

Prediction of Groundwater Level in The Shallow Aquifer Using Artificial Neural Network Approach

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Prediction of Groundwater Level in The Shallow Aquifer Using Artificial Neural Network Approach

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Abstract. In these regions, groundwater is often the most significant source of water. Groundwater level estimation accuracy is a vital component of efficient water supply management. In this paper, an artificial neural network (ANN) with gradient descent with momentum and adaptive learning rate backpropagation algorithm for groundwater level forecasting applications is proposed. The ANN model used an 8-5-3-1 and 8-10-5-1 network architecture with the input parameter of the form such as precipitation, evaporation, atmospheric pressure, wind, humidity, long exposure to the sun and temperature simultaneously and a relatively short length of groundwater level data recorded from January 2017 to December 2019 at two observation wells in the North Denpasar, Bali, Indonesia. The study's findings show that ANN models can predict groundwater levels. It is suggested that more research be conducted on this proposed process, which can then be used to help establish and incorporate more efficient and long-term groundwater management strategies.

1. Introduction

Groundwater is a very important resource for human life. In some regions, groundwater is the only reliable means of supply, while in others, it is preferred for its immediate availability. These resources are usually of high quality, chemical treatment is usually not required, and they are generally free from pathogenic variables. All these factors make groundwater an essential and dependable resource for various users [1]. The use of groundwater that is not properly managed is increasingly evident around the world, especially in developing countries. So that the main concern at this time is how to maintain groundwater so that it can be available in the long term [1–4]. As a result, long-term conservation of groundwater is vital for current and forthcoming generations. It is necessary to manage groundwater resources sustainably to maintain the availability of this groundwater. Accurate and reliable prediction of groundwater levels is a critical component of achieving this goal

Groundwater level fluctuations are affected by anthropogenic activities such as over-pumping and natural processes such as precipitation, evaporation, atmospheric pressure, wind, long exposure to the sun, temperature, earthquake, tides and external loads, which may be a measure of the integrated control of water management [1]. Challenges arise in predicting groundwater level fluctuations when natural factors affect groundwater levels coupled with highly irregular anthropogenic effects. Also, when the availability of hydrogeological information is very limited, it is difficult to make such predictions. Several approaches have been applied in estimating or predicting groundwater level fluctuations such

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as time-series models such as autoregressive integrated moving average (ARIMA) [5,6] and the numerical model such as MODFLOW [8,9] as a physical-based model. However, both of these methods have limitations in their application because they are still linear, require a lot of data and parameters and are expensive. Moreover, the system is complex and non-linearity, requiring a larger volume of data and increasing model instability [10].

It is incredibly difficult to foresee changes in groundwater levels because of complexity and non-linearity. As an alternative, in a dynamic and highly uncertain system, artificial neural network (ANN) models can provide a more appropriate solution to predicting groundwater levels. Time series-based ANN models have been commonly used in the field of hydrology for streamflow, water quality and rainfall estimation and forecast, as well as groundwater levels [11–16]. ANN models only need time series data for input parameters, not physical or hydrogeological properties, which is a complex system that would have a lot of uncertainty. Many groundwater level forecast studies have been carried out to find the optimum prediction and to strengthen the ANN model itself [12,13,17–19]. The time series of groundwater levels under the influence of natural factors, stream phase, and tidal effects have been studied by most of these studies. Specifically for hydro-climatological factors, a study has never been conducted using the input of hydro-climatological parameters simultaneously to estimate groundwater levels [20]. However, in the present study, an approach is offered to predict groundwater levels fluctuation from hydro-climatology parameters such as precipitation, evaporation, atmospheric pressure, wind, humidity, long exposure to the sun and temperature simultaneously and even with a relatively short length of groundwater level data by employing an artificial neural network (ANN) approach. As a consequence, the technique is highly valuable. The implementation of the method is shown by the use of teaching algorithms such as gradient descent with momentum and adaptive learning rate backpropagation (traingdx) with 8-5-3-1 and 8-10-5-1 architecture for expecting groundwater levels fluctuation in a shallow aquifer that functions as a groundwater recharge area in the northern part of Denpasar City, Bali-Indonesia.

2. Material and method

2.1. Study area

The study area is located in the north of Denpasar City, Bali-Indonesia which has an area of 31,42 km² and it lies between 08°35'31" - 08°44'49" south latitude and 115°12'09" - 115°04'39" east longitude [20]. The aquifer in the city of Denpasar, especially the north of Denpasar, is an unconfined aquifer with a shallow groundwater level and this aquifer is a with flow through fissures and spaces between grains and is a highly productive aquifer [21]. This aquifer is part of the Tabanan-Denpasar groundwater basin [22]. Denpasar is the region covered by volcanic sediments and generally, alluvium and young volcanic sediments are highly permeable, and lower quaternary and tertiary sediments have wide-ranging permeability due to the formation. Denpasar as a part of Bali island consists of Miocene to Pliocene volcanic products and marine sediment as basement rock, overlain by a thick pyroclastic flow, volcanic products and volcanic mudflow that originated from intensive volcanic activities in The Pleistocene to Holocene of Quaternary period [23]. Figure 1 shows the location of the study area.

2.2. Data collecting

General data on groundwater obtained from the Department of Manpower and Energy and Mineral Resources of Bali Province included data of geography, geology, topography, and hydrogeology. Furthermore, the data of hydro-climatology obtained from the Meteorological, Climatological, and Geophysical Agency III Bali Province and other precipitation data were also obtained from The Bali-Penida River Basin Department. The technical data analyses especially for the conversion of point rainfall data to area rainfall were conducted by using the basic formula of hydrology that is The Polygon Thiessen method. Due to the very limited data on the groundwater level, which is only available for 3 years, the hydro-climatological data also adjusts to the availability of groundwater level data. In this study, 36 months period of hydro-climatology data and water tables have been documented since January 2017 to December 2019. Modelling is practical to 2 observation wells unconnectedly. The location of each well is obtainable in Table 1.

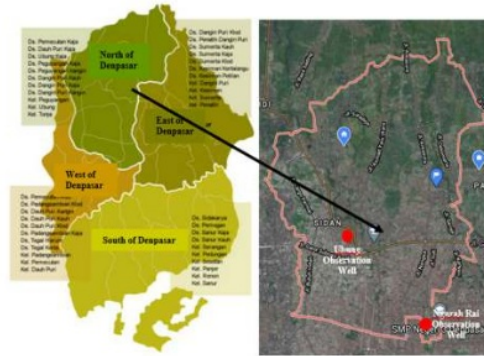


Figure 1. Location of North Denpasar and observation well

Table 1. Position of observation well.

	Well Number	Coordinate
Ngurah Rai	SP No. 02/DP/Distam	08° 39' 05,0" LS; 115° 13' 23,6" BT
Ubung	SP No. 04/DP/Distam	08° 43' 56,3" LS; 115° 10' 36,4" BT

2.3. Artificial neural network

Artificial neural network (ANN) is a widely distributed information processing device that has many output properties that mimic the human brain's biological neural networks [21]. The relation pattern between nodes, the system for evaluating connection weights, and the activation mechanism all contribute to the design of a neural network [22]. Feedforward neural network architecture was used in this research, along with gradient descent with momentum and adaptive learning rate backpropagation (traingdx) for training algorithms, in order to find the best algorithm for predicting groundwater levels over the study field.

2.3.1. Feedforward Neural Network. Feedforward neural networks have been successfully applied to a number of problems since the advent of the error propagation learning algorithm. This network design is the simplest of all neural network architectures. In a feedforward network, the nodes are typically ordered in layers, starting with the first input layer and terminating with the final output layer. There are one or two nodes in each layer in the hidden layer. For the present study, Figure 2 shows the feedforward network having one hidden layer with 5 neurons, one hidden layer with 3 neurons, multiple input and one output layer nodes (8-5-3-1) and Figure 3 shows the feedforward network having one hidden layer with 10 neurons, one hidden layer with 5 neurons, multiple input and one output layer nodes (8-10-5-1). Information interchanges to the output layer from the input trough the hidden layer. The primary benefit of feedforward neural networks is that they are simple to manage and, as defined by [23], can estimated any input/output map.

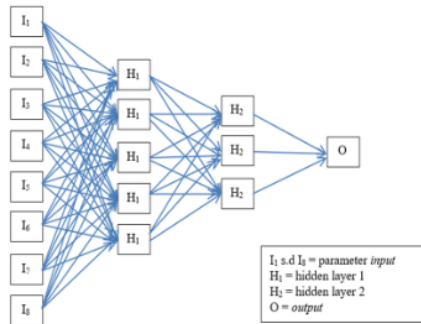


Figure 2. 8-5-3-1 architecture.

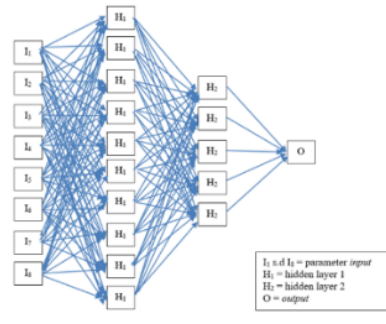


Figure 3. 8-10-5-1 architecture.

