# Forecasting Urban Groundwater Level Applying Artificial Neural Network (ANN)

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**ABSTRACT:** Groundwater beneath the cities is becoming an important and valuable resource. Conjunctive use of surface and groundwater is likely to become increasingly more common as urban population grows by time. Therefore, one important requirement for urban water management planning is forecasting the groundwater level fluctuations. Less experience and information is available to evaluate the fluctuations of groundwater level in urban environment compare to the natural systems, also different processes (sources) are involved in an urban water cycle, which all together make it more complicated to study.

Similar to many other megacities, there is a serious lack of hydrogeological and long-period time-series data in a megacity like Tehran, Iran, which is mostly due to the limitations of allocated budget and complexity of data gathering processes. Artificial Neural Network (ANN) has a great ability in combining different types of data from different sources; therefore, ANN is an intelligent method which takes the common and available hydrological data such as groundwater level, precipitation, temperature and in-city streamflow time-series as input data to be used in groundwater modeling instead of more scarce data such as hydrogeological data.

In this study, we investigate the capability of two ANN models to predict the urban groundwater level using different sets of available input data, and then we compare the results of these two models. A multi-input-single-output network has been trained using Levenberg-Marquardt algorithm. The aforementioned models are evaluated using three statistical performance criteria namely mean square error (MSE), root mean squared error (RMSE), and efficiency ($R^2$).

This paper identifies the proficiency of ANN modeling technique to capture the complex dynamics involved in urban groundwater level fluctuations. The results show the importance of input data selection and its effect on prediction accuracy. Also, this study confirms that ANN models are capable in predicting the groundwater level even in complicated urban water cycles by using common hydrological data.

**KEY WORDS:** Forecasting, Urban groundwater level, Artificial Neural Network

## INTRODUCTION

Intensive use of groundwater is becoming a common situation in many areas of the world, especially in semiarid and arid areas, and in small islands and coastal zones. When studying groundwater it is necessary to consider that it is not only an important mineral resource (in recent years geologists often call groundwater the 'number one mineral resource') but a component of the total water resources and water balance and is one of the main components of the environment (Zektser et al., 2004). Groundwater level is an indicator of groundwater availability, groundwater flow, and the physical characteristics of an aquifer or groundwater system.

A choice of a method for prediction depends on the complexity of hydrogeological conditions, volume of information, water demand, purpose of calculations made and experience in exploitation of operating well fields. In recent years, Artificial Neural Network (ANN) has shown a great ability in forecasting nonlinear and nonstationary time series in hydrology due to the highly flexible function estimator that has self-learning and self-adaptive feature, therefore it has been widely applied in the hydrology and water resource engineering.

Urban groundwater in recent years has emerged as a specialized area of study within hydrogeology. While the basics of groundwater as a science are well established, the specific aspects of groundwater in urban environments have only recently been recognized. These events have been motivated by the strong interaction between city growth and groundwater impacts.

Because of lack of proper data and planning, quantification of groundwater fluxes and modeling in an urban area are difficult tasks and usually includes expensive, imprecise and difficult to understand methods which require site specific validation. Although conceptual and physically-based models are the main tool for depicting hydrological variables and understanding the physical processes taking place in a system, they do have practical limitations. When data is not sufficient and getting accurate predictions is more important than conceiving the actual physics, empirical models remain a good alternative method, and can provide useful results without a costly calibration time (N. Daliakopoulos et al., 2004). A significant advantage of the ANN approach in system modeling is that one need not have a well-defined physical relationship for systematically converting an input to an output (Nayak et al., 2004).

Artificial Neural Networks (ANNs) has been increasingly applied in various aspects of science and engineering because of its ability to model both linear and non-linear systems without the need to make assumption as are implicit in most traditional statistical approaches. Neural networks are one computational methodology for hydrological forecasting. Although widely used in other research and application fields they are employed less by hydrologists.

Several researchers have applied ANNs to groundwater problems, such as Daliakopoulos et al. (2004), who examined the performance of different neural networks in a groundwater level forecasting in order to identify an optimal ANN architecture that can simulate the decreasing trend of the groundwater level and provide acceptable predictions up to 18 months ahead. Coulibaly et al. (2001) calibrated three types of functionally different artificial neural network (ANN) models using a relatively short length of groundwater level records and related hydrometeorological data to simulate water table fluctuations in the Gondo aquifer, Burkina Faso. Nayak et al. (2006) used ANN to forecast groundwater level in a shallow aquifer and so many researches predicted the groundwater contaminates like Yesilnacar et al. (2007) who predicted nitrate in groundwater.

The purpose of this paper is to identify the need of ANN models that can capture the complex dynamics of urban groundwater table fluctuations. This paper examines and compares the capability of an artificial neural network (ANN) with different sets of inputs for predicting urban groundwater level in urban area, with it's complicated conditions, and determination of the best sets of inputs which increase the accuracy of the prediction.

**Study Area**

Tehran plain (Tehran-Karaj area), locates to the southern piedmont zone of Alborz mountain range, in an area of more than 5,000 km2 bordering to Namak (salt) Lake desert to the south. The average annual precipitation in Tehran is still less than the figure for the country and is about 230 mm. In this regards, Tehran stands among those major cities with almost low rainfall amount in the country. Groundwater has a big share nowadays in supplying water for different purposes to Tehran. The general direction of groundwater flow in the area is from northern Alborz piedmont zone towards the southern deserts in Varamin area. There are two main water bearing zones in the area; in the north, local perched aquifers are formed in the piedmont zone and in the south, the main Tehran aquifer is formed in the Tehran alluvium formation as an unconfined aquifer in Tehran plain. Study area is located in the south zone. To the south, the aquifer material is fine grained and the wells are less productive. There are clay layers but no confined aquifer is logged yet. Transmissivity amounts to 1,200 square meters per day on average, the lower values belong to southern parts. Storage coefficient or specific yield is reported as 3 to 6 percent (JAMAB 1993).

