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Application of synthetic observations to develop an artificial neural network for mine dewatering

Sage Ngoie[1], Jean-Marie Lunda[2], Adalbert Mbuyu[3], Jean-Felix Kabulo[4]

[1]*Philosophiae Doctor, IGS, University of the Free State, Republic of South Africa*
[2]*Philosophiae Doctor, Prof. of Geotech. Eng., Univ. of Lubumbashi, Dem. Rep. of Congo*
[3]*Junior Lecturer, Dept. of Geology, University of Kolwezi, Dem. Rep. of Congo*
[4]*Junior lecturer, Dept. of geology, University of Likasi, Dem. Rep. of Congo*

Abstract - *This study investigated the possibility of predicting the impacts of pit dewatering on the aquifer system in the vicinity of open pit mines where geohydrological inputs are limited, using Artificial Neural Networks (ANNs). First, the performance of the ANNs in predicting hydraulic head responses was evaluated by using synthetic datasets generated by a numerical groundwater model developed for a fictional mine. The synthetic datasets were then used to both train and evaluate the performance of the ANNs. The Artificial Neural Network (ANN) found to give the best predictions of the hydraulic heads had an architecture of 2-6-1 (input-hidden-output layers) and was based on the hyperbolic tangent transfer function. This network was selected for application to real open pit mines.*

Key Words: ANN, Architecture of the ANN, Transfer function, Learning rate, momentum, mine dewatering

1. INTRODUCTION

Dewatering is critically important to open pit mining operations to provide access to ore for removal and transport to processing facilities, as well as for the safety of mining personnel. One of the methods used to plan dewatering programmes, and to support ongoing dewatering programmes, is based on the results from numerical groundwater modelling.

Groundwater models simulate the lowering of the water level elevation as the mines develop deeper below the original ground surface and into the groundwater table. The behaviour of aquifers is typically complex. Aquifers are often highly heterogeneous and anisotropic and their behaviour depends on the physical and chemical properties of the geological unit forming the aquifer. They are controlled by numerous hydraulic and physical parameters.

Numerical models based on FDM and FEM are often used to solve geohydrological problems (Konikow, 1996). These methods discretize continuous media and assign to them some principles of behaviour and conservation characterized by constitutive parameters found from field and laboratories investigations (Levasseur, 2007). Their main disadvantages are that they typically require many inputs, including the geomorphology and geology of the area, hydraulic parameters, geohydrological characteristics, structural data, piezometer records and pumping data, which are often expensive to gather. The models are also limited by uncertainties associated with the availability and quality of the data.

By contrast, Artificial Intelligence, in particular ANNs, is known to be able to model complex systems in various disciplines (Sarkar, 2012). These networks can be defined as systems that reproduce the cognitive function by simulating the architecture of the brain. ANNs are powerful tools that can provide simple and accurate solutions to very complex systems. The accuracy of these solutions are, however, also typically dependent on the number and quality of the available data used as inputs to train the networks to perform specific tasks (Hsu et al., 1995). These observations lead to the following research question:

Is it possible to develop ANNs, using limited input data, that can accurately predict aquifer behaviour during the dewatering of open pit mines?

2. LITTERATURE REVIEW

ANNs are part of Artificial Intelligence. They are a mechanism that reproduces the cognitive function of the brain by simulating its architecture. By imitating the human brain's structure and function, ANNs are well-known to be powerful in solving complex, noisy and non-linear problems (Hsieh, 1993). They are successfully used for approximating functions, task classifications and clustering (Allende et al., 2002; Hsieh, 1993; Khashei and Bijari, 2009; Wilamowski, 2007). ANNs learn from the available data describing the behaviour of a system and attempt to establish a relationship between these data, even if the physical mechanisms controlling the behaviour of the system are poorly understood. They are thus suitable to model the complex behaviour of aquifers which by nature are anisotropic and heterogeneous.

The learning and generalisation processes of ANNs are based on neurophysiological processes, and are described through mathematical relations that mimic the neurophysiological functioning.

3. METHODOLOGY

Sage N., *et al.*, 2017, developed a synthetic numerical model to predict the aquifer response at an open pit during various dewatering strategies. The calculated responses formed a dataset that was used to train ANNs and evaluate their performances in predicting the aquifer behaviour under different conditions. The developed ANNs were used to reproduce the FEM datasets using various non-linear transfer functions. Of these ANNs, those yielding the smallest error were selected and evaluated by statistical techniques.

4. IMPLEMENTATION OF THE ARTIFICIAL NEURAL NETWORK MODEL

Neuro*XL* Predictor, an add-in to Microsoft Excel and part of NeuroSolutions software, was used to develop the ANNs. The most commonly used ANNs in the sciences are multi-layer perceptron networks (MLPs). MLPs have an input layers, one or more hidden layers and an output layer. They make use of a feed-forward architecture, and have a process where parameters (momentum, weight and number of neurons in the hidden layer) are manually adjusted until the targeted output is reached.

According to Cybenko (1989), an MLP with just one hidden layer can be used to approximate any non-linear function. The choice of the transfer function is also very important in the model construction.

The available dataset used for training and testing the ANNs has only two inputs, namely: time (date) and water levels. Seventy-five per cent of the time-water level data are used as inputs (time) and outputs (water level) during training. The remaining 25% is used to validate the performance of the ANNs. Based on a supervised learning process, the trial-and-error method is used by adjusting the weights, iteration numbers, learning rate momentums, transfer functions and number of neurons in the single hidden layer until the smallest error is attained.

When designing any ANN, it is important to find a transfer function, which can accurately predict the system of the study. Among all known transfer functions (Sage N., 2017), only hyperbolic tangent and sigmoidal functions are used in this research, because they are known to be able to make non-linear approximations, and are therefore well suited to predict the non-linear behaviour of groundwater impacted by dewatering processes (Pushpa and Manimala, 2014). In addition, Neuro*XL* Predictor is used in this study because it has the capability to handle non-linear transfer functions.

5. ARCHITECTURE OF THE ARTIFICIAL NEURAL NETWORK

There are several possible architectures for ANNs that are suitable for groundwater studies. The feed-forward ANNs used in this research, have a unidirectional signal flow. After several trial-and-error adjustments of the network architectures, four ANNs, using sigmoidal and hyperbolic tangent transfer functions, were found to give acceptable results in reproducing the hydraulic heads of the synthetic observations made during the numerical modelling of mine dewatering simulation (Sage N. *et al.*, 2017). These ANNs are described in **Table - 1.**

Table - 1: The ANNs best suited for groundwater level predictions

ANNs PARAMETERS	ANN 1	ANN 2	ANN 3	ANN 4
Learning rate	0.3	0.3	0.3	0.3
Momentum rate	0.2	0.2	0.1	0.2
Initial weight	0.2	0.2	0.1	0.2
Neurons in hidden layers	6	6	15	6
Transfer function	ZBLSF	HTF	LSF	BSF

Three of the ANNs (ANNs 1, 2 and 4) have the same architecture in terms of learning rates, momentum rates, initial weights and the number of neurons in the hidden layer. The remaining model (ANN 3) has quite a different structure, as can be seen when comparing the network architectures (refer to **Figure - 1** and **Figure - 2**). As mentioned above, these architectures correspond to those ANNs yielding the smallest errors after several trial-and-error adjustments. The architectures that provided the most accurate water level predictions for dewatering purposes have the following characteristics:

- ANNs 1, 2 and 4 have two inputs layers, six hidden layers and one output layer for the zero-based log-sigmoidal function (ZBLSF), bipolar sigmoidal function (BSF) and hyperbolic transfer function (HTF);

- ANN 3 has two inputs layers, 15 hidden layers and one output layer for log-sigmoid transfer function (LSF).

The minimum weights assigned in the ANNs was 0.001, and the training involved a maximum number of 20 000 complete cycles (epochs).

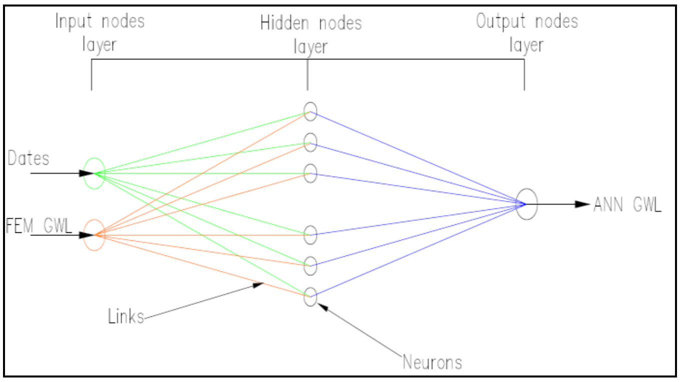

Figure - 1: Architecture of the ANNs 1, 2 and 4, using the zero-based log sigmoid, hyperbolic tangent, and bipolar sigmoidal transfer functions

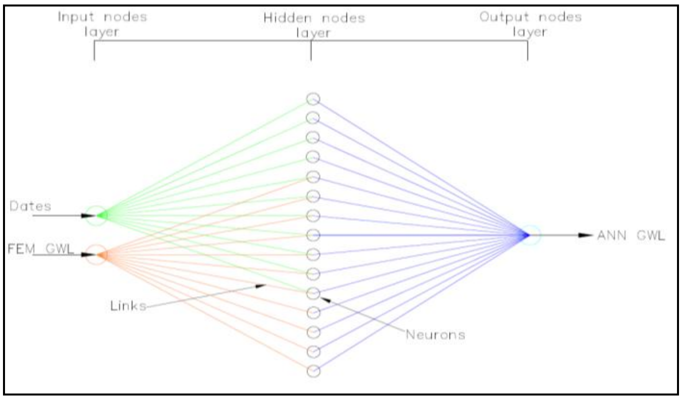

Figure - 2: Architecture of the ANN 3, using on log-sigmoidal transfer function

6. PERFORMANCE ANALYSIS OF ARTIFICIAL NEURAL NETWORKS

Since the finite-difference numerical model included nine observation wells, and since four abstraction scenarios (3, 6, 9 and 12 abstraction wells) were modelled (See Sage N. *et al.*, 2017), 36 different datasets of modelled groundwater elevations are available against which the performance of the ANNs can be evaluated. Each dataset consists of 36 modelled values of the groundwater elevations at different times.

Since the performances of four different ANNs using four different transfer functions are to be evaluated in this section, it will not be possible to include the evaluations for each observation well, under each abstraction scenario, for each choice of transfer function. For this reason, only a selected number of evaluations will be shown and discussed.

In Figure -3, the modelled and predicted groundwater elevation at observation well OBS_9 are shown for the four dewatering strategies as examples of the responses obtained. In this figure, the modelled (FEM) groundwater elevations, as well as the groundwater elevations predicted by four ANNs using different transfer functions, are plotted against the dates of measurement.

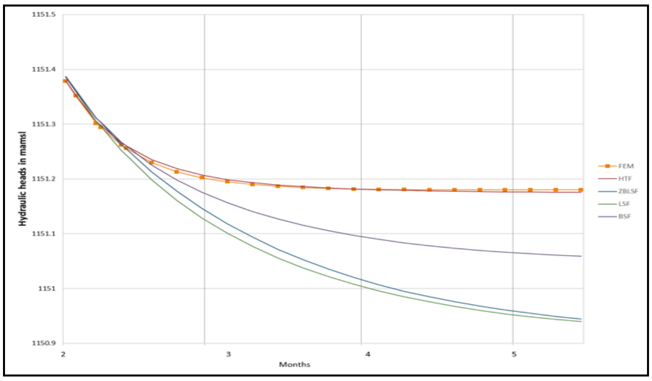

Figure -3: Modelled and predicted hydraulic heads at observation well OBS_9 for a dewatering strategy using 12 dewatering wells

It can be seen that the predictions of hydraulic heads made by the ANNs models generally underestimate the hydraulics heads from the numerical model. It can be also seen that ANN using the hyperbolic transfer function (HTF) yielded the best predictions of the modelled (FEM) hydraulic heads. It can furthermore be seen that the accuracy of the head predictions made by the ANNs generally decreased over time. However, the difference between the modelled and predicted hydraulic heads seldom exceeded 0.5 m.

To verify the accuracy of the hydraulic head predictions, statistical techniques were used to assess the performance of the different ANNs. The performance analyses were carried by considering the modelled and predicted hydraulic heads at all nine observation points (OBS_1 to OBS_9) for all four dewatering simulations (using 3, 6, 9 and 12 abstraction wells).

In Figure - 4, the Root Mean Square Errors (RMSEs) for the hydraulic head predictions made by the ANNs using the four different transfer functions are shown at all nine observation points. The RMSEs for the ANNs using the BSF, LSF, ZLBSF and HTF are shown in green, blue, brown and orange, respectively. From this figure, it can be seen that the HTF yielded the smallest errors at most observation wells, followed by the BSF. The ANN using the ZLBSF and LSF gave the largest errors (poorest predictions). Similar observations can be made when considering the Normalised Root Mean Square Errors (NRMSEs) (refer to **Figure -5**).

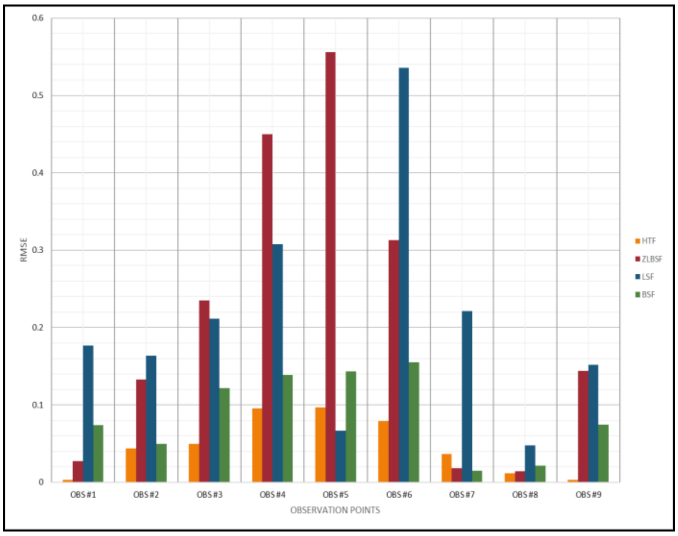

Figure - 4: Root Mean Square Errors (RMSEs) for the hydraulic head predictions at the different observation wells

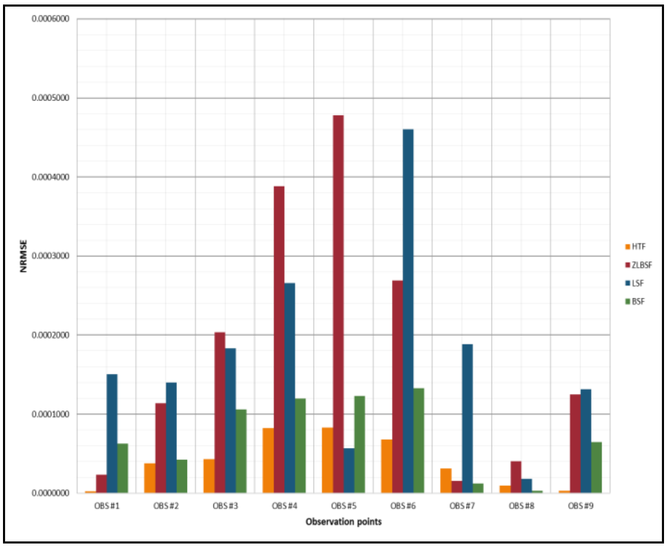

Figure -5: Normalized Root Mean Square Error (NRMSE) for the hydraulic head predictions at the different observation wells

Figure -6 shows the Nash-Sutcliffe Efficiency (NSE) at all the observation wells. NSE-values between zero and one indicate acceptable performance, whereas negative values indicate unacceptable performance. From **Figure -6** it is seen that large negative NSE-values were calculated at some of the observation wells for the predictions made by the ANNs using the ZLBSF, LSF and BSF. Positive or small negative NSF-values were calculated for the ANN using the HTF. This ANN therefore outperformed the others in its predictions of the hydraulic heads.

In Figure -7, the PBIAS for the groundwater elevation data at all the observations wells is shown. Again the ANN with the HTF gives the lowest (closest to zero) values for the PBIAS at most observation wells. This ANN therefore performed the best in predicting the hydraulic heads.