2.3.2. Training algorithms. According to [24], over 23 learning rules were formulated to train the model; nevertheless, none of them can ensure the minimum total explanation. Therefore, a demanding aspect of network design is successful network training. A precarious analysis of the obtainable information shows that more than 90% of the studies use the standard feedforward backpropagation neural network, which is essentially a gradient-based optimization technique developed by [25]. A gradient descent algorithm in which network weights are pushed along the negative of the output function gradient is normal backpropagation. For nonlinear multilayer networks, the term 'backpropagation' refers to how the gradient is computed. Even though backpropagation training has proven successful in many implementations, gradient-based approaches have clear disadvantages, such as sluggish convergence and the difficulty of local searching. One of the proposed alterations to optimize the backpropagation algorithm is gradient descent with momentum and adaptive learning rate backpropagation (traingdx). This function will improve the weights based on the gradient descent with an adaptive learning rate and also by using momentum so that it will speed up the convergence process. This is one of the most popular and commonly used approaches for training a network [17].

2.3.3. Model training, testing, and evaluation criteria. ANN architecture consists of three layers, namely input, hidden, and output layers. The optimal value for nodes in the hidden layer is determined by trial and error and by using the log-sigmoid activation function. In the present study, a supervised type of learning with a batch mode of data feeding was used for ANN modelling. For the models, 24 months of data were applied to training or calibrating models and 12 months period was left for testing or validating the model. The ANN modelling was performed using MATLAB software where previously the normalization process was carried out on the input data. For visual testing of the model results, both experimental groundwater level hydrographs and ANN model simulated groundwater level hydrographs were plotted. Aside from visual observation, the efficacy of the developed ANN model was evaluated using five statistical metrics (goodness-of-fit criteria): correlation coefficient (r), coefficient determination (R^2), root mean squared error (RMSE), mean squared error (MSE), and mean absolute error (MAE).

3. Results and discussion

All tests and results derived through programming in Matlab R2018b. Utilizing trial and error, an optimum network and parameter configuration for all two networks was derived. Thus the input layer in all networks consisted of 8 input nodes such as precipitation, evaporation, atmospheric pressure, wind, humidity, long exposure to the sun and temperature and groundwater level. The output of the network is a prediction of the level of 2 observation wells in North Denpasar that is Ubung and Ngurah Rai. The optimum forecasting model was developed by comparing the performance of the different neural

network models that were investigated. Multiple neural network topologies were tested regarding the number of the hidden layers (two hidden layers with different neurons amount) and the most common transfer functions for the hidden layers and also the most common learning algorithms. The most common transfer functions that were tested for the hidden layers are the following: log-sigmoid and purelin. The most common training algorithms that were tested for training every neural network model was gradient descent with momentum and adaptive learning rate backpropagation (traingdx) algorithm. The optimum model was evaluated according to the value of r , R^2 , the minimum RMSE, MSE and MAE among all the other constructed models. The various statistical goodness of fit) expressed as:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (1)$$

$$R^2 = \frac{((n) \sum xy) - (\sum x)(\sum y))^2}{(n(\sum x^2) - (\sum x)^2)(n(\sum y^2) - (\sum y)^2)} \quad (2)$$

$$MSE = \frac{\sum_{i=1}^n (x_i - y_i)^2}{n} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}} \quad (4)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |x_i - y_i| \quad (5)$$

The values of performance measures for the two models in the training and testing set are shown in Tables 2 and 3, respectively. Comparing the performance of 2 ANN models in the training or testing phase all the models performed in a more or less similar way. According to the performance of the ANN model, the model with 8-5-3-1 architecture produces a good performance to predict the groundwater level in the Ubung monitoring well. Can be seen from the higher value of r , R^2 and MSE, RMSE, and MAE which smaller than the value generated by the model of 8-10-5-1 architecture. However, in the Ngurah Rai monitoring well has the opposite result. Model 8-10-5-1 gives better results. However, in general, the model with two architectures still shows good results to describe the forecasting of the groundwater level during the training phase.

Table 2. The performance of ANN models in training phase.

Well	Training data number	Architecture	r	R^2	MSE	RMSE	MAE
Ubung	24	8-5-3-1	0.954	0.91	0.059	0.242	0.188
Ubung	24	8-10-5-1	0.925	0.855	0.165	0.407	0.308
Ngurah Rai	24	8-5-3-1	0.927	0.859	0.434	0.659	0.459
Ngurah Rai	24	8-10-5-1	0.968	0.937	0.419	0.647	0.199

Table 3. The performance of ANN models in testing phase.

Well	Testing data number	Architecture	r	R ²	MSE	RMSE	MAE
Ubung	12	8-5-3-1	0.998	0.996	1.574	1.254	1.094
Ubung	12	8-10-5-1	0.956	0.914	1.411	1.187	0.149
Ngurah Rai	12	8-5-3-1	0.998	0.996	0.069	0.263	0.215
Ngurah Rai	12	8-10-5-1	0.999	0.998	0.07	0.265	0.32

Table 4 show the performance of ANN models in a testing phase. The model with 8-5-3-1 or 8-10-5-1 architecture shows good results in predicting groundwater level fluctuations in the Ubung monitoring well and at the Ngurah Rai monitoring well. Based on the results of the overall assessment by comparing the observed value with the predicted value, it is found that the ANN model with an 8-5-3-1 or 8-10-5-1 architecture gives good results in terms of forecasting groundwater levels in the two monitoring wells in The North Denpasar area. The overall model performance value can be seen in Table 4 and Figure 4-7.

Table 4. The general performance of ANN models.

Well	Architecture	r	R ²	MSE	RMSE	MAE
Ubung	8-5-3-1	0.865	0.748	0.564	0.751	0.49
Ubung	8-10-5-1	0.845	0.714	0.58	0.762	0.255
Ngurah Rai	8-5-3-1	0.664	0.442	0.313	0.559	0.378
Ngurah Rai	8-10-5-1	0.707	0.499	0.303	0.55	0.239

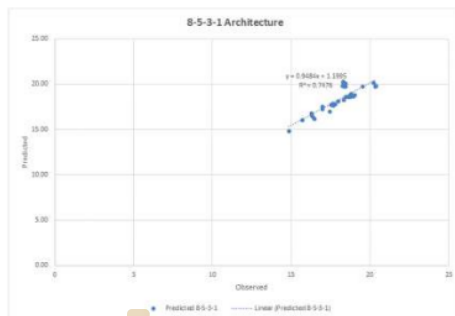


Figure 4. Scatter plots of observed and predicted groundwater levels using an ANN of 8-5-3-1 architecture in Ubung observation well.

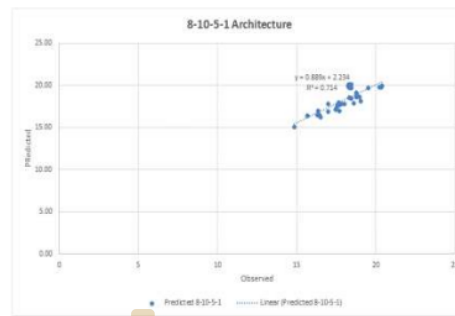


Figure 5. Scatter plots of observed and predicted groundwater levels using an ANN of 8-10-5-1 architecture in Ubung observation well.

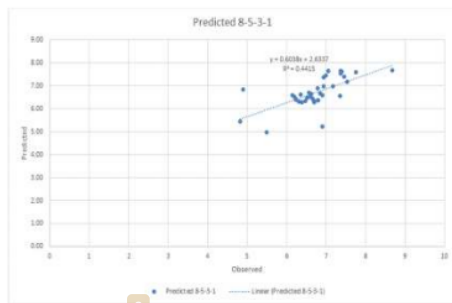


Figure 6. Scatter plots of observed and predicted groundwater levels using an ANN of 8-5-3-1 architecture in Ngurah Rai observation well.

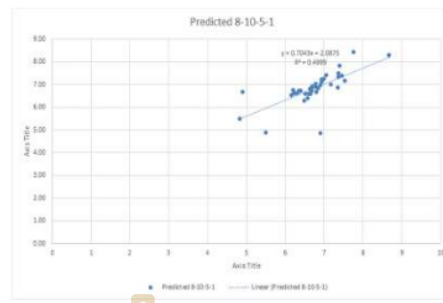


Figure 7. Scatter plots of observed and predicted groundwater levels using an ANN of 8-10-5-1 architecture in Ngurah Rai observation well.

4. Conclusion

ANNs are relatively modern analytical methods that have been commonly used to solve a wide variety of complex real-world problems. They are especially appealing because of their impressive learning and generalization capabilities, including strongly non-linear problems. Monthly fluctuations in the levels of the Ubung and Ngurah Rai observation wells, as well as precipitation, evaporation, atmospheric pressure, wind, humidity, long exposure to the sun and temperature simultaneously, were chosen to characterize the physical phenomena used to predict monthly groundwater levels.

The efficacy of artificial neural network (ANN) simulation in predicting groundwater levels in two shallow aquifer wells is shown in this article. The gradient descent with momentum and adaptive learning rate backpropagation (traingdx) algorithm was found to be appropriate for forecasting groundwater levels due to its low memory requirements. The groundwater level fluctuation is modelled using two architecture models. In the forecasting process, the models 8-5-3-1 and 8-10-5-1 are used. The model's efficiency is strong, according to the findings, since it can model groundwater level variations. The correlation coefficient, which ranges from 0.925 to 0.999; the coefficient of determination, which ranges from 0.855 to 0.998; the mean square error, which ranges from 0.059 to 1.574; the root mean square error, which ranges from 0.242 to 1.254; and the absolute mean error, which ranges from 0.149 to 1.094. The developed ANN model was capable of reliably forecasting groundwater levels in the study area.

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