیبی.