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Research Article

Predicting of Groundwater Level Fluctuation Using ANN and ANFIS in Lailakh plain

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ABSTRACT:
Forecasting of groundwater level and its fluctuations is one of the essential measures(actions) for integrated management planning of groundwater resources. Considering the nonlinear and complex relations that govern groundwater flow, designing a precise and simple model is considered as an inevitable necessity for simulating the groundwater resources behavior. Nowadays, the connoisseur systems such as Artificial Neural Networks (ANN) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) have regarded as the useful and reliable tools for modeling the nonlinear mappings. The purpose of this study is developing the ANN and ANFIS models, to predict water table fluctuations of groundwater resources system in Lailakh Plain. The time-values of monthly average groundwater level, rainfall, temperature and evaporation were used to develop the proposed models. And, ANN and ANFIS dynamic, static andhybrid models were developed for predicting water table depths. Finally, the proposed models were compared and prioritized by the using of Analytical Hierarchy Process (AHP). The resultes of the research showed that the dynamic and static models were respectively the most accurate and careless groundwater table predicting models. The ANN dynamic model with three input parameters and MSE=0.776 and R=0.975, was the best model for the more accurately predicting of water table fluctuations in Lailakh plain.

Keywords: Lailakh plain, groundwater, ANN, ANFIS

INTRODUCTION

One of the plain the plainLailakh the important province of Kurdistan is in the talent of enjoying the potential of the soil and agriculture has always been of major importance has been urethras, this plain area with 624 square miles and an area of 2550 square miles Point round little urinal average 1876 feet from sea level in the east province is located. With regard to the amount of rainfall (350 feet in dismay) years, this part of the plain areas and half dry cold province is considered one of the potential surface waters within the limits the plain Lailakhweak and therefore groundwater only major source supplier water consumption in different agricultural sectors, drinking, industry in this plain is (24). For that lack of water an impediment against economic growth and social cycle is the plain is necessary by relying on the concept of management and comprehensive water resources sustainable, total knowledge of underground water resources system this plain. In this regard can be predicted by the level fluctuations Static and son, management strategies including a suitable planning timetable suitable for pumping water from the wells and determining the amount of optimal understanding of underground water tanks etc. and presented and in this way protect Water

Resources and survival of the plain underground Lailakh and long term use of them guarantee. present study in order to develop models of Static and predicted to level fluctuations Static using artificial neural network contains provisions level fluctuations nose Static, predicted fluctuations Static level using artificial neural network system and deduce Water Fast phase, predicted Static level fluctuations by using deduction system Water Fast phase, Hebrides extension model to predict fluctuations Static level with the use of the deduction system Water Fast phase and compared the results of the models based on artificial neural network system and deduced from phase Water Fast. In recent years many efforts in order to solve issues that for them the solution to the existing analysis is not easily solved or are the (1). In this regard the system of intelligent based on the experimental data have been developed and many advances have. networks and artificial neural systems Water Fast phase deduced from a part of this system is considered to be of that processed on the experimental knowledge and hidden behind the law are discovered and the predicted variables for resolving outstanding issues needed using different(16). In this research the special capabilities of the networks and artificial neural systems phase deduce Water Fast for predicted that underground water level fluctuations and simulations it is used. The above methods and the existing relationships in the structure of their ANATOMY. The existing study of resources and articles that showed the field level simulations with underground water use of artificial neural networks and systems Water Fast deduction phase in the plain Lailakh no similar research has not been. Simulations the flow of water with the plain underground system of the above can be a solution for optimal utilization of proper management and the sustainable resources of the plain is.

2. MATERIALS AND METHODS

The plain Lailakh in Kurdistan province and in geography during the Convention at 08 47 12 48 to that eastern and wide geographical and 35 to 36 wide north. Is the scope as the field of little urinal Lailakh with code 1-1308 it is clear that. Dehgolan plain area equal to 494/644 km and a catchment area of over 2550 km [7]. In general, water resources in plain Dehgolan into two parts, surface water and groundwater resources are divided. Taluoar and black stones in the major river basin plains are Lailakh [7]. The main source of underground water table, regardless of rainfalls in the plains, numerous rivers that originate from the nearby mountains and enter the plains are. The major maritime polar air masses originating rainfalls area is about eight months of the year (from October to mid-May) will affect the region? Plain Dehgolan 1/355 mm average rainfall per year. [7]. Hydro-geological parameters and climatic parameters, affect the groundwater level fluctuations are. The study of climate parameters, including evaporation, precipitation and temperature, as well as hydro-geological parameters such as depth of water table observation as input parameters of the models were used to predict groundwater. The data are normalized to the average data to be close to 5.0 [21]. Modeling the behavior of different phenomena requires the existence of three sets of training data, validation and testing is considering the different percentages of input data can be obtained. Training data. Data validation and test data to determine the structure of the neural network consists of two steps determine the type of network and network architecture was determined [38]. The study of the multi-layer perceptron with back propagation algorithm to predict groundwater level fluctuations were Lailakh Aquifer.

Mean square error threshold method was used to design the network. The design method based on neural network training and validation to reduce the error rate threshold can be specified. Select the appropriate network architecture is the first step in learning. The study of various laws such as the conjugate gradient Marquardt neural network was used for training. For each of the models are dynamic, static and hybrid above 4 different combinations of systems and fuzzy membership functions obtained in this study, three types of static model, dynamic and hybrid expressing different combinations were developed.If in a model, exit every step as long as only the problem of the entrance model in the same step as long as, network Static call. Unlike networks Static nervous in their dynamic time and there is no model of timed of the structural and in the determination of output in each time step of the entrance channel in the time step before the. Models of Hebrides, a combination of input of the network in step current time step and time before the entrance as the network in. In research to predict fluctuations in the plain level static Dehgolan 5 of model 2 and model 4 model static Hebrides develop in a research model of a factor, three models of two factors and a model of three factor based on methods of artificial neural network system and deduce Water Fast-phase extended. The ANN-1 model and ANFIS-1, respectively, which represents a dynamic factor model based on artificial neural networks and fuzzy systems are go-developed and developed. Groundwater level and groundwater level a month ago as an input parameter to the next month, as the output of these models were considered. Dynamic two-factor models for each of the methods go-fuzzy inference systems and neural networks were designed. ANN-2 and ANFIS-2 models of the groundwater level in a month and two months ago as input parameters and output parameters of the ground water level in the coming months as the model was introduced. ANN-3 models and ANFIS-3 levels of underground water a month before and three months ago as input and models ANN-4 and ANFIS-4 levels of groundwater two months before and three months before the entrance and the still water out next month, the models were considered. Takagy Sugeno fuzzy inference system is the best system on all models and selection algorithm, Levenberg Marