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Forecasting Groundwater Level under Climate Change and Water Resources Management Scenarios

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Abstract

Groundwater is an important source of freshwater the world over, especially in arid and semiarid regions. In recent years, groundwater overextraction has led to a serious drawdown in groundwater level in many aquifers. Hence, the projecting groundwater level is essential for the planning and management of water resources in a basin scale. This study aimed to project the mean groundwater level in Najafabad Plain in central Iran. Najafabad Plain is one of the most important aquifers in the Zayandeh-Rud River basin currently facing a negative hydrologic balance, which has been aggravated by the excessive agricultural demand that has adversely affected its groundwater level. For the purpose of the study, a multilayer perceptron Artificial Neural Network (ANNs) was developed. Recently, alternative algorithms have been used for training ANNs to overcome the disadvantages of the Back Propagation (BP) algorithm that is easily stuck in local minima and slow training convergence. In this regard, the Levenberg–Marquardt algorithm as the classical method and the Particle Swarm Optimization (PSO) as the evolutionary algorithm are adopted for training the feed forward ANNs and improving their performance. The obtained results from LM-NN were then compared with those from ANN-PSO model and observed information. Comparison of the results projected by the ANN-PSO and the observed mean groundwater levels using 58 piezometric wells with monthly time steps over a 20-year period showed that the ANN-PSO model is superior to LM in predicting groundwater level. As an illustration, for models run using nine hidden neurons for Nekouabad right zones the root mean square error (RMSE) of the testing dataset for ANN-PSO was the lowest (1.50) compared to those for LM-NN (1.76). Accordingly, the ANN-PSO models are able to be used as a reliable tool for evaluating different scenarios of the water resources management in the study aquifer. Finally, three management scenarios under two climate change scenarios, A2 and B1 (obtained from GCMs), were defined and the trained ANN-PSO was subsequently used to project the effects of each scenario on the groundwater level in the plain.

Keywords: Groundwater Level, Artificial Neural Networks, Particle Swarm Optimization.

1. Introduction

Over the past decades, there has been a dramatic increase in the number of studies which have focused on predicting groundwater level. Groundwater resources has received much attention in recent years because of its importance as a source of freshwater especially during drought periods. The exploitation of groundwater has grown as agricultural, industrial, and domestic uses have led to a greater drawdown in many basins of the world. On the other hand, climate change has also affected water resources adversely due to changes in the components of the hydrologic cycle (USEPA, 2008). Nowadays, water crisis is an imminent challenging issue due to the global warming, changes in the pattern and intensity of rainfall, amounts and duration of snow cover, rising sea level, increasing evapotranspiration, and quantitative and qualitative changes in surface water and groundwater resources (Kolsoumi and Salehnia, 2009). These changes can substantially affect water resources management practices (Ashofteh et al., 2016, Safavi et al., 2016). The impacts of climate change on groundwater are relatively limited compared to surface water (USEPA, 2008). Recently, some researchers investigated the climate change impacts on groundwater recharge and groundwater level (Croley and Luukkonen, 2003, Brouyère et al., 2004, Scibek and Allen, 2006, Tapoglou et al., 2014, Zhang, 2015, Mani et al., 2016, Goodarzi et al., 2016, Smerdon, 2017, Cuthbert et al., 2019, Chunn et al., 2019, Guermazi et al., 2019).

To date, there have been many studies to predict the groundwater level using mathematical models. Models are categorized as black-box models, conceptual models and physically based distributed models. In view of accuracy, the physically based distributed model can be considered a better choice. However, the notable data requirements of such models, coupled with the time involved in model development, calibration and validation compared to other model categories, make them an undesirable choice. Lumped conceptual models are favored in terms of their limited data requirements and inclusion of a conceptual framework, but they require a lengthy calibration and parameterization process (Sarangi et al., 2005).

In other words, physical models work best when data on the physical characteristics of the watershed are available at the model grid scale. This kind of data is rarely available, even in heavily instrumented research watersheds. Furthermore, these models require historical data for model calibration purposes (ASCE, 2000). In this context, use of Artifical Neural Network[1] models offer an alternative to the distributed and physics-based modelling approaches. It enjoys the capacity to distinguish any connections between input and output data in the absence of any physical assumptions or principles (Coppola Jr et al., 2003). Many studies worldwide have examined the ability of ANN for the prediction of groundwater levels using such varied input parameters as precipitation, temperature, pumping rate, and evapotranspiration. (Coppola Jr et al., 2003, Lallahem et al., 2005, Mohanty et al., 2010, Safavi et al., 2010, Trichakis et al., 2011, Bozorg-Haddad et al., 2013, Karthikeyan et al., 2013, Sahoo and Jha, 2013, Fallah-Mehdipour et al., 2014, Chang et al., 2015, Mohanty et al., 2015, Safavi and Rezaei, 2015, Yan and Ma, 2016, Khaki et al., 2016, Yoon et al., 2016, Jeihouni et al., 2019). Back Propagation (BP) algorithm is the most common technique that has been used for ANN training in a host of studies. However, being a gradient-based method, it has certain disadvantages; for instance, it easily gets stuck in local minima and has a slow training convergence (Garro et al., 2009). Many studies have been developed to improve the performance of the back-propagation algorithm by developing training algorithms such as Levenberg–Marquardt algorithm. Levenberg–Marquardt algorithm is the most popular and commonly used neural network training algorithm. Furthermore, several studies have developed evolutionary algorithms such as Genetic Algorithms (Leung et al., 2003, Jha and Sahoo, 2015) and Particle Swarm Optimization (Zhao and Qian, 2011) to improve the performance of classical neural network training.