Some decades ago, Tehran was very much less expanded and the north parts of the city were covered with coarse grained alluvium cut with numerous perennial and seasonal rivers. This condition provided a big component of surface flow with the opportunity to percolate through the soil and recharge groundwater. Recharge to groundwater was also possible by surface runoff and precipitation penetrating directly from the surface of the Tehran plain. Following to expansion of the city, a big part of surface runoff and precipitation over the city is conducted through urban surface drainage system to the southern deserts, out of the reach of aquifer.

Now, the natural recharge to groundwater is totally changed in Tehran. One source of recharge to the aquifer is the irrigation return water from the fields throughout the plain which amounts to 380 MCM annually. The other source which seems the most important one is urban returned water or the public and industrial wastewater which is continuously leaving the absorption wells towards the deeper parts and the water table. It may also be discharged from industrial units to surface streams, which then percolates to underground. The total volume of returned water amounted to 800 MCM per year at present. The Tehran aquifer is also recharged through north-south rivers bed percolation, among them the Kan River is the most important one. The general direction of groundwater flow in Tehran area is from north to south.

The depth to water table is less than 100 m in the north and around 5 m in some areas in the south. In the latter case, the water table is influenced by evaporation. As it is shown in Figure 5, in a big part of the city (mainly to the southern part) water table is situated in a depth not more than 30 m. Especially in Rey area, water table is almost close to the surface and continuous pumping operations are performed to make live possible there (Figure 1).

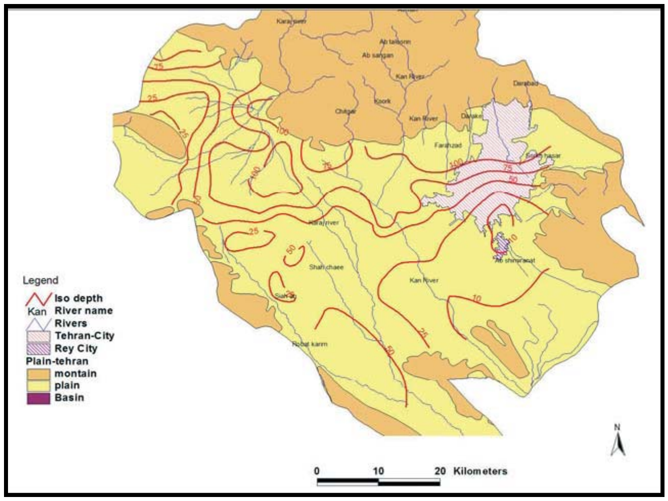

Figure 1. Iso-depth map for Tehran aquifer

**Motivation**

The principal motivation for the neural network approach in urban groundwater prediction is twofold: (1) urban groundwater data is highly complex, scarce and hard to model, therefore a non-linear model is beneficial and (2) large set of interacting input series is often required to explain urban groundwater fluctuation, which suites neural networks.

**Methodology**

**Artificial Neural Network**

Neural networks are massively parallel, distributed processing systems representing a new computational technology built on the analogy to the human information processing system. An ANN is an information-processing construct that consists of a number of interconnected processing elements called nodes, analogous to neurons in the brain. Each node combines a number of inputs and produces an output, which is then transmitted to many different locations, including other nodes. The difference between the various types of ANNs usually comes from the many different ways to arrange the nodes (architecture) and the many ways to determine the weights and functions for training the network (figure 2).

Each processing element in a specific layer is fully or partially connected to many other processing elements via weighted connections. The scalar weights determine the strength of the connections between interconnected neurons. From many other processing elements, an individual processing element receives its weighted inputs, which are summed and a bias unit or threshold is added or subtracted. The bias unit is used to scale the input to a useful range to improve the convergence properties of the neural network. The result of this combined summation is passed through a transfer function (e.g. logistic sigmoid or hyperbolic tangent) to produce the output of the processing element. For node *j*, this process is summarized in Equations 4 and 5 and illustrated in Fig. 2.

$$I_j = \theta_j + f(x) \sum_{i=1}^{n} w_{ji}\, x_i \qquad (4)$$

$$y_j = f(I_j) \qquad (5)$$

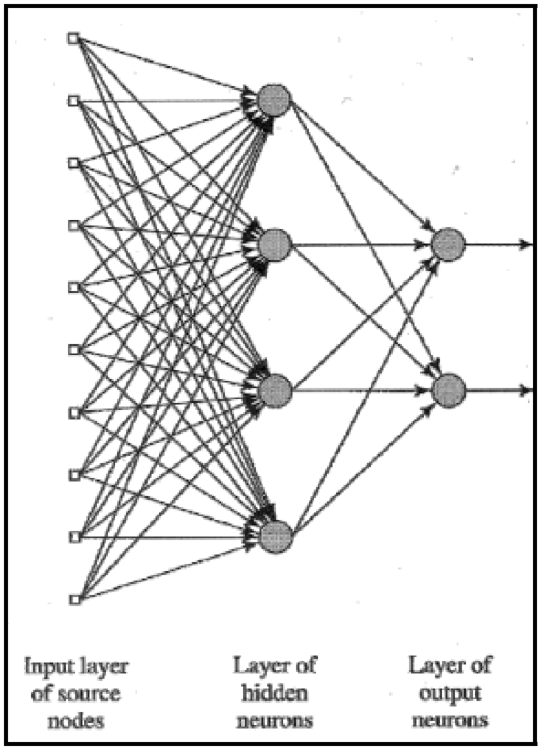

Figure 2: Basic structure of a layered ANN

Where, $I_j$ is the activation level of node $j$; $w_{ji}$ is the connection weight between nodes $j$ and $i$; $x_i$ *is* the input from node $i$ ($i = 0, 1, \ldots, n$), $\Theta_j$ is the bias or threshold for node $j$; $y_j$ is the output of node $j$, and $f(.)$ is the transfer function. The propagation of information in networks starts at the input layer where the input data are presented. The inputs are weighted and received by each node in the next layer. The weighted inputs are then summed and passed through a transfer function to produce the nodal output, which is weighted and passed to processing elements in the next layer. The network adjusts its weights on presentation of a set of training data and uses a learning rule until it can find a set of weights that will produce the input-output mapping that has the smallest possible error. The above process is known as , learning□ or ,training□.
The key attributes of neural networks can be summarized as learning from experience, genera using from examples, developing solutions faster and with less reliance on domain expertise, computational efficiency and non-linearity**.**

Although in the meantime the variety of proposed neural network structures has grown, the multilayered perceptron has remained the prevailing one and also the most widespread network structure. This particularly holds for the three-layer network structure in which the input layer and the output layer are directly interconnected with the intermediate single hidden layer. Cybenko (1989) proved that a single hidden layer neural network is a universal approximator because it can approximate an arbitrary continuous function with the desired accuracy provided that the number of perceptrons in it is high enough.

**Recurrent Networks**

A neural network is called recurrent, if cross, auto and backward connections are allowed. Research in the area of sequential and time-varying patterns recognition has created the need for time-dependent nonlinear input-output mapping using neural networks. To achieve this extended network capability, the time dimension has to be introduced into the network topology, which would enable network to perform time-dependent mappings. In this research recurrent neural network has been used for urban groundwater prediction.

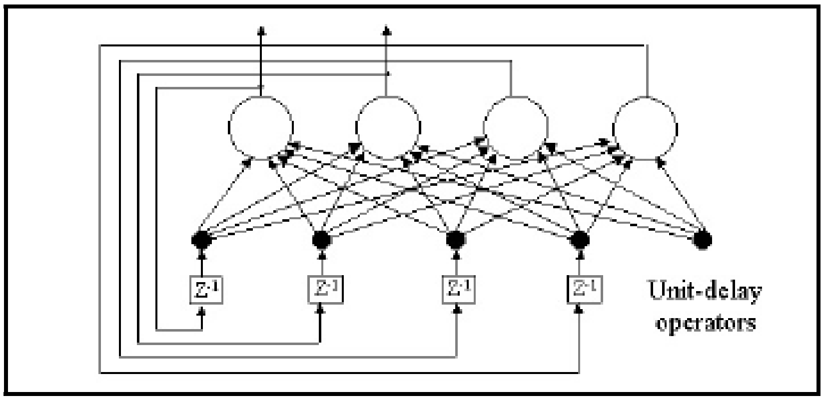


Figure 3: A recurrent network with hidden neurons

**Activation Functions**

A non-linear function (activation function) is applied to the net input of the neuron to produce an output. This activation function output is called the ‘response’ of a given neuron. This nonlinear activation function of the neuron is also simply called the “neuron function”. In this research sigmoid function for hidden layer and linear function for output layer is chosen.

**Levenberg–Marquardt (LM)**

The Levenberg–Marquardt method is a modification of the classic Newton algorithm for finding an optimum solution to a minimization problem. It uses an approximation to the Hessian matrix in the following Newton-like weight update

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (1)$$

where x the weights of neural network, J the Jacobian matrix of the performance criteria to be minimized, μ a scalar that controls the learning process and *e* the residual error vector. When the scalar μ is zero, Eq. (1) is just the Newton’s method, using the approximate Hessian matrix. When μ is large, Eq. (1) becomes gradient descent with a small step size. Newton’s method is faster and more accurate near an error minimum, so the aim is to shift towards Newton’s method as quickly as possible.

Levenberg–Marquardt has great computational and memory requirements and thus it can only be used in small networks (Maier and Dandy, 1998). Nevertheless, many researchers have been successfully using it.

**Data preprocessing**

It is important to pre-process the data in a suitable form before they are applied to the ANN. Moreover, pre-processing usually speeds up the learning process. Monthly Groundwater level, in-city streamflow, rainfall and temperature data in the period of 1992-2007 were collected. We have performed some data preprocessing steps on raw set of monthly data as shown below:

(1) A monthly data were cleaned by filling in missing values. Groundwater level time series contains gaps in some months. These needed to be filled to make the series complete for modeling. Since the gaps were short and the groundwater level data were highly correlated, simple linear interpolation between known values was adequate. The other time series like temperature and streamflow had no gap.

(2) All monthly data were normalized by min-max normalization into a specified range. According to so many empirical trials this has been concluded that ANN responds better using normalized input data set in contrast with raw data because it seemed that normalized data had adapted to the nonlinearities of the neurons.

**Selecting the input data**

An important step in developing ANN models is to select the model input variables that have the most significant impact on model performance (Faraway and Chatfield 1998). In this research all kinds of urban groundwater recharge mechanisms, in study area, have been surveyed. There were 4 kinds of recharge mechanisms, (1) direct recharge, (2) indirect recharge, (3) localized recharge and (4) artificial recharge. The mechanism of recharge in this area is so complicated. The four mechanisms of recharge generally combine to increase recharge.

