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Artificial Neural Network Technique for Modeling of Groundwater Level in Langat Basin, Malaysia

(Teknik Rangkaian Neuron Buatan untuk Pemodelan Paras Air Bawah Tanah di Lembangan Langat, Malaysia)

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ABSTRACT

Forecasting of groundwater level variations is a significantly needed in groundwater resource management. Precise water level prediction assists in practical and optimal usage of water resources. The main objective of using an artificial neural network (ANN) was to investigate the feasibility of feed-forward, Elman and Cascade forward neural networks with different algorithms to estimate groundwater levels in the Langat Basin from 2007 to 2013. In order to examine the accuracy of monthly water level forecasts, effectiveness of the steepness coefficient in the sigmoid function of a developed ANN model was evaluated in this research. The performance of the models was evaluated using the mean squared error (MSE) and the correlation coefficient (R). The results indicated that the ANN technique was well suited for forecasting groundwater levels. All models developed had shown acceptable results. Based on the observation, the feed-forward neural network model optimized with the Levenberg-Marquardt algorithms showed the most beneficial results with the minimum MSE value of (0.048) and maximum R value of (0.839), obtained for simulation of groundwater levels. The present research conclusively showed the capability of ANNs to provide excellent estimation accuracy and valuable sensitivity analyses.

Keywords: Artificial neural network (ANN); groundwater level; simulation

ABSTRAK

Ramalan variasi paras air bawah tanah adalah sangat diperlukan dalam pengurusan sumber air bawah tanah. Ketepatan ramalan paras air dapat membantu penggunaan secara praktikal dan optimum sumber air tanah. Objektif utama penggunaan rangkaian neuron buatan (ANN) adalah untuk mengkaji kebolehan suap ke hadapan, Elman dan Cascade rangkaian neuron ke hadapan dengan algoritma yang berbeza dalam menentukan paras air tanah di Lembangan Langat dari 2007 hingga 2013. Untuk memastikan ketepatan ramalan paras air tanah bulanan, keberkesanan pekali kecuraman dalam fungsi sigmoid model ANN yang dibangunkan dinilai dalam kajian ini. Prestasi model dinilai berdasarkan purata ralat kuasa dua (MSE) dan pekali korelasi (R). Keputusan menunjukkan bahawa teknik ANN adalah sangat sesuai digunakan dalam meramal paras air bawah tanah. Semua model yang dibangunkan menunjukkan keputusan yang boleh diterima. Berdasarkan pemerhatian, model rangkaian neuron ke hadapan yang dioptimumkan dengan algoritma Levenberg-Marquardt menunjukkan keputusan yang paling bermanfaat dengan nilai minimum MSE (0.048) dan nilai maksimum R (0.839) diperoleh daripada simulasi paras air bawah tanah. Kajian ini secara muktamadnya menunjukkan keupayaan ANN dalam memberikan penganggaran ketepatan terbaik dan analisis sensitiviti bernilai.

Kata kunci: Paras air bawah tanah; rangkaian neuron buatan (ANN); simulasi

INTRODUCTION

Groundwater is one of the most important domestic, industrial and agricultural resources. It is a valuable natural resource, without which there could be no life on Earth. Predicting the level of water is a significant engineering problem. Therefore, appropriate management of water resources in general and groundwater specifically is extremely important for both the present and future decades. Consequently, to develop successful methods to accurately estimate groundwater levels and its quality (Ashraf et al. 2011; Mohanty et al. 2010; Verma & Singh 2013). In previous decades, an artificial neural network (ANN) was applied as strong tools and accurate solutions to many of the extremely difficult challenges faced by water sciences and hydrology, and this usage has increased. The ANN model is certainly a model, which can be treated as a global approximator and therefore is the best for dynamic nonlinear system modeling (ASCE Task 2000). The growing AI approaches have the ability to fill the gaps of the measurements and to forecast future values without long observation data (Karimi et al. 2013). ANNs are now widely applied in a broad range of fields. Concepts and applications of ANN models in hydrology have been discussed by many researchers (ASCE Task 2000, Govindaraju & Rao 2000; Hussain at al. 2014). Kin et al. (2001) employed ANN technique to simulate precipitation, Selventhiran et al. (2012) used ANNs for river flow forecasting, Khaki et al. (2015) developed ANN models to prediction the water quality parameters, Singh et al. (2004) employed ANNs to recognize unidentified groundwater contamination sources at several locations utilizing erroneous measurement data, Mohanty et al. (2002) developed neural networks to simulate the chemical oxygen demand reduction and a wide range of ANN applications in water use and quality (Mishra et al. 2007; Singh et al. 2009; Talebizadeh et al. 2010; Yusoff et al. 2013; Zhang et al. 2002).

The forecasted result is useful to create awareness among residents and furthermore, will result in increased attention from the state and central government to develop and manage the groundwater policy for this area. ANNs were carried out to effectively forecast groundwater levels in confined sand and gravel aquifer with several different architectures of neural networks in the Langat Basin, Malaysia.

Methods

ARTIFICIAL NEURAL NETWORKS (ANNS)

The composition of an ANN is influenced by the human nervous system. ANNs are a combination of three separate types of layers which are one input layer, one or more hidden layers and one output layer (Figure 1). The data running paradigm consists of many interconnected nodes (neurons) in which a complicated input structure is mapped to a related output structure (Hagan et al. 1996). The main benefit of an ANN is that without having a priori knowledge of the actual physical procedure as well as the precise connection among sets of input and output data, if they are identified as existing, the network can be trained to learn such a input-output relations. The ability to train and learn the output from a given input is an interesting property of ANNs to explain significant-scale arbitrarily complex behaviors of nonlinear systems (Maier & Dandy 2000). ANNs are distinguished by their architecture, which depicts the structure of connections among nodes, its approach to identifying connection weights and the activation function (Fausset 1994). In this research, three different ANN architectures were utilized together with four ANN training algorithms: the Levenberg-Marquardt (LM) algorithm, the gradient descent with momentum and adaptive learning rate back propagation (GDX) algorithm, the scaled conjugate gradient (SCG) algorithm, and the resilient back propagation (RP) algorithm have been used for the estimation of groundwater levels (Saghravani et al. 2013).

FEED-FORWARD NEURAL NETWORK (FNN)

One of the most well-known neural networks is the feed-forward neural network (FNN). FFNs were utilized effectively in various issues since the appearance of the error back propagation learning algorithm. The back propagation algorithm modifies the weights according to the idea of modifying the MSE. The main advantage of feed-forward neural networks is that they are easy to manage, which enables them to approximate any kind of input and output mapping, as established by Hornik et al. (1989). The weighting of the nodes is key to the training of the FNN. The difference between the network's output and the predicted result is determined at each iteration. The training process will become manageable, by differentiating the neural network with respect to the nodes.

ELMAN NEURAL NETWORK (RNN)

The Elman neural network (recurrent neural network) is characterized by an additional feedback cycle from the output of a hidden layer to the input of this layer, which makes up the context layer that maintains information between observations (Elman 1990). The effect of processing in a previous period stage can be employed in the present period stage. This quality of the Elman network provides an extremely important benefit, particularly in real-time applications to follow the dynamic change of water variables in practice. These recurrent networks may have an unlimited memory level and so discover relationships through time as well as through the immediate input space (Haykin 1999).

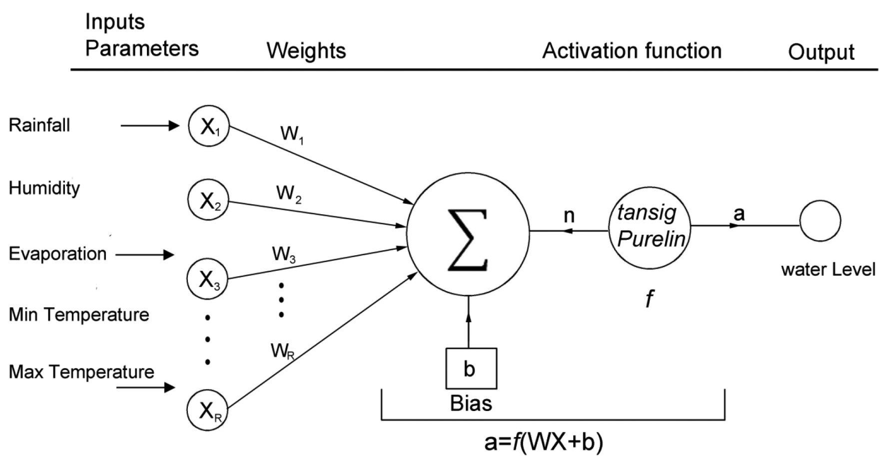

FIGURE 1. Non-linear model of a neuron

CASCADE FORWARD NETWORK (CFN)

The cascade back propagation algorithm is the basis of a conceptual pattern intended for accelerated learning in ANNs. The CFN neural networks are similar to feed-forward networks, but consist of a weighted relationship to the input to each layer and also through each layer to the effective layers (Lashkarbolooki & Shafipour 2012). Filik and Kurban (2007) identified which cascade forward back propagation technique can be more effective than feed-forward back propagation technique in these cases.

GRADIENT DESCENT WITH MOMENTUM AND ADAPTIVE LEARNING RATE BACK PROPAGATION (GDX)

This approach utilizes a common back propagation algorithm in order to compute derivatives of the performance cost function according to the changeable weights and biases of the network. This technique utilizes gradient descent with momentum to adjust each variable. For each stage of the modification, if performance reduces, the learning rate is enhanced. This is probably the simplest and most common way to train a network (Haykin 1999).

LEVENBERG-MARQUARDT (LM)

The Levenberg-Marquardt (LM) algorithm is essentially the neural network algorithm that is most used to update MLP weights and biases (Hagan & Menhaj 1994). The Levenberg-Marquardt approach is an optimization based on the classic Newton algorithm intended for obtaining the best solution to a minimization problem. This approach decreases the volume of oscillation in the learning process. It utilizes an approximation to the Hessian matrix within the following Newton such as weight update (Mohanty et al. 2010):

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e, \tag{1}$$

where x is the weight of the neural network; J the Jacobian matrix of the performance criteria to be minimized; μ the scalar that controls the learning process; and e the residual error vector.

If the scalar μ is actually zero, that is simply Newton's technique while using the approximate Hessian matrix. When μ is large the equation has a gradient descent with small step size. Newton's technique is quicker as well as more precise to an error minimum; therefore the purpose should be to shift in the direction of Newton's technique as fast as possible. Nevertheless, because of the excessive memory requirement, it can only be applied to small networks (Maier & Dandy 1998). However, many researchers have recently been using it effectively (Anctil et al. 2004; Coulibaly et al. 2000; Mohanty et al. 2010; Zulkifley at al. 2013).

RESILIENT BACK PROPAGATION (RBP)

As a local adaptive learning scheme, the algorithm resilient back propagation fulfills interesting batch learning in feed-forward neural networks. Elimination of the detrimental effect of the size of the partial derivative on the weight step is a main principle of RBP. As a result, the sign of the derivative identifies the direction of the weighting update. In this method, for each weight individual update values which only indicate the size of the weight update (Riedmiller & Braun 1993).

SCALED CONJUGATE GRADIENT (SCG)

The quadratic approximation to the error in the neighborhood of a point is defined by the scaled conjugate gradient (SCG) algorithm (Møller 1993). SCG is a second-order conjugate gradient algorithm, which helps to minimize a multi dimensional target function. Møller (1993) proved this theoretical foundation, which remains a first-order technique for the first derivative such as standard back propagation and discovered a premier way to local minimum for second-order techniques in second derivatives. SCG is fast algorithm and employs a step size scaling mechanism which avoids time-consuming line search per learning iteration (Karmokar et al. 2012). The SCG method presents super-linear convergence for most problems as confirmed by Møller (1993).

STUDY AREA AND MODEL APPLICATION

STUDY AREA

The selected well for modeling of groundwater fluctuations in the Langat Basin area is shown in Figure 2(a). Langat Basin is an important water catchment area, which provides the supply of raw water and other benefits for around one million people within the basin area. The geological condition of the groundwater is based on quaternary sediments, which consist of unconsolidated gravel, sand, silt and clay of the Simpang Formation in the Pleistocene and Gula and Beruas Formations in the Holocene (Mineral and Geosciences Department 2002). The range of annual precipitation is from 1585 and 2729 mm. The average humidity of the study area is estimated to be around 80%. The highest and lowest temperature reached in average during noon and night is 24 and 32°C, respectively.

MODEL APPLICATION

According to the water balance equation, changes in the amount of water within any hydrological system can be given in terms of the difference between inflow and outflow:

$$X - Y = \Delta S, \tag{2}$$

where X shows inflow like precipitation; Y is outflow like surface run-off, evaporation, infiltration, groundwater flow; and ΔS shows water level variations.

Figure 2(b) displays the minimum, maximum and mean monthly rainfall in the study area during the investigated.

a)

b)

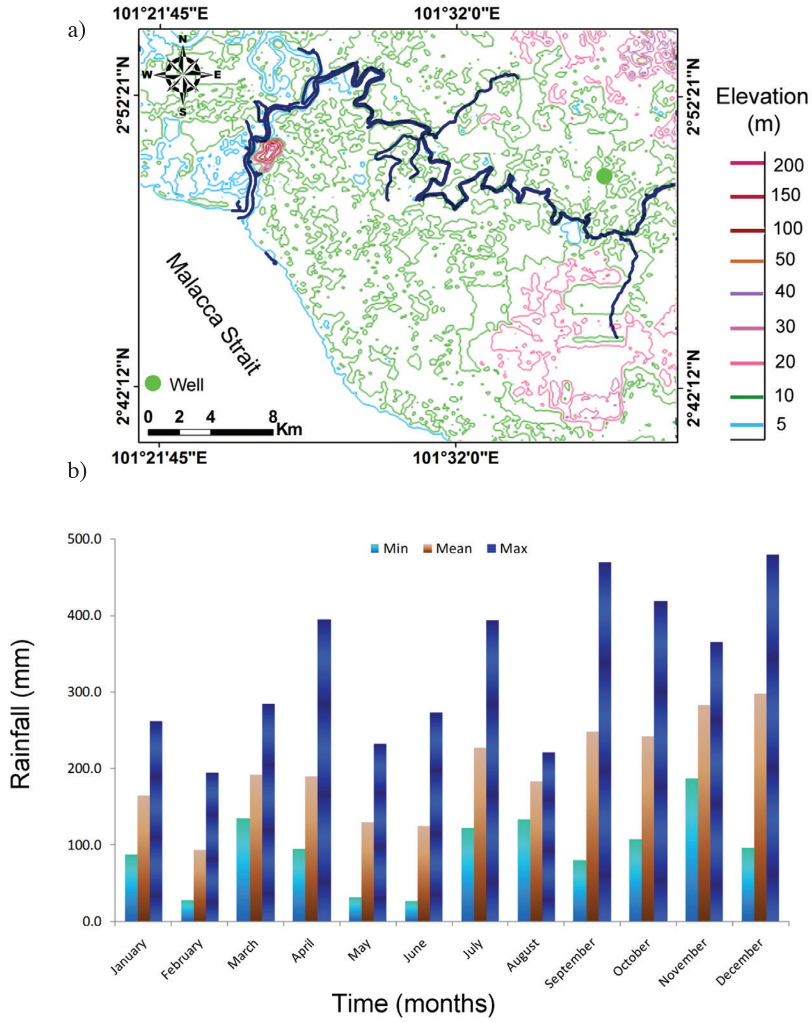

FIGURE 2. (a) Location of the boreholes in the Langat Basin and (b) Average of monthly rainfall from 2007 to 2013 in the study area

The maximum rainfall occurred between September and December with a mean of 433 mm. The highest amount of rainfall (480 mm) occurred in December 2012. The minimum rainfall occurred in February 2012 with a mean of 94 mm. In addition the number of rainy days in a year varies from 140 to 210 days. Temperature has a major impact to the water budget as it increases evaporation (Te Chow et al. 1988). Monthly mean temperature measurements at the meteorological station in the study area are represented in Figure 3(a). A slight increasing trend is found in the values, which change steadily over the years as identified by the bold line in Figure 3(a). This minor trend is neutralized when compared with larger data sets where significant temperature variations over a long period of time could not be observed. Furthermore, the monthly evaporation and humidity in the Langat Basin are represented in Figures 3(b) and 3(c), respectively. The average monthly relative humidity lies between 77 and 85% varying from place to place of the investigated area and from month to month. The minimum range of average relative humidity varies from 67% in February to 79% in November. The maximum range of mean relative humidity varies from 82% in June to 89% in November. In Peninsular Malaysia, the lowest relative humidity occurred on January and February while the relative humidity normally reaches it minimum on November (MMD 2013). Consequently, monthly values for the variations of evaporation, humidity, rainfall, minimum and maximum temperature and variations of water level, for 2007 to 2013, were identified and trained with ANNs in the present study. Therefore, the numbers of input and output data were arranged at five and one, respectively. The transfer function in the hidden layer was set to sigmoid, because it was found in the initial evaluation that the sigmoid function provides better outcomes than other transfer functions, although the pure linear transfer function has been utilized in the output layer. Trial and error is the most effective technique to identify the number of neurons in the hidden layer (Sheela & Deepa 2013). The data were randomly divided into three sets: 70% of the data for model training, 15% for model testing and 15% data for model validity.

Input and output data have been normalized to give them equal attention in the training process. In order to consider the effectiveness of each network and its ability

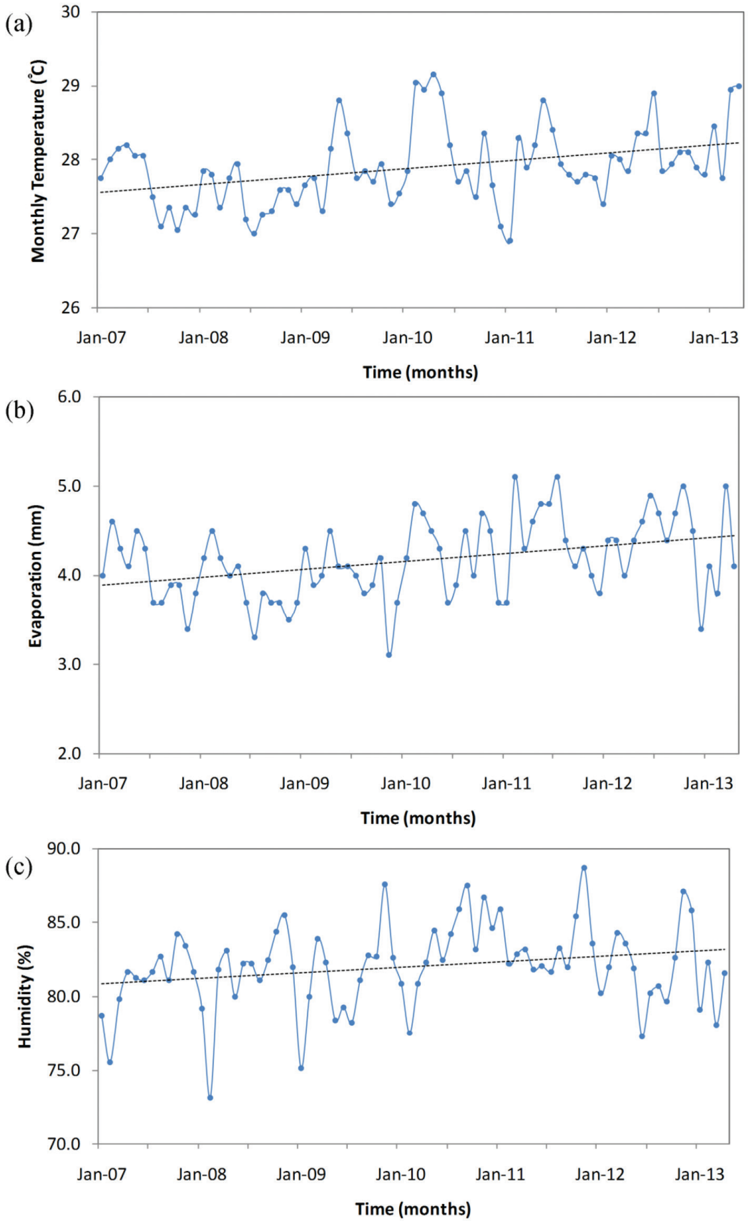

FIGURE 3. (a) Average monthly temperature (°C), (b) monthly evaporation (mm) and (c) monthly humidity (%) in Langat Basin

to simulate precisely, two different criteria are employed. The first one was the mean square error (MSE) calculated by:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}{N}, \qquad (3)$$

where y is the observed data; $\bar{y}$ the computed data; N and the number of observations. MSE reflects the difference between the observed and computed values; the lower the MSE, the more precise the simulation.

The second one was the correlation coefficient between network result and network target outputs in three training, testing and validation groups were used and calculated as follows:

$$R = \sqrt{1 - \frac{\Sigma\left(y_i - \bar{y}_i\right)^2}{\Sigma y_i^2 - \frac{\Sigma \bar{y}_i^2}{N}}}. \qquad (4)$$

RESULTS AND DISCUSSION

Forecasting of the groundwater level was carried out for various networks from 2007 to 2013 in the Langat Basin, Malaysia. Figure 4 shows the maximum (500 mm) and the minimum (27 mm) of precipitation between December of 2012 and June 2009. In general, the groundwater level increases by rainfall enhancement. The best condition occurred in September 2010 when the groundwater level reached its highest level (roughly 1 m) and after a large rainfall event which is 470 mm. After a prolonged period of

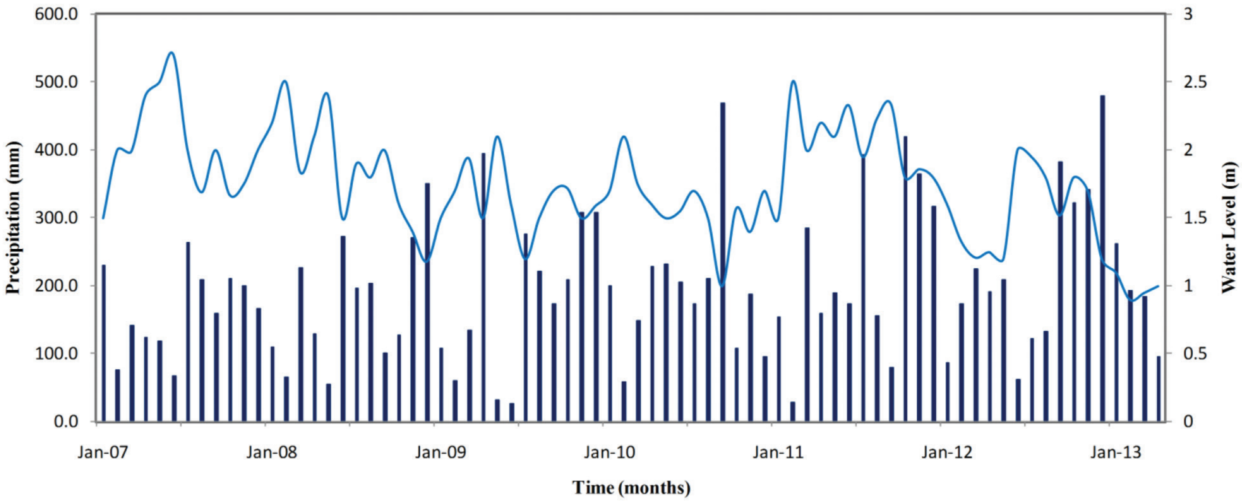

FIGURE 4. Monthly precipitation (mm) and depth to groundwater level (m) for observation well from 2007 to 2013 in Langat Basin

low rainfall (< 300 mm per month), it reached to one of the lowest levels (2.5 m) in February 2011. All three networks derive a parameter configuration and optimum network, by means of trial and error. Table 1 shows the evaluation of all three networks for the observation well. Achievements by the cascade forward network trained with the Levenberg-Marquardt algorithm show the best overall performance as is shown in Table 1 and by the feed-forward network trained with the same algorithm known as the second best is shown by their small MSE. A recurrent neural network trained with the gradient descent algorithm was considered as the most unsuitable network. This may be interpreted that more complex training algorithms are required by RNN (Coulibaly et al. 2001). Figures 5-7 shows the evaluation of the ability of the ANN model compared with various networks that refer to the training step, which is displayed in the form of a scatter plot. Additionally, the groundwater level forecast of every model in the training phase to get the best input combination is shown in Figures 5-7 in the form of hydrographs. Moreover, Figure 8 shows the observed depths to groundwater and simulated ones per month and from 2007 to 2013. The depths to groundwater for all three networks by various training algorithms are compared with the observed groundwater levels and presented in Figure 8. The observed and simulated groundwater levels for all of the networks are very well matched, as is presented in these figures. The FNN and CFN simulation are closer to the corresponding observed values than other networks, which is confirmed by the hydrographs and scatter plots. The structure of the networks may be the reason for the better performance of these networks. It matches better the principal processes that are involved in aquifer response to stresses such as evaporation, precipitation and other parameters.

TABLE 1. Comparison of performance of models developed for all, training, testing and validation periods

				All		Training		Testing		Validation	
		Structure	Epoch	R	MSE	R	MSE	R	MSE	R	MSE
FNN	LM	(8,10,1)	500	0.839	0.048	0.998	0.0004	0.443	0.265	0.642	0.136
	GDX	(8,10,1)	500	0.672	0.087	0.648	0.097	0.645	0.087	0.802	0.043
	SCG	(7,9,1)	500	0.708	0.072	0.915	0.021	0.463	0.367	0.802	0.091
	RP	(7,9,1)	500	0.78	0.064	0.865	0.042	0.654	0.119	0.725	0.117
RNN	LM	(8,9,1)	500	0.761	0.086	0.976	0.008	0.477	0.314	0.59	0.143
	GDX	(8,9,1)	500	0.692	0.107	0.694	0.118	0.494	0.112	0.917	0.051
	SCG	(8,10,1)	500	0.694	0.104	0.696	0.109	0.488	0.125	0.761	0.057
	RP	(8,10,1)	500	0.737	0.073	0.828	0.049	0.669	0.084	0.604	0.178
CFN	LM	(9,11,1)	500	0.811	0.058	0.95	0.015	0.5	0.165	0.743	0.095
	GDX	(9,11,1)	500	0.629	0.088	0.754	0.066	0.526	0.19	0.478	0.153
	SCG	(8,11,1)	500	0.751	0.081	0.845	0.049	0.546	0.14	0.532	0.117
	RP	(9,11,1)	500	0.787	0.061	0.848	0.055	0.592	0.112	0.546	0.036

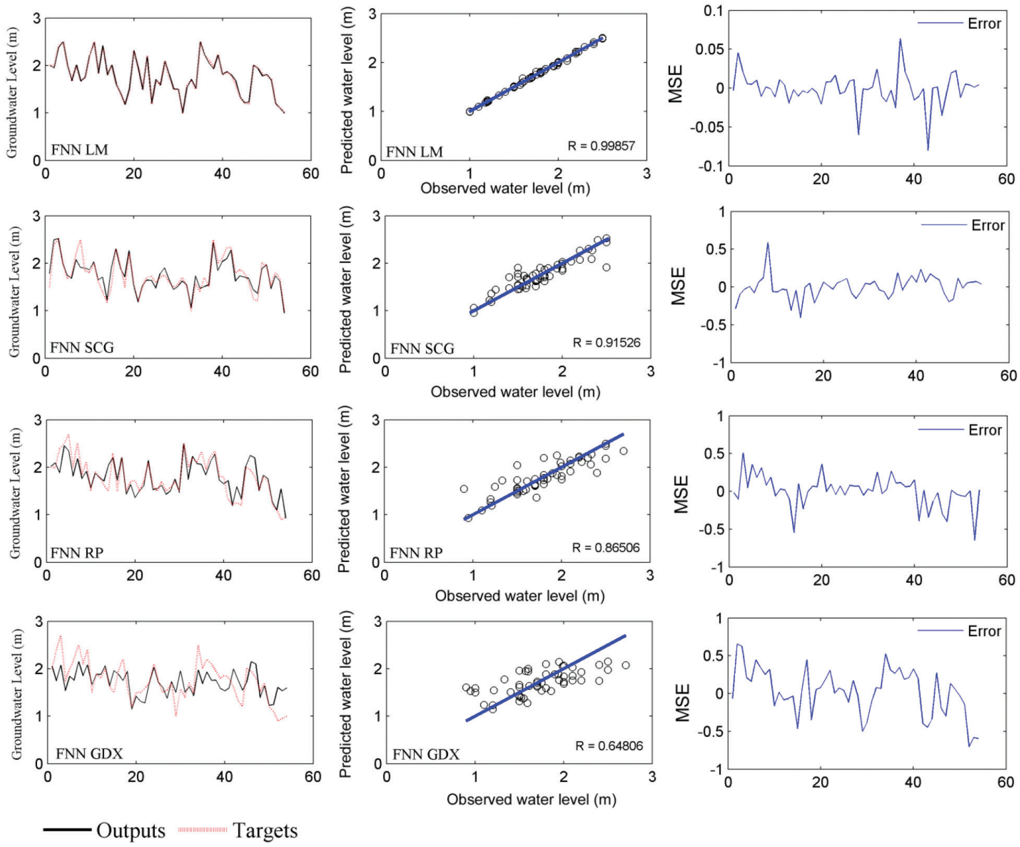

FIGURE 5. Scatter plots of the observed and forecasted water levels at training period for FNN network with different algorithms

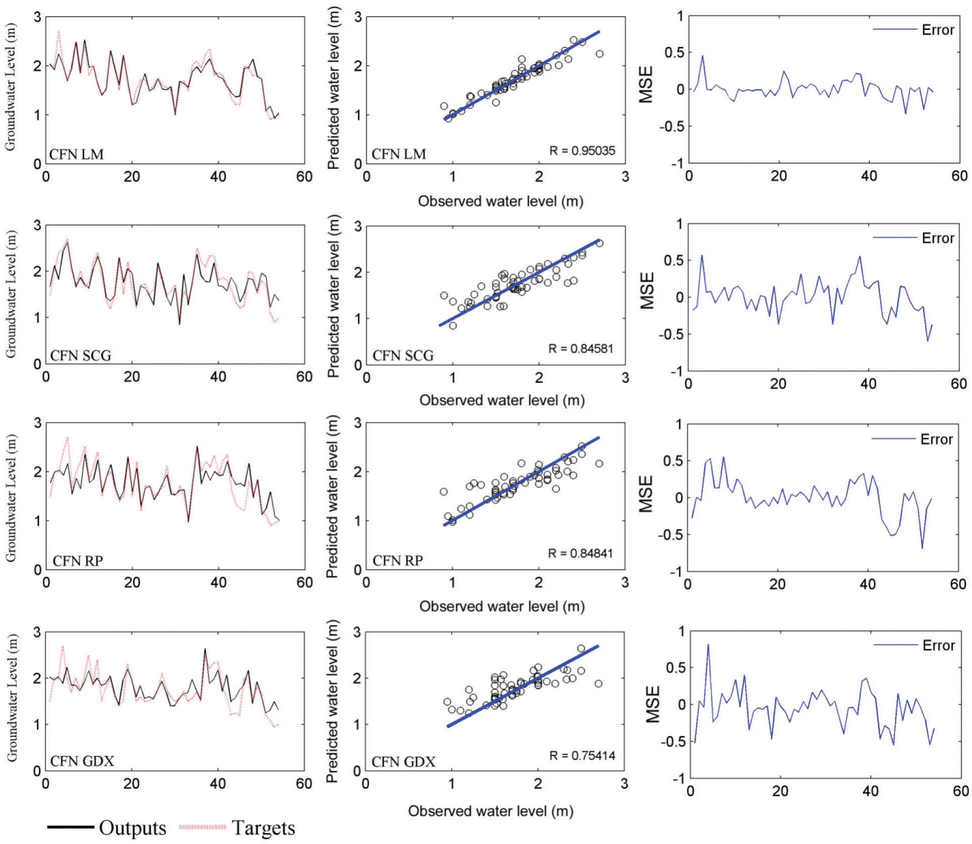

FIGURE 6. Scatter plots of the observed and forecasted water levels at training period for CFN network with different algorithms

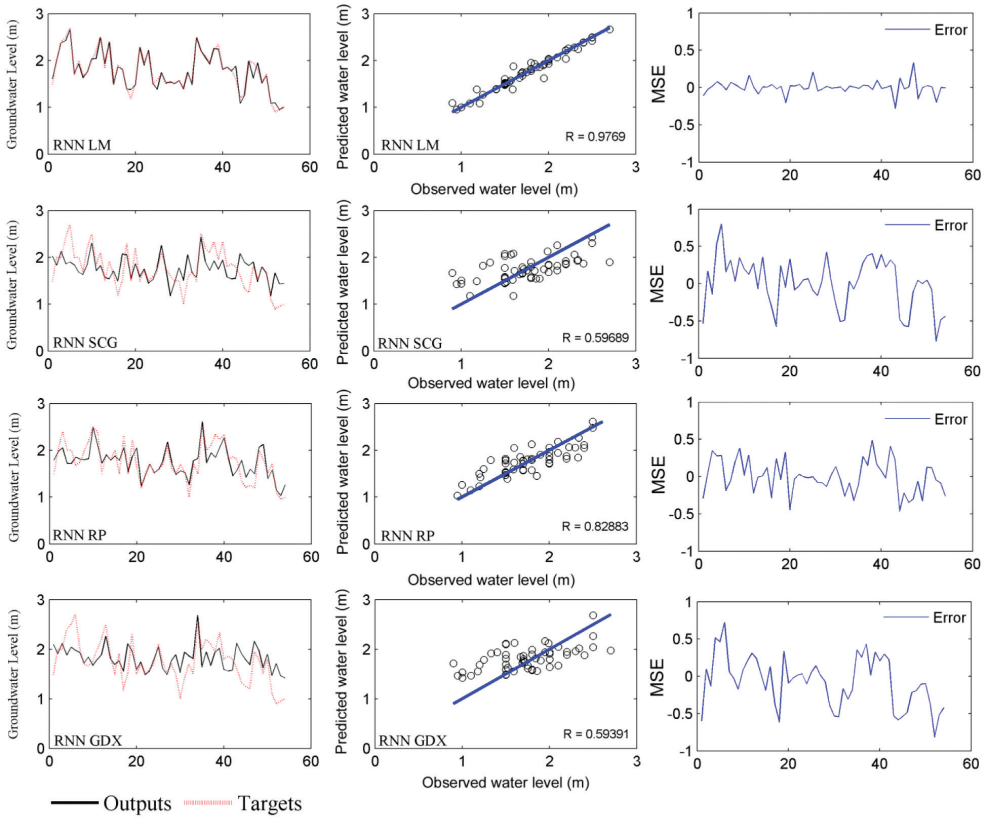

FIGURE 7. Scatter plots of the observed and forecasted water levels at training period for RNN network with different algorithms

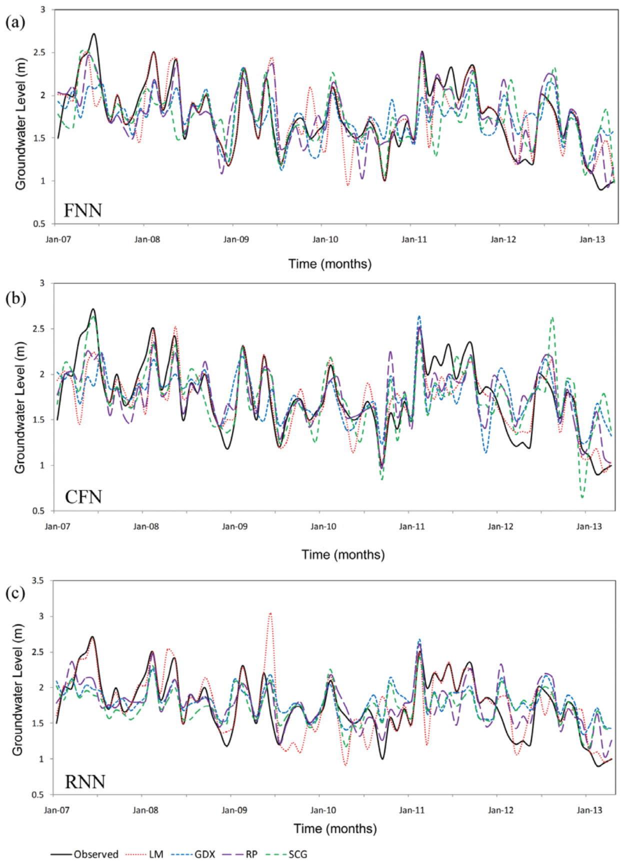

FIGURE 8. Comparison of results to observed groundwater level with different networks and algorithms

Conclusion

In this research, the ability of the ANNs model with various networks to simulate water levels fluctuations was analyzed. Moreover, the effect of various algorithms was also studied. Consequently, ANNs computing is considered as a successful technique to apply for monthly groundwater level simulation from the available groundwater data. The performance evaluation criteria, namely the MSE and the correlation coefficient for simulated groundwater levels, are consistent and excellent. Moreover, the results successfully represent the network's forecasted depth to groundwater in all observation data with a mean square error (MSE) of 0.048–0.107 m^2. As a result of the research, the most suitable method for the networks trained with the Levenberg-Marquardt approach as it demonstrated the most precise simulations of the groundwater levels. Nevertheless, the networks with various architectures have been compared and the FNN model with an MSE of 0.048 – 0.087 m^2 achieved the best overall performance and the CFN with an MSE of 0.058 – 0.088 m^2 was known as the second best. It was concluded that, once satisfactorily trained and calibrated, FNN and CFN will most likely provide better results in simulating groundwater level in other plains. In general, the obtained results from the study area were acceptable and confirmed that artificial neural networks can be a beneficial simulation tool to employ in the area of groundwater hydrology.

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REFERENCES

Anctil, F., Perrin, C. & Andréassian, V. 2004. Impact of the length of observed records on the performance of ANN and of conceptual parsimonious rainfall-runoff forecasting models. *Environmental Modelling & Software* 19(4): 357-368.

ASCE Task C. 2000. Artificial neural networks in hydrology. I: Preliminary concepts. *Journal of Hydrologic Engineering* 5(2): 115-123.

Ashraf, M.A., Maah, M.J., Yusoff, I. & Mohamadreza Gharibreza. 2011. Proposed design of anaerobic wetland system for treatment of mining waste water at former tin mining catchmet. *Scientific Research and Essays* 6(28): 6001-6022.

Coulibaly, P., Anctil, F., Aravena, R. & Bobée, B. 2001. Artificial neural network modeling of water table depth fluctuations. *Water Resources Research* 37(4): 885-896.

Coulibaly, P., Anctil, F. & Bobee, B. 2000. Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. *Journal of Hydrology* 230(3): 244-257.

Elman, J.L. 1990. Finding structure in time. *Cognitive Science* 14(2): 179-211.

Fausset, L. 1994. *Fundamentals of Neural Networks*. New Jersey: Prentince Hall. p. 461.

Filik, U.B. & Kurban, M. 2007. A new approach for the short-term load forecasting with autoregressive and artificial neural network models. *International Journal of Computational Intelligence Research* 3(1): 66-71.