Particle Swarm Optimization[2] is an evolutionary computation technique first developed by (Kennedy and Eberhart, 1995). PSO is a population-based search algorithm based on the study of colonies or swarms of social organisms such as birds or fish (Kennedy and Eberhart, 1995). Use has been made of this technique in various water engineering studies such as reservoir modeling and operation (Guo et al., 2013, Luo et al., 2015), water quality management (Afshar et al., 2011), hydraulic modeling and optimization (Zhen-zhong et al., 2010, Buyukyildiz and Tezel, 2015), estimating hydrologic parameters (Chu and Chang, 2009, Moghaddam et al., 2016), rainfall-runoff modeling (Liu, 2009), water distribution systems (Sheikholeslami and Talatahari, 2016), and groundwater utilization (Gaur et al., 2013, Cyriac and Rastogia, 2015). The ANNs are coupled with PSO in many hydrological studies. Some cases include the prediction of water levels in the Shing Mun River in Hong Kong (Chau, 2006), modeling the daily rainfall-runoff relationship (Kuok et al., 2010), prediction of storage coefficient and transmissivity of aquifers (Ch and Mathur, 2012, Mohammad Rezapour Tabari, 2015), simulation of hydraulic head changes in an observation well in the area of Agia in Greece (Tapoglou et al., 2014), prediction of future stream flow discharges in the Shenandoah River watershed (Taormina and Chau, 2015), and daily runoff forecasting

[1] Artifical Neural Network (ANN)

[2] Particle Swarm Optimization (PSO)

(Cheng et al., 2015).

This study focuses on projecting groundwater level under different management scenarios and climate change conditions. An artificial neural network trained by PSO is developed to simulate the mean groundwater level in Najafabad Plain as the case study. Zayandehrud River basin is located in central Iran with semi-arid region. In recent years, increased demand has led to pumping of groundwater from aquifer for irrigation, industrial development and domestic uses. This over extraction and climate change have led to increasing pressure on groundwater resources.

2. Materials and methods

2.1. Study Area

To assess the applicability of the proposed methodology, it is applied to the Najafabad plain, part of the Zayandehrud River basin located in the western part of central Iran (Fig. 1). Najafabad plain has an area of around 1,720 km^2 and its aquifer has an area of around 1,142 km^2 with geographical coordinates between 50′ 57″ to 51′ 44″ north longitude and 32′ 20″ to 32′ 49″ east latitude. The aquifer is recharged by irrigation percolation, channel and river seepage, and direct precipitation. Aquifer recharge incidental to irrigation is a significant component of the water budget and varies with the evolution of irrigation practices (Safavi et al, 2010).

Modern surface irrigation practices in the area started some 45 years ago after the construction of the Nekouabad diversion weir. This diversion weir controls both the left and right bank main zones (Fig. 1).

Assessment of water exchanges in a given area is based on the principle of conservation of mass. Hydrological equilibrium is defined as the persistence of the water cycle in an area. In fact, all the water within a specific period of time in a particular area is either used or stored, or exists in the area in different ways. The components that feed the aquifer include surface and subsurface inflow and outflow, precipitation, imports from rivers and irrigation channels, and the return water from agricultural lands. The components of aquifer depletion contain abstraction of groundwater from wells and evapotranspiration.

In this study, all required data from hydrometrical and meteorological stations, history of channels operation and extraction wells data such as their groundwater levels and pumping rates were obtained from a report published by Isfahan Regional Water Company, 2014. Rainfall and temperature data for the statistical period of October 2000 to September 2019, extracted from Zefre station on a monthly basis, are used as the input variable for the ANN models in calibration. The historical data was collected from 51 piezometric wells within the study area and 7 piezometric wells outside the region (Fig. 2). ArcGIS was used to interpolate the data and to derive the mean groundwater level for each of the Nekouabad left and right irrigation zones. One of the best ways to calculate the amount of water recharged into the aquifer from the river is to measure simultaneously the river flows at at least two consecutive sections along the river. The difference may be considered as the water recharged by the river into the aquifer. There are two hydrometric stations with long-term data, namely the Leng Station at the entrance to the aquifer and Musian Station near the exit from the aquifer (Fig. 3). No water is extracted along the distance between these two sections.

2.2. Artificial Neural Networks

ANNs belong to the category of empirical models because they regard the process as a black box system with inputs and outputs (Dawson and Wilby, 2001). Unlike physical models, ANNs do not require the physical characteristics or conditions of the systems analyzed. They are less data and labor intensive but more cost effective than their counterparts (Mohanty et al., 2010).

Feed forward neural network is one of the simplest architectures widely used in water resources management. In this type of neural network, the data flows through the network in a single direction from an input layer to the output one via hidden layer(s) (Mohanty et al., 2010).

Three data sets are commonly recommended to be employed for an accurate analysis of ANN: a training (calibration) set, a testing set, and a validation set. The training data set is the initial dataset used to adjust the weights and biases to minimize the error function and to maximize accuracy in each iteration. In order to ensure that the network does not overfit, the test set is helpful. This set is regarded as part of the training set which is used to fine tune the parameters and to determine when the training process should be terminated. Finally, the validation set is necessary to evaluate the accuracy of the model against unseen data (Dawson and Wilby, 2001). Data normalization is also essential to avoid overturning. The normalization technique used in this study is the Gaussian function with a mean of 0 and the unit standard deviation is expressed as follows

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where

X_{max} and X_{min} are maximum and minimum data and X_n represents normalized data.

In order to evaluate the accuracy and effectiveness of the ANN model, three different criteria are used. The first one is the Coefficient of Determination calculated as follows

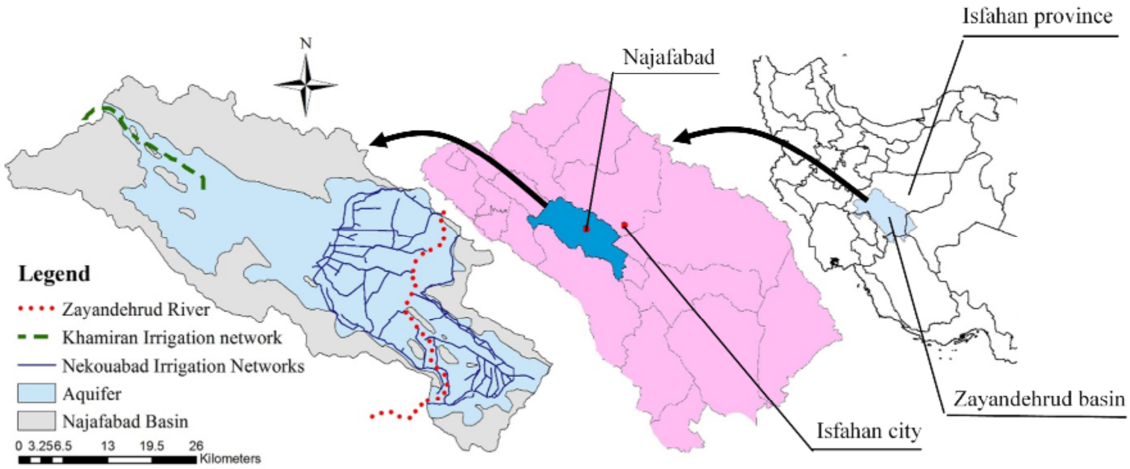

Fig. 1. Location of the Najafabad plain in the Zayandehrud River basin and Nekouabad irrigation network

Fig. 2. Locations of the piezometric wells in Najafabad plain

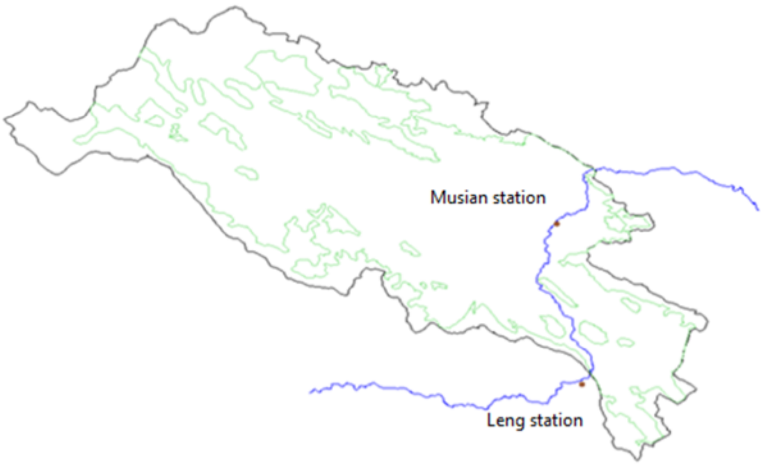

Fig. 3. Locations of the Leng and Musian hydrometric stations

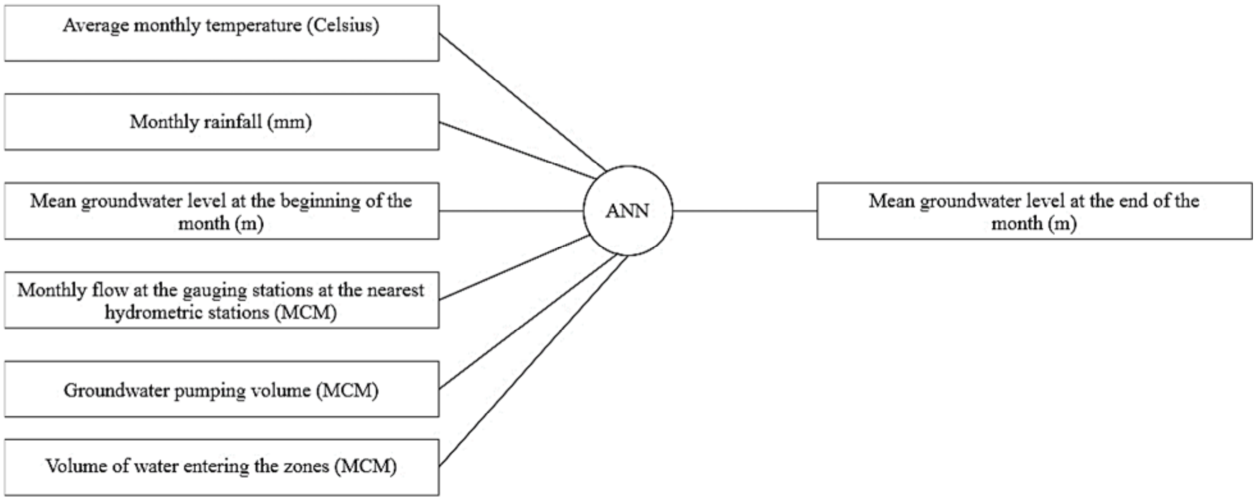

Fig. 4. Artificial neural network input and output diagram

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(T(i) - O(i))^2}{\sum_{i=1}^{N}(T(i) - \overline{T})^2} \quad (2)$$

The second one is the RMSE[1] and the last one is the APE[2] given by (3) and (4), respectively

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(T(i) - O(i))^2}{N}} \quad (3)$$

$$APE = \frac{1}{N}\sum_{i=1}^{N}\frac{T(i) - O(i)}{T(i)} \quad (4)$$

where
T(i) is the observed data, O(i) is the calculated data, and N is the number of observations made. The best fit between the observed and the calculated data will give RMSE and APE close to zero and R^2 close to 1.

In this study, a multi-layer perceptron feed forward neural network architecture was employed to simulate the water equilibrium in the study plain. In addition, tansig is the neural transfer function in all layers. As shown in Fig. 4, the ANN model has six nodes in its input layer that consist of mean groundwater level at the beginning of the month, monthly rainfall, average monthly temperature, groundwater pumping volume, volume of water entering the zones, and the monthly flow at the gauging stations at the nearest hydrometric stations. The set of inputs to the ANN are selected according to previous studies in this basin and the experts and relevant specialist opinions. Selected input parameters are the most important and have the greatest impact on groundwater levels. For example, the evaporation is not considered as an input variable because of the low groundwater level in this area. Due to the fact that the evaporation variable cannot have a direct effect on low groundwater level fluctuations. Also, there are no absorption wells in the area and due to the presence of the sewerage network, the leakage of sewage into groundwater is negligible.

The collected data cover a period of 240 months from October 2000 to September 2019. The mean groundwater level at the end of the month is considered as the only node for the output layer. The database is randomly divided into three patterns to ensure each pattern comprises the dry, wet, and normal periods. Out of the available data, 60% (144 patterns) is used as the training (or calibration) set, 20% (48 patterns) is set aside for testing, and 20% (48 patterns) for validation.

2.3. Particle Swarm Optimization

PSO is an evolutionary population-based model which has been successfully applied to a wide variety of optimization problems. It has attracted considerable attention of researchers because of its advantages such as simple concept, easy implementation, computational efficiency, rapid convergence, lower number of parameters to be tuned, and less sensitive parameters (Lee and Park, 2006).

PSO is initialized with a population of random solutions called particles. The particles constitute a swarm that move around in the search space and look for the best solution. Each particle in PSO is also associated with a velocity which is adjusted according to its own

[1] Root Mean Square Error (RMSE)
[2] Average Percentage Error (APE)

flying experience as well as the flying experience of other particles. Each particle keeps track of its "best" (highest fitness) position in the solution space. This is called "Pbest" for an individual particle and "Gbest" for the best in the population.

The basic concept of the PSO can be found in (Tsafarakis et al, 2013). Fig. 5 shows the flowchart of PSO.

The first new parameter added to the original PSO algorithm is the inertia weight (Shi and Eberhart, 1998). It has been introduced in order to control the exploration and exploitation abilities of the swarm and to eliminate the need for velocity clamping. Hence, the velocity of each particle is updated according to Equation 5. The major inertia weight facilitates the global search while the minor inertia weight facilitates the local search. A number of different strategies have been suggested for determining the value of inertia weight during a run. Three main groups of these approaches are constant, time-varying, and adaptive inertia weights (Nickabadi et al., 2011)

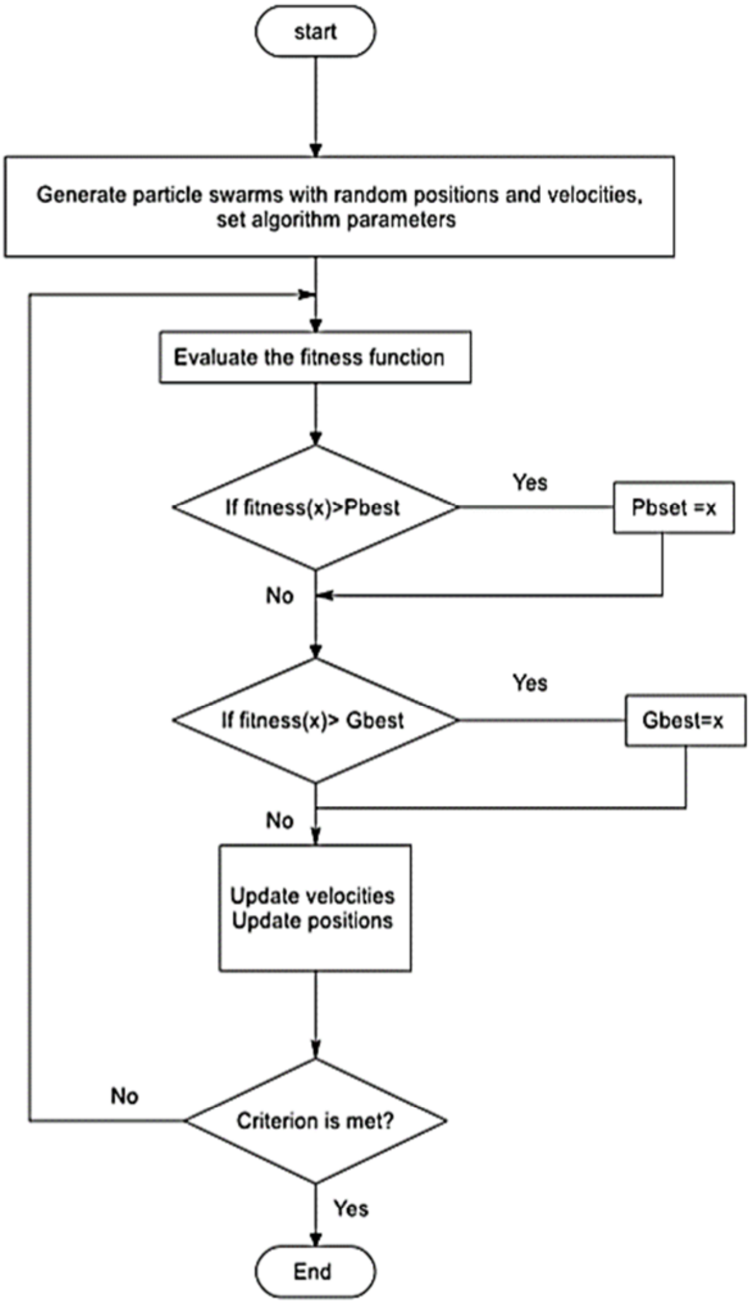

Fig. 5. Flowchart for particle swarm optimization (Tsfarakis et al., 2013)

$$\nu_{ij}(t+1) = w\nu_{ij}(t) + c_1 r_{1j}(t)[Pbest_{ij}(t) - x_{ij}(t)] + c_2 r_{2j}(t)[Gbest_j - x_{ij}(t)] \tag{5}$$

(Clerc and Kennedy, 2002) introduced the constriction factor in order to improve the standard algorithm and to control the particle's path without limiting its velocity. The velocity equation may be replaced with Equation 6 below

$$\nu_{ij}(t+1) = x(\nu_{ij}(t) + \phi_1(t)[Pbest_{ij}(t) - x_{ij}(t)] + \phi_2(t)[Gbest_j - x_{ij}(t)]) \tag{6}$$

where

χ is the constriction factor which is fixed during a run according to (7) below

$$x = \frac{2}{\left|2 - \phi + \sqrt{\phi^2 - 4\phi}\right|} \tag{7}$$

While

$$\phi = \phi_1 + \phi_2 \tag{8}$$

and

$$\phi > 4 \tag{9}$$

Typically, ϕ_1 and ϕ_2 are set to 2.05, which corresponds to a value of 0.7298 for χ. In this case, the particle's efficiency is excellent (Qiu and Liu, 2009).

2.4. Particle Swarm Optimization Feed Forward Neural Network[1]

There are three important points for neural network training, namely finding a near optimal topology, synaptic weights, and transfer function for each neuron (Yusiong and Naval, 2006). In this study, PSO is applied to find a near optimal set of synaptic weights for a fixed structure. In order to achieve this goal, each particle is represented by a matrix composed of synaptic weights and biases. The fitness function for each particle is the MSE[2]. The particle will move within the weight space to optimize its fitness function. The PSONN algorithm can be described by the text outlined in 2.3 above. The search space is an important aspect of convergence to the solution. An insignificant search space does not provide enough freedom for the particles to explore the space and, thus they fail to find the best position. Hence, the convergence rate decreases when there is no limit on the search space range (Gudise and Venayagamoorthy, 2003). The swarm size depends on the problem. In this study, 80 particles are limited in the range [-10,10] and the stopping criterion is defined as a limit of up to 800 iterations.

3. Results and discussion

3.1. ANN-PSO simulation model

With the aim of this study, two independent models are developed for simulating the Nekouabad left and right irrigation zones. With respect to this case study, two different algorithms, PSO-based and Levenberg–Marquardt, were employed to identify the more efficient network. Considering that there are no specific rules for formulating the ANN structure, the number of hidden layers and the neurons in each layer could be determined by trial and error in order to achieve the most accurate simulation. However, a general rule to follow is that the lower the number of neurons, the more accurate the simulation of the network will be, whereas too many nodes lead to overfitting (ASCE, 2000).

Coulibaly et al., suggested more than twenty-three rules for training neural networks, though none guaranteed a global solution (Coulibaly et al., 1999). A review of recent studies reveals that neural networks trained by the standard back-propagation algorithm account for more than 90 percent of the ones used in most studies (Mohanty et al., 2010).

A trial and error procedure was needed to determine the network architecture. The network architecture has a significant influence on the performance of ANNs. If the network architecture is too simple, the ANN model might not have much freedom to train, while too complicated architectures might take a long time for the network to be trained due to over-fitting. So in this study, three categories of network architecture for each LM and PSO training algorithm were tested to determine the best network architecture. Three architectures are defined in such a way that they are in the low, medium and high complexity levels, respectively.

Table 1 and Table 2 provide the comparison results of two different algorithms with three different networks for Nekouabad left and right zones, respectively. Clearly, the PSO-based algorithm with nine hidden neurons outperformed the LM[3] one, especially as regards the validation process. This structure recorded a lower Average Percentage Error and a higher Coefficient of Determination. This was, therefore, selected as the best structure.

3.2. Scenario development

The selected ANN was used to evaluate the impacts of different management scenarios on the mean groundwater level under climate change conditions in

[1] Particle Swarm Optimization Neural Network (PSONN)

[2] Mean Squared Error (MSE)

[3] Levenberg- Marquardt (LM)

Table 1. Simulation results for Nekouabad left irrigation zone

Nekouabad left	Network structure		APE (%)			R^2 (%)			RMSE		
Algorithm	First layer	Second layer	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
PSO-based	9	0	3.52	5.68	4.31	97.58	93.82	95.80	1.39	2.05	1.66
	8	6	4.17	5.41	5.37	96.19	95.43	91.25	1.71	1.75	2.33
	11	4	4.51	7.03	7.82	96.41	87.11	90.12	1.61	3.01	2.67
LM	8	0	1.62	5.83	6.44	99.57	90.36	91.15	0.57	2.55	2.48
	8	6	2.91	6.26	6.86	98.19	92.78	90.51	1.07	2.30	2.58
	10	5	3.84	7.00	7.83	96.23	89.99	88.61	2.76	2.68	1.69

Table 2. Simulation results for Nekouabad right irrigation zone

Nekouabad left	Network structure		APE (%)			R^2 (%)			RMSE		
Algorithm	First layer	Second layer	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
PSO-based	9	0	4.39	5.17	5.80	92.65	90.12	91.17	1.43	1.50	1.61
	9	4	4.75	5.97	6.15	92.03	88.35	89.42	1.44	1.68	1.78
	11	4	6.48	8.82	9.31	89.94	76.05	76.54	1.71	2.32	2.35
LM	9	0	4.45	6.18	5.73	92.06	88.20	90.12	1.48	1.76	1.64
	9	4	4.24	6.22	5.24	93.17	86.82	88.40	1.37	1.83	1.75
	11	5	4.05	5.97	6.20	93.93	88.35	86.51	1.28	1.67	1.96

the study area. The results obtained from the AOGCMs[1] (Wilby and Harris, 2006) serve as the best tool for making projections. These models are solved for a global 3D gridded network by considering atmosphere-ocean interactions.

In this study the obtained results by (Safavi et al., 2016) have been used. In the mentioned study, 15 general circulation models have been used to predict changes in precipitation and temperature parameters in Zayandrood Basin for the next period around 2015-2044. For more details about downscaling and using probabilistic ensemble modeling, see (Safavi et al., 2016).

Management scenarios were then developed in accordance with the characteristics of the water resources in the study area where agricultural irrigation accounts for the main water consumption. These scenarios are considered for the period 2020 to 2024 that correspond to the scenario of trend analysis aimed at reducing groundwater abstraction and increasing surface water supply in order to keep the area under cultivation. Finally, time series were generated in accordance with the scenarios defined and considered as input to the trained ANN.

3.2.1. Scenario 1 (Trend scenario)

In the trend scenario, which is considered as a zero-conjunctive scenario, volume of surface water regardless of climate change issues, has been considered historically, and groundwater abstraction despite the development has been considered in the current situation. The aim of this scenario was to estimate fluctuations of mean groundwater level for each irrigation zone in Najafabad Plain under the two climate change scenarios of A2 and B1. Fig. 6 presents the mean groundwater level results of this scenario under the climate change scenarios for the Nekouabad left and right irrigation zones. Overall, A2 led to a greater decline in the mean groundwater level of the aquifer in Nekouabad left irrigation zone than B1 did, while an opposite trend was observed in the case of Nekouabad right irrigation zone.

3.2.2. Scenario 2 (Reducing groundwater extraction)

One of the most critical factors affecting water level in the study area is groundwater abstraction. The amount of water extracted under Scenario 2 reduces by an annual quantity of ten percent over the period from 2020 to 2024 while other parameters remain constant. Comparison results for two scenarios which are trend analysis and reducing groundwater abstraction under the two climate scenarios A2 and B1 for the Nekouabad left and right irrigation zones are presented in Fig. 7 and 8 respectively. Obviously the reducing groundwater extraction coupled with the A2 scenario in Nekouabad left irrigation zone leads to less decline in groundwater level by mid 2021, this is while under scenario B1 the aquifer thickness generally grows due to reduced pumping except for 2022 and 2023. In Nekouabad right irrigation zone, however, both scenarios A2 and B1 lead

[1] Atmosphere-Ocean General Circulation Models (AOGCMs)

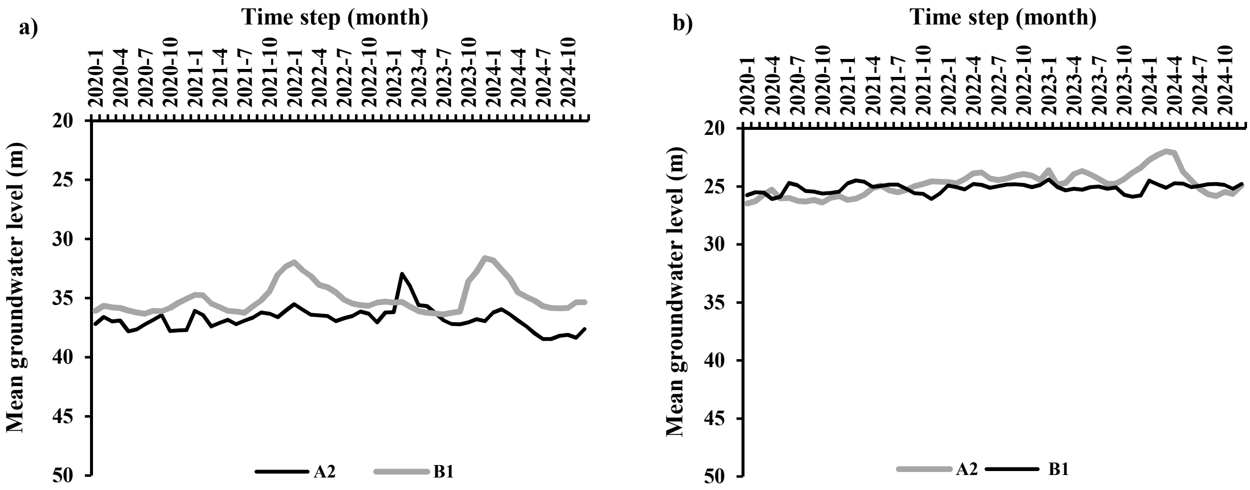

Fig. 6. Mean groundwater level in the trend analysis under the two climate change scenarios A2 and B1. a) Nekouabad left, b) Nekouabad right

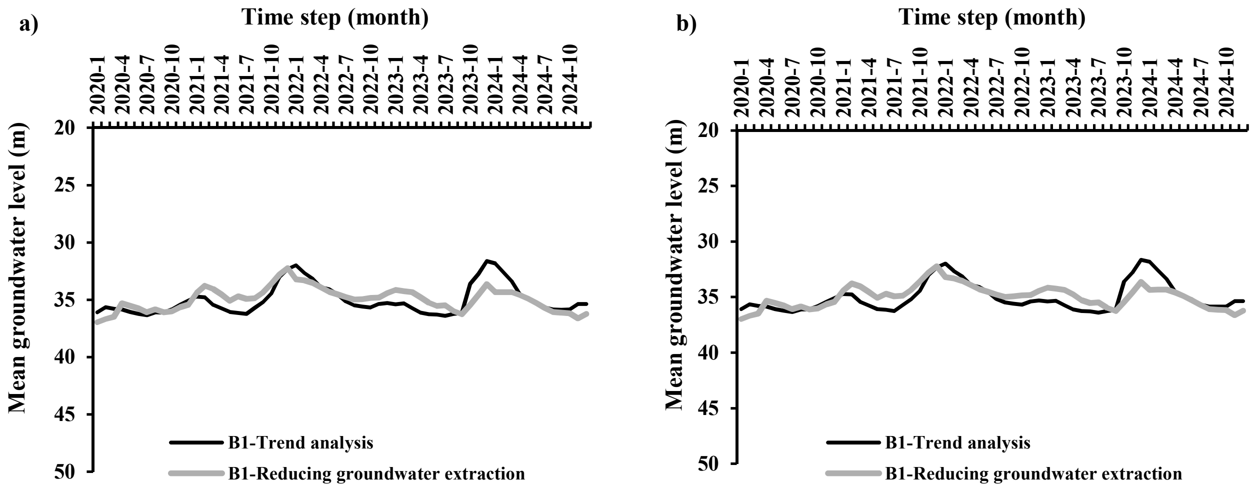

Fig. 7. Comparison of mean groundwater levels in the trend analysis and reducing groundwater extraction scenarios in Nekouabad left: a) A2, and b) B1 climate change scenarios