Neural networks have a great ability in combining different types of data from different sources. It is not necessary to know the nature of the relationship between the input data X and the target output Y, only that there is a strong possibility that there is a relationship. The neural network will determine an approximation to the function f (where $y = f(x)$) during the training process. So it is an appropriate method to replace the available data with usual but scarce data. In this method in place of using parameters like transmissivity and storage coefficient we use common and available data (groundwater level, precipitation, temperature and in-city streamflow time-series).

In this paper two models with two input data set have been developed. For the first model groundwater level and rainfall have been chosen as an input set and for the second model in-city streamflow and temperature has been added to the input data set. The output variable in both models was urban groundwater level.

**Determination of Model Architecture**

After selecting the input data set and Levenberg–Marquardt algorithm, the number of neurons was optimized keeping all other parameters constant. ANN topology is problem dependent. Whatever the type of ANN model used, it is important to determine the appropriate network architecture in order to obtain satisfactory generalization capability.

During the training of the prototype, a series of training runs took place until the optimal architecture and the 'optimal' set of weights was obtained. In this research the data divided into three sets: training, testing and validation. The training set is used to adjust the connection weights, whereas the testing set is used to check the performance of the model at various stages of training and to determine when to stop training to avoid over-fitting. The validation set is used to estimate the performance of the trained network.

Determining the network architecture is one of the most important and difficult tasks in ANN model development. It requires the selection of the optimum number of layers and the number of nodes in each of these. There is no unified approach for determination of an optimal ANN architecture. It is generally achieved by fixing the number of layers and choosing the number of nodes in each layer. Hecht-Nielsen (1989) provided a proof that a single hidden layer of neurons, operating a sigmoidal activation function, is sufficient to model any solution surface of practical interest (Hecht-Nielsen, R., 1987).

In this research we use recurrent neural network. The number of input depends on the parameters and their lags selection. Trial-and-error procedure, which is generally used in engineering to determine the number and connectivity of the nodes, has been used. The models have been trained until stopping criterion has been met. The optimal network has been chosen. Selecting the best time lags for input layer was even a challenge. The MSE decreased for the training set with increasing neuron numbers in hidden layer. However, after optimum neuron number, the MSEs did not change significantly and even worse off.

Thus for the first model the input layer consisted of 8 input nodes; time-lag was included t-1, t-2, t-3, and t-4 for precipitation, and groundwater level. In the first model, after so many trial and errors the number of neurons in hidden layer determined to 5. For the second model the input layer consisted of 20 input nodes; time-lag was t-1, t-2, t-3, t-4 and t-12 and for precipitation, groundwater level, temperature and in-city streamflow. In the second model, the hidden layer consists of 11 nodes. Out-put layer of both models consists one node, it is groundwater level which is the depth of water from the surface. 12 months ahead prediction has been examined in both models.

**Stopping Criteria**

Stopping criteria are used to decide when to stop the training process. As mentioned before, to overcome problems like model stopping prematurely or over-training, *cross-validation* technique has been used. It is considered to be the most valuable tool to ensure overfitting does not occur (Smith 1993). The cross-validation technique requires that the data be divided into three sets; training, testing and validation. Training is stopped when the error of the testing set starts to increase.

**Model Validation**

Once the training phase of the model has been successfully accomplished, the performance of the trained model should be validated. The purpose of the model validation phase is to ensure that the model has the ability to generalize within the limits set by the training data in a robust fashion, rather than simply having memorized the input-output relationships that are contained in the training data. The models are evaluated using three statistical performance criteria namely Mean Square Error (MSE), Root Mean Squared Error (RMSE), $R^2$ efficiency criterion.

**Mean Square Error (MSE)**

For every data point, take the difference of the observed to the corresponding estimated values, and square the values. Then add up all those values for all data points, and divide by the number of points. The squaring is done so negative values do not cancel positive values. Smaller MSE indicates better prediction of the data. The MSE has the units squared of the parameter estimated.

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

**Root Mean Square Error (RMSE)**

It is probably the most easily interpreted statistic, since it has the same units as the parameter estimated. The RMSE is thus the difference, on average, of an observed data and the estimated data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{3}$$

**$R^2$ efficiency criterion,**

Also, the $R^2$ efficiency criterion, given by

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n} {x_i}^2 - \frac{\sum_{i=1}^{n} {y_i}^2}{n}} \tag{4}$$

representing the percentage of the initial uncertainty explained by the model. The best fit between observed and calculated values, which is unlikely to occur, would have RMSE=0 and $R^2$=1.

**Data description**

The time series used in this project are summarized in the following figures. Monthly precipitation in figure 4 shows the typical characteristics of Tehran climate comprised of medium rainfall during the winter months and no rainfall during the summer months, as shown in Fig. 6. Direct recharge in cities takes place by percolation in unpaved areas, and to a lesser extent through paved surfaces that are not always perfectly “impervious”. According to Davision et al. (2002) roughly 50% of the impervious cover should be treated as permeable.

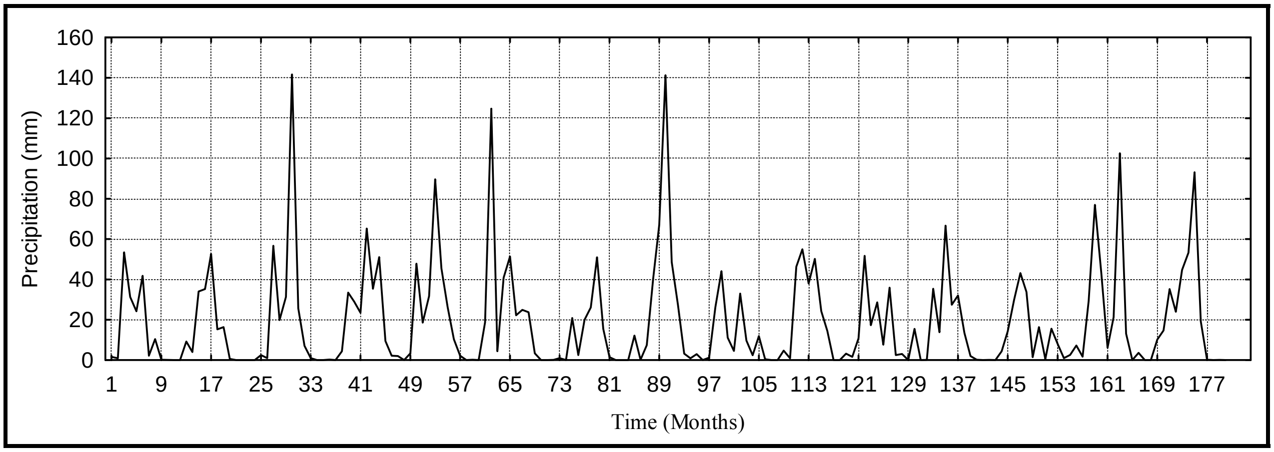


Figure 4. Monthly precipitation in mm versus time in months for 15 years in Tehran.

Temperature also plays an important role in the water budget as it affects evapotranspiration. Fig. 5 shows monthly temperature measurements at the meteorological station of Tehran. Values appear to vary steadily through the years with a slight increasing trend as shown by the bold line in figure 5.

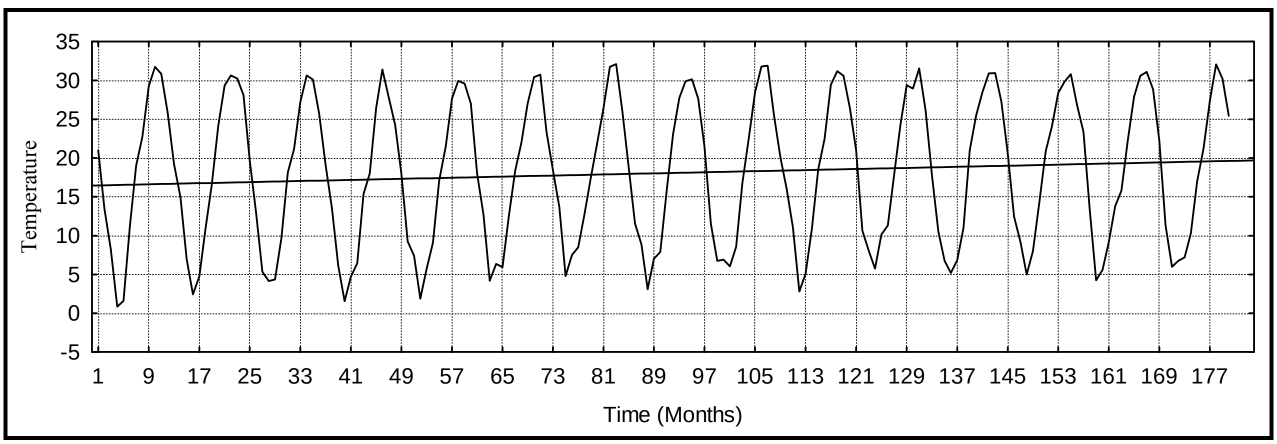


Figure 5. Monthly temperature in degrees Celsius versus time in months for 15 years in Tehran.

Figure 6 represents the monthly streamflow of Kan River which runs through Tehran aquifer. The Tehran aquifer is recharged through Kan River bed percolation. The streamflow of Kan River has been steadily decreasing for the 15 years as shown in Fig 6. There is a significant interaction between the Kan River and groundwater level. The groundwater level fluctuation changes the gradient in the area between groundwater and river so usually it cause stream to have less than normal flow during most of the year.

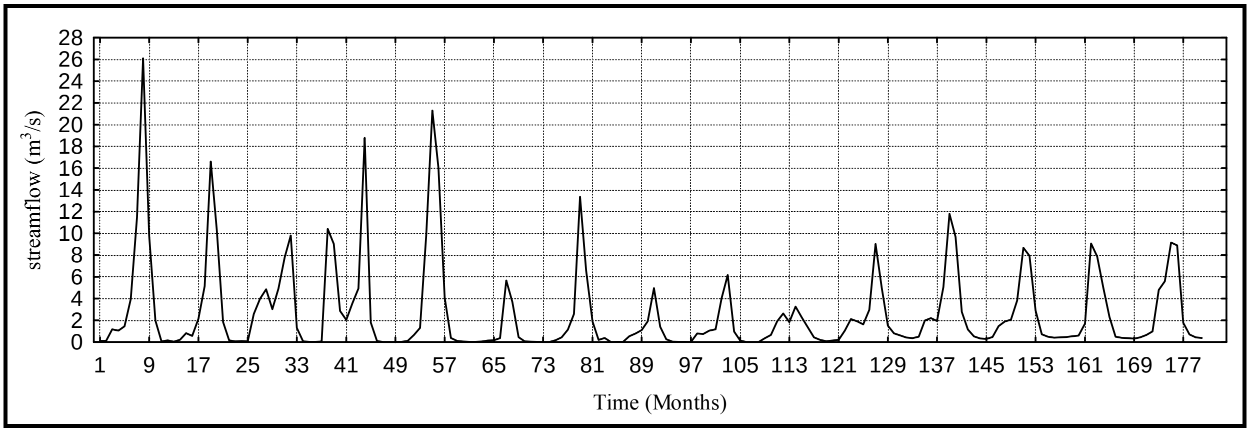


Figure 6. Monthly streamflow of Kan river in M³/s versus time in months for 15 years in Tehran.

The monthly level of a characteristic well located in Tehran is represented in figure 7. This figure indicates the depth of water from the surface. This fact also indicates that the transition between different levels of the aquifer through the year is not so smooth and steady. The statistical groundwater characters are shown in figure 8. One of the goals of this paper is to evaluate the ability of artificial in modeling such complex behavior of urban groundwater in the area.

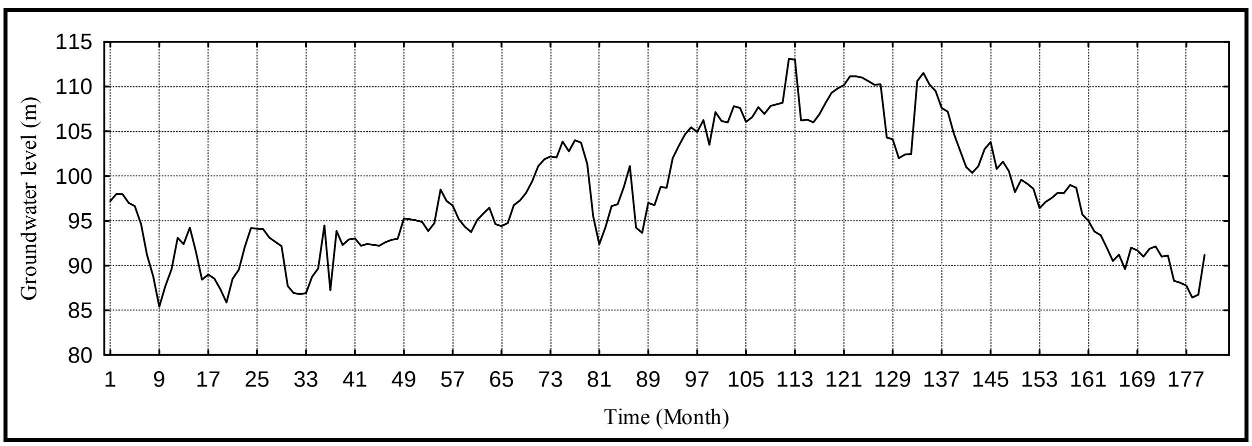


Figure 7. Monthly groundwater level (depth from the surface) in m versus time in months for 15 years for a well in Tehran.

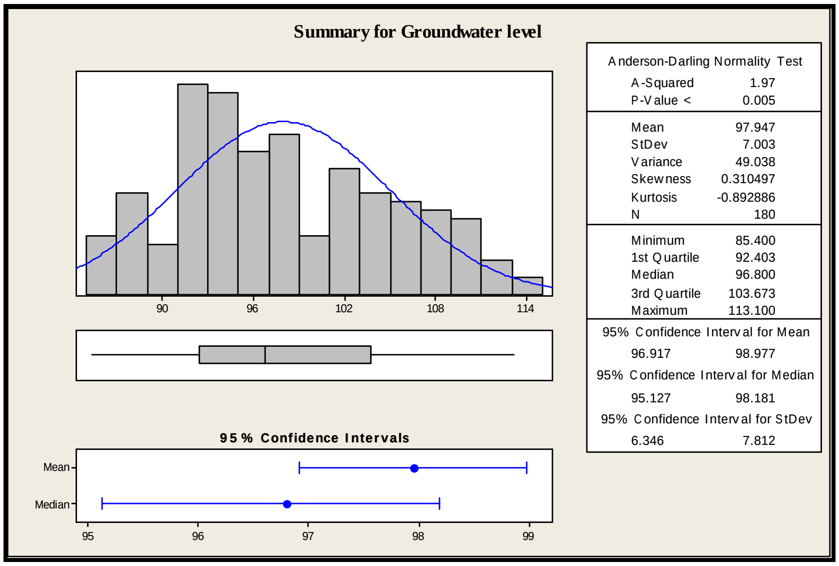


Figure8. Statistical characteristic of urban groundwater level

Table 1 summarizes the performance of forecasting for all of the observation data in terms of Mean Square Error (MSE), Root Mean Squared Error (RMSE), $R^2$ efficiency criterion during the training and testing period, which took place after a number of trial-and-error runs. In general, the results were satisfactory. However, the forecasting of the both models seems perfect but the second model has a better forecasting. It is concluded that ANN has a great capability in modeling urban groundwater management but the accuracy of prediction can be increased by using even common data but relative to the recharge mechanisms. In the following, results from the empirical study are presented. Both model responses for training period, prediction period (1 step ahead for all 12 months of a year), correlation between observed and predicted data and is shown in figure 9 and 11.

Table1. Performance of forecasting

| ANN architecture | MSE ($m^2$) | RMSE (m) | $R^2$ |
|---|---|---|---|
| Model (1) | 2.06 | 1.43 | 0.97 |
| Model (2) | 1.14 | 1.06 | 0.98 |

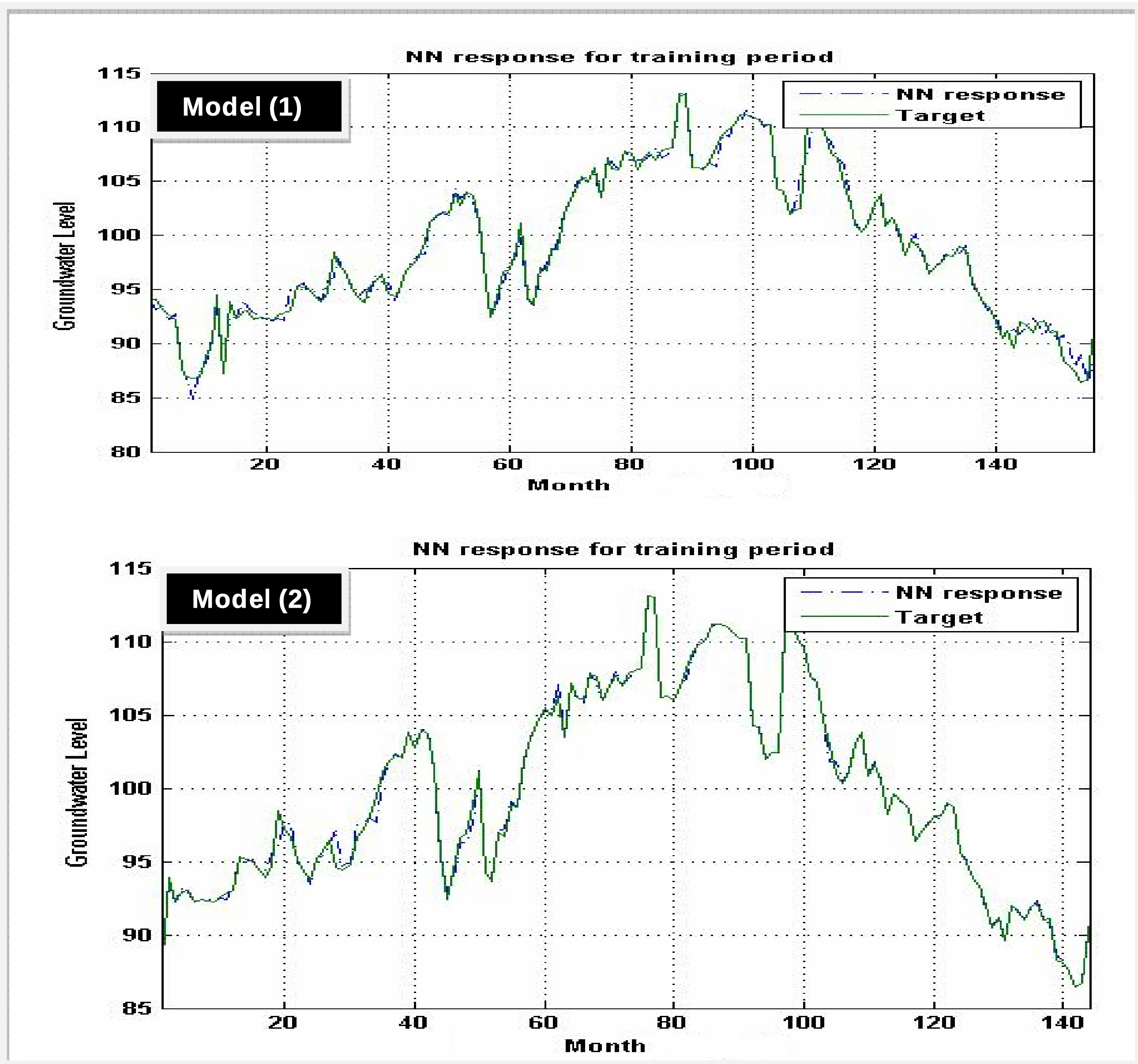


Figure 9. Models responses for training period

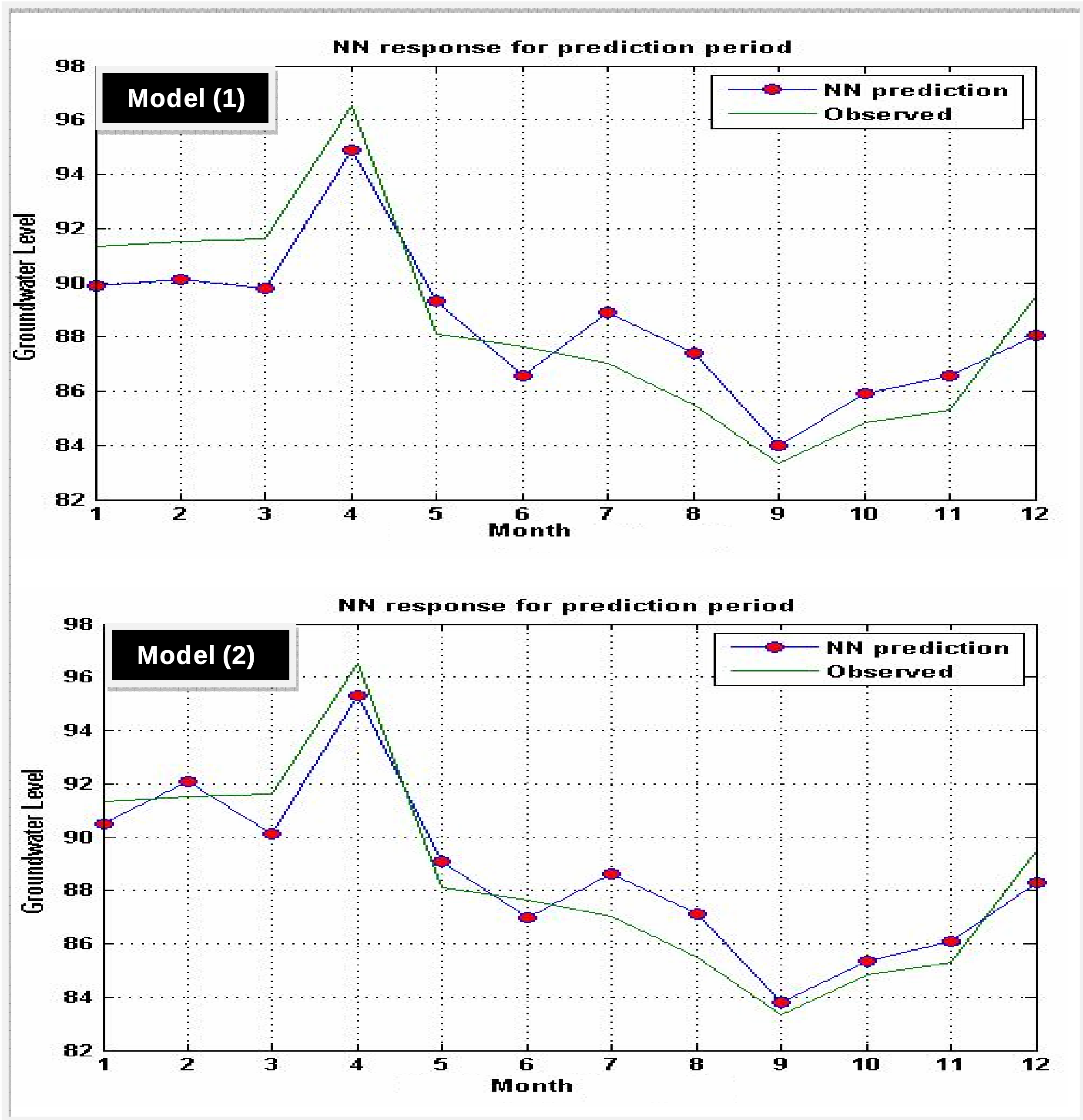


Figure 10. Models responses for prediction period

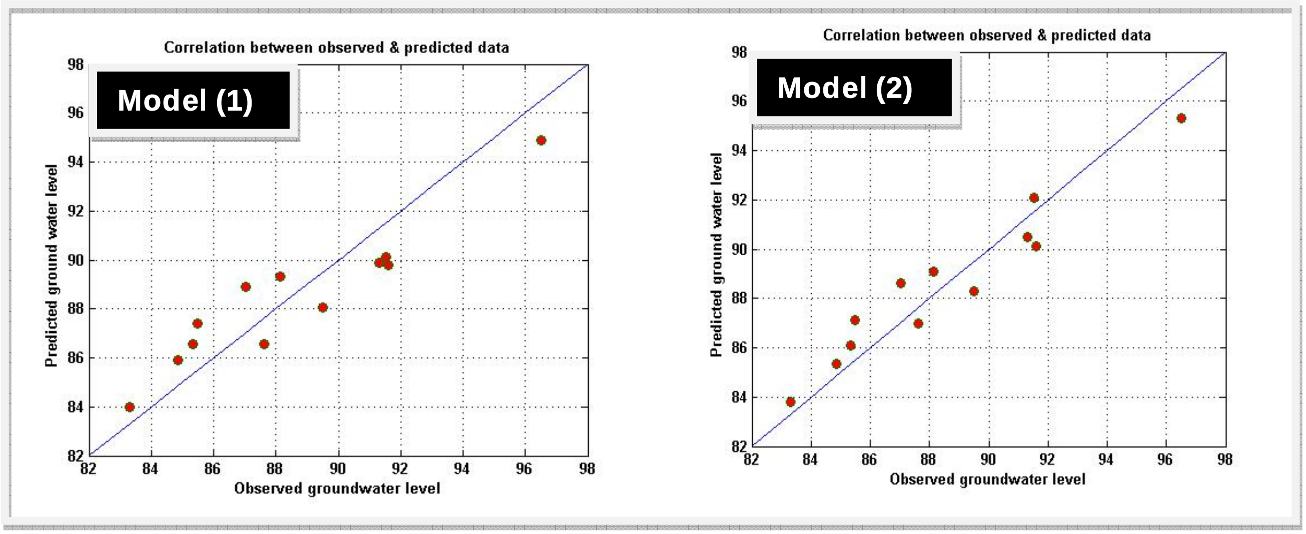


Figure 10. Models responses for prediction period

Articles in which the groundwater level in the urban area has been simulated applying ANN, is so rare.
The first finding is, proving the sufficiency of common and available data (like GW level, precipitation, in-city streamflow and temperature time-series), for groundwater level prediction without any need to geohydrological data applying artificial neural network.
The second finding is the illustration of the importance of input selection and the effect of them on the accuracy of prediction. In this research as the third finding we find that this is correct that the artificial neural network can use common data for predicting the urban groundwater level and we can make the prediction more accurate by use of the best set of input data but for making the prediction more and more accurate we must use some special data like the leakage from the water and sewer utilities and land use distribution in the city.

## Conclusions

Urban groundwater fluctuation is more complex than the groundwater in rural or natural area. The greatest finding of this study is, proving ANN capability in simulation of groundwater fluctuation in an urban area by use of available data (GW level, precipitation, in-city streamflow and temperature time-series), without any need to geohydrological data.

An artificial neural network model has been developed to simulate the urban ground water level fluctuation in an observation well with a case study of an observation well in Tehran as a megacity. This study has shown that neural networks are effective at predicting monthly urban groundwater level fluctuations in the Tehran aquifer. Several networks have been developed and finally sigmoid activation function has been selected for hidden layer, (the output layer has linear activation function) in our case. The performance criteria, showed an encouraging value. A significant advantage of these models is that they can provide satisfactory predictions with common data due to the scarce in hydrogeological data in Tehran. As it showed even first model had a good response in prediction. The experimental results suggest that beside input data set, lag time selection is so effective in increasing prediction horizon and accuracy. However, the difficulty in identifying good raw data, data preprocessing, training a network and repeating this process until a good model is developed should not be discounted. The individual investor should be warned that model accuracy is difficult to obtain and can take months or years of investigation.


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