Govindaraju, R.S. & Rao, A.R. 2000. *Artificial Neural Networks in Hydrology*. Berlin, Heidelberg: Kluwer Academic Publishers. p. 332.

Hagan, M.T., Demuth, H.B. & Beale, M. 1996. *Neural Network Design*. Boston: PWS Publishing. p. 734.

Hagan, M.T. & Menhaj, M.B. 1994. Training feedforward networks with the Marquardt algorithm. *IEEE Transactions on Neural Networks* 5(6): 989-993.

Haykin, S. 1999. *Neural Networks: A Comprehensive Foundation*. 2nd ed. New Jersey: Prentice Hall. p. 823.

Hornik, K., Stinchcombe, M. & White, H. 1989. Multilayer feedforward networks are universal approximators. *Neural Networks* 2(5): 359-366.

Hussain, N.H., Yusoff, I., Alias, Y., Mohamad, S., Rahim, N.Y. & Ashraf, M.A. 2014. Ionic liquid as a medium to remove iron and other metal ions: A case study of the North Kelantan Aquifer, Malaysia. *Environmental Earth Sciences* 71(5): 2105-2113.

Karimi, S., Kisi, O., Shiri, J. & Makarynskyy, O. 2013. Neuro-fuzzy and neural network techniques for forecasting sea level in Darwin Harbor, Australia. *Computers & Geosciences* 52: 50-59.

Karmokar, B.C., Mahmud, M.P., Siddiquee, M.K., Nafi, K.W. & Kar, T.S. 2012, Touchless written English characters recognition using neural network. *International Journal of Computer & Organization Trends* 2(3): 80-84.

Khaki, M., Yusoff, I. & Islami, N. 2015. Application of the artificial neural network and neuro fuzzy system for assessment of groundwater quality. *CLEAN - Soil Air Water* 43: 551-560.

Kin, C.L., Ball, J.E. & Sharma, A. 2001. An application of artificial neural networks for rainfall forecasting. *Mathematical and Computer Modelling* 33(6): 683-693.

Lashkarbolooki, M. & Shafipour, Z.S. 2012. Trainable cascade-forward back-propagation network modeling of spearmint oil extraction in a packed bed using SC-CO2. *The Journal of Supercritical Fluids* 73: 108-115.

Maier, H.R. & Dandy, G.C. 2000. Neural networks for the prediction and forecasting of water resources variables: A review of modelling issues and applications. *Environmental Modelling & Software* 15(1): 101-124.

Maier, H.R. & Dandy, G.C. 1998. Understanding the behaviour and optimising the performance of back-propagation neural networks: An empirical study. *Environmental Modelling & Software* 13(2): 179-191.

Malaysian Meteorological Department (MMD). 2013. http://www.met.gov.my.

Mishra, A., Kar, S. & Singh, V. 2007. Prioritizing structural management by quantifying the effect of land use and land cover on watershed runoff and sediment yield. *Water Resources Management* 21(11): 1899-1913.

Mohanty, S., Jha, M.K., Kumar, A. & Sudheer, K. 2010. Artificial neural network modeling for groundwater level forecasting in a River Island of Eastern India. *Water Resources Management* 24(9): 1845-1865.

Mohanty, S., Scholz, M. & Slater, M. 2002. Neural network simulation of the chemical oxygen demand reduction in a biological activated-carbon filter. *Water and Environment Journal* 16(1): 58-64.

Møller, M.F. 1993. A scaled conjugate gradient algorithm for fast supervised learning. *Neural Networks* 6(4): 525-533.

Riedmiller, M. & Braun, H. 1993. A direct adaptive method for faster backpropagation learning: The RPROP algorithm, paper presented at neural networks. *IEEE International Conference*. pp. 586-591.

Saghravani, S.R., Yusoff, I., Mustapha, S. & Saghravani, S.F. 2013. Estimating groundwater reharge using empirical method: A case study in the tropical zone. *Sains Malaysiana* 42(5): 553-560.

Selventhiran, U., Premaratne, H. & Sonnadara, D. 2012. An artificial neural network model for river flow forecasting. Paper presented at *Proceedings of the Technical Sessions*. 28: 15-21.

Singh, K.P., Basant, A., Malik, A. & Jain, G. 2009. Artificial neural network modeling of the river water quality - a case study. *Ecological Modelling* 220(6): 888-895.

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

Sheela, K.G. & Deepa, S. 2013. Review on methods to fix number of hidden neurons in neural networks. *Mathematical Problems in Engineering*. Article ID 425740.

Talebizadeh, M., Morid, S., Ayyoubzadeh, S.A. & Ghasemzadeh, M. 2010. Uncertainty analysis in sediment load modeling using ANN and SWAT model. *Water Resources Management* 24(9): 1747-1761.

Te Chow, V., Maidment, D.R. & Mays, L.W. 1988. *Applied Hydrology*. Singapore: Tata McGraw-Hill Education. p. 572.

Verma, A. & Singh, T. 2013. Prediction of water quality from simple field parameters. *Environmental Earth Sciences* 69(3): 1-9.

Yusoff, I., Alias, Y., Yusof, M. & Ashraf, M.A. 2013. Assessment of pollutants migration at Ampar Tenang landfill site, Selangor, Malaysia. *ScienceAsia* 39: 392-409.

Zhang, Y., Pulliainen, J., Koponen, S. & Hallikainen, M. 2002. Application of an empirical neural network to surface water quality estimation in the Gulf of Finland using combined optical data and microwave data. *Remote Sensing of Environment* 81(2): 327-336.

Zulkifley, M.T.M., Ng, N.T., Raj, J.K., Hashim, R., Bakar, A.F.A., Paramanthan, S. & Ashraf, M.A. 2013. A review of the stabilization of tropical lowland peats. *Bulletin of Engineering Geology and the Environment* 73(3): 733-746.

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