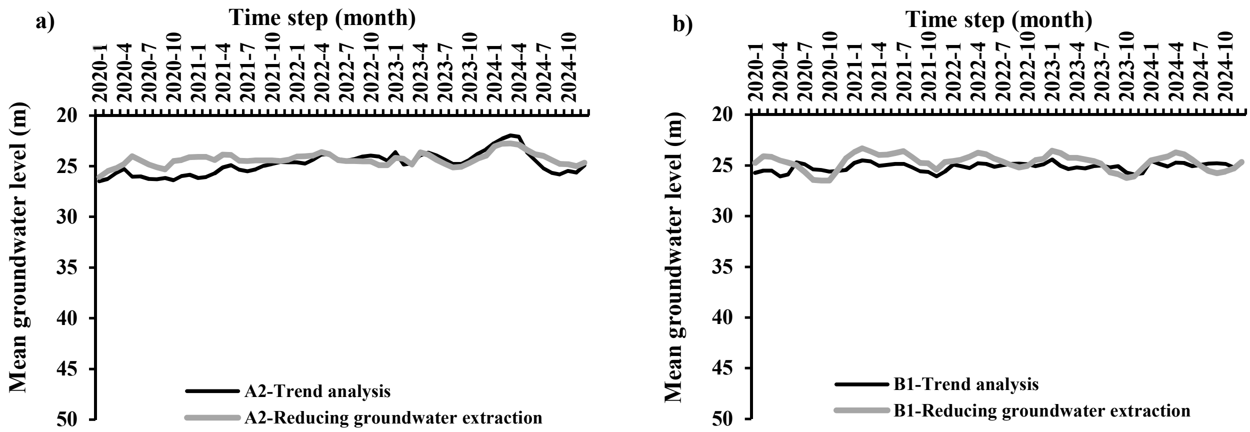

Fig. 8. Comparison of mean groundwater levels in trend analysis and reducing groundwater extraction scenarios in Nekouabad right: a) A2, and b) B1 climate change scenarios

to a rise in the mean groundwater level albeit it experiences some fluctuations rather than being steady.

3.2.3. Scenario 3 (Increasing surface water supply)

Another critical factor affecting the mean groundwater level in this area is the amount of surface flow entering the zones. In this scenario, the entered volume of surface water increases as much as the groundwater pumping reduction in the previous scenario. In other words, the cultivation area will remain unchanged but the source of water supply will change from groundwater to surface water. Comparison results for two scenarios which are trend analysis and increasing surface water supply under the two climate scenarios A2 and B1 for the Nekouabad left and right irrigation zones are presented in Fig. 9 and 10 respectively. Clearly, under the A2 and B1 climate change scenarios, applying the increasing surface water supply scenario to the Nekouabad left irrigation zone led to a lower decline in the groundwater level throughout the study years. Applying the same scenario to the Nekouabad right irrigation zone under the climate change scenario B1, however, led to a clearly lower decline in groundwater level towards the end of the year 2020 by up to the mid-2022. Adopting the increasing surface water scenario under the climate scenario A2 increased the water level in the plain in all the study years albeit with some fluctuations.

To illustrate the accuracy of simulation models, the mean groundwater levels projected by the ANN trained with PSO and the observed data for the reducing groundwater extraction scenario coupled with the B1 climate change scenario for the left irrigation zone are provided in Fig. 11.

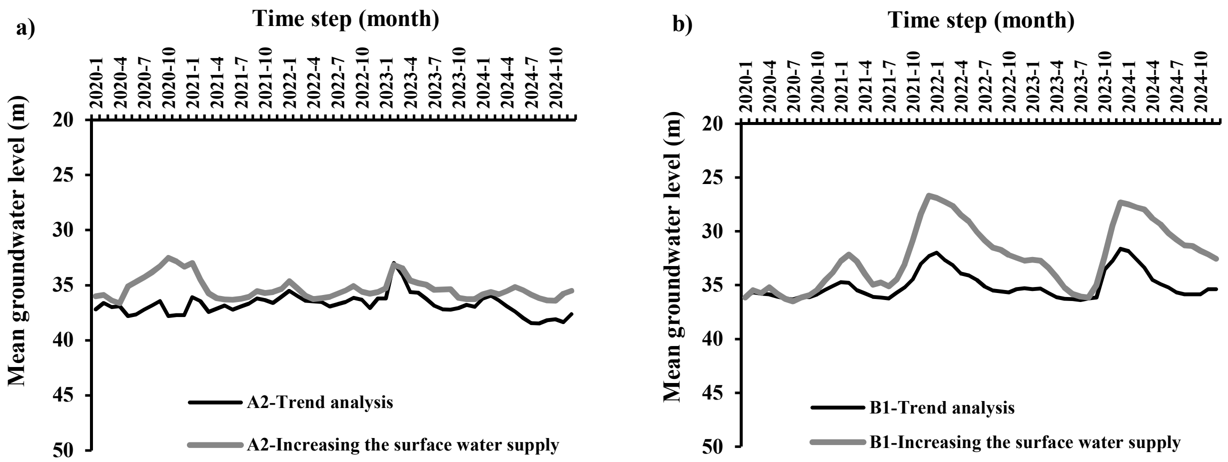

Fig. 9. Comparison of mean groundwater levels in trend analysis and increasing surface water supply scenarios in Nekouabad left: a) A2 and b) B1 climate change scenarios