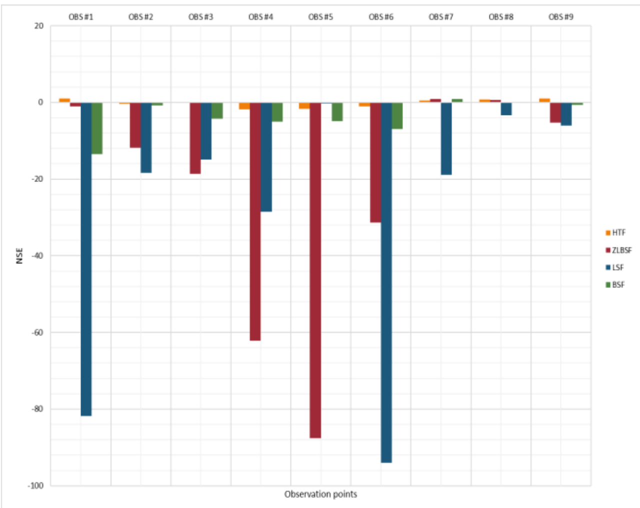

Figure -6: Nash-Sutcliffe Efficiency (NSE) for the hydraulic head predictions at the different observation wells

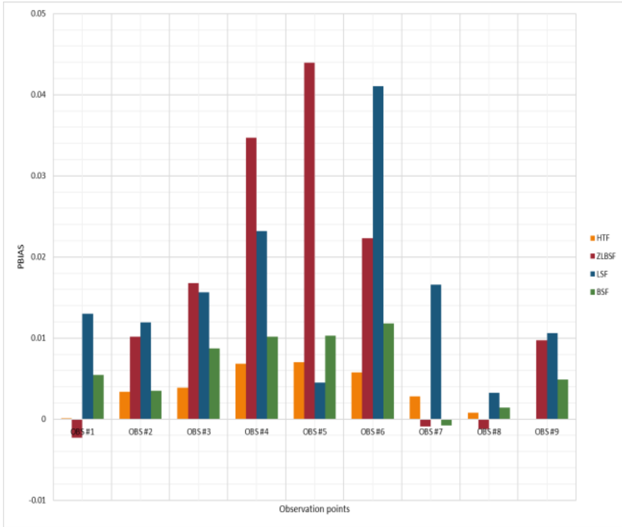

Figure -7: Percent BIAS (PBIAS) for all observation points

7. DISCUSSION AND CONCLUSION

This study investigated the possibility of predicting the impact of dewatering operations at open pit mines where limited geohydrological data are available, by using ANNs. The advantage that ANNs offer is that these networks are able to recognise patterns in the observed data, without considering the underlying physical principles that govern the phenomena being studied. The values of specific parameters that influence the phenomena are also not required as inputs to the ANNs. ANNs can therefore operate in data-scarce environments.

In the current study, ANNs with different internal architectures were used to predict the aquifer response to dewatering strategies. First, the ANNs were applied to synthetic datasets, generated through a numerical groundwater model developed for a fictional mine. Different dewatering strategies, corresponding to different numbers of dewatering wells, were used to generate datasets of the hydraulic heads versus time at different observation points at the fictional mine. The ANNs were trained using parts of the generated datasets, and their performances were evaluated by using the remaining data in the datasets. Performance analyses were carried out by using different statistical and graphical evaluation techniques to assess the degree of agreement between the modelled and predicted datasets.

An advantage of using ANNs to predict mine dewatering is the fact that the size of the dataset available for training constantly increases as new hydraulic head data are recorded. The potential of the ANNs to make accurate predictions increases accordingly as the historical record of the hydraulic heads expands.

In this research, statistical techniques were used to evaluate which transfer function used by the different ANNs results in the best prediction of the hydraulic heads obtained from the numerical model. ANNs using four different transfer functions were used and their performances were evaluated based on four statistical evaluation techniques. The statistical evaluation results show that the ANN using the HTF best predicts the effects of the dewatering process at the open pit.

The ANN found to give the best predictions of the hydraulic heads had an architecture of 2-6-1 (input-hidden-output layers) and was based on the hyperbolic tangent transfer function. For further research, it is suggested to apply the found ANN to real open pit mines.

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BIOGRAPHY

Sage Ngoie was born in Democratic Republic of Congo. He obtained a degree in Geology and a Master's Degree in Geotechnical and Hydrogeological Sciences. He holds a PhD in Geohydrology from the University of the Free State in South Africa where he specialized in Artificial intelligence and mathematical modeling applied to groundwater.