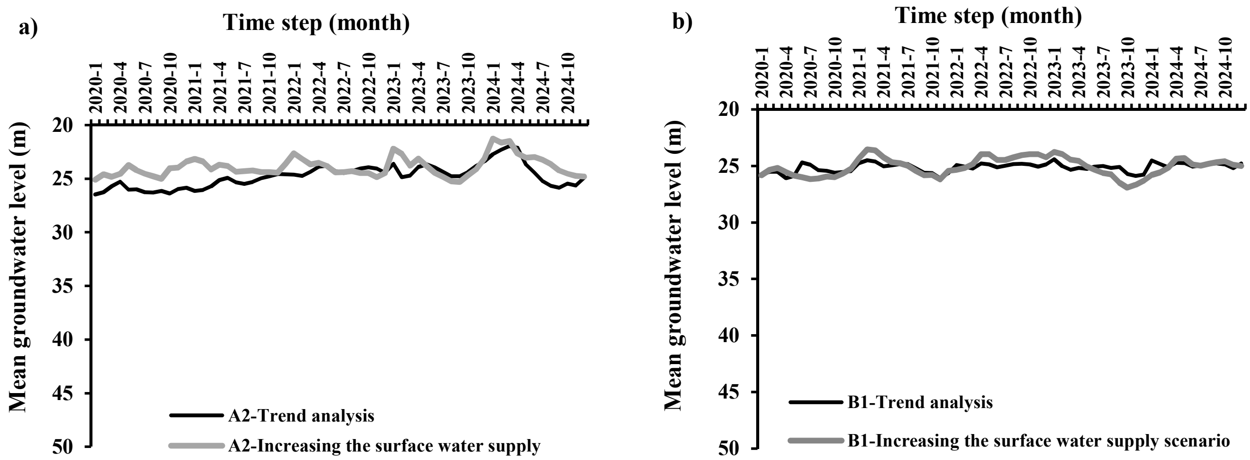

Fig. 10. Comparison of mean groundwater levels in trend analysis and increasing surface water supply scenarios in Nekouabad right: a) A2 and b) B1 climate change scenarios

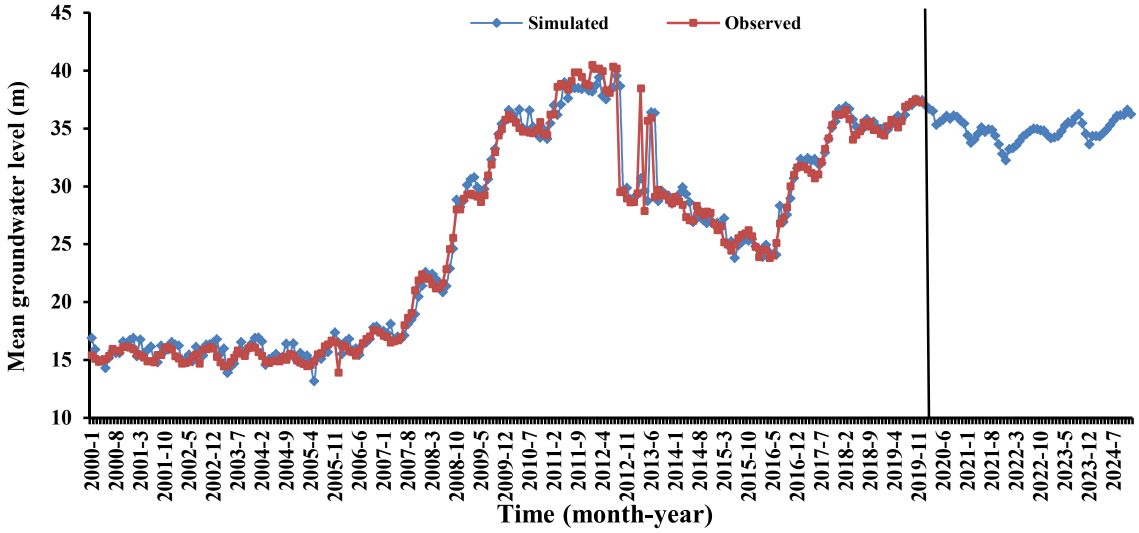

Fig. 11. Mean groundwater levels for the entire historical period: the scenario of reducing groundwater extraction under the B1 climate change scenario in the left irrigation zone

4. Conclusions

This study set out to investigate the PSONN model for forecasting mean groundwater levels using such parameters as the observed mean groundwater level at the beginning of the month, monthly rainfall, average monthly temperature, groundwater pumping, volume of water imports into the study zones, and the monthly flows at the gauging stations at the nearest hydrometric stations in Najafabad Plain. Weights and biases of the neural network were taken as the decision variables, and the network error was regarded as the objective function to be minimized. The finding revealed that the forecasted water level by the PSO-based training was more accurate than those rendered by the commonly used Levenberg–Marquardt model.

Three management scenarios coupled with two climate change scenarios of A2, B1 were defined, and their effects in the study area were investigated. The first scenario was based on the assumption that the current groundwater abstraction trend will continue over the next 5 years as a baseline scenario. The second scenario assumed a decreasing trend in abstraction from the wells in the study area, and the third scenario involved an increase in surface water imports into the irrigation zones to maintain the present area under cultivation. The volumes of groundwater abstraction and surface water diversion were determined for each scenario. The results from the present study clearly indicate that PSONN is a successful model as it helps water manager to forecast groundwater level. Fluctuations in the mean groundwater levels under the three management scenarios and the two climate change scenarios A2 and B1 showed that surface water diversion into the irrigation zones needs to be increased while pumping from the study aquifer should be reduced in order to lessen the present trend in groundwater level drawdown over the next five years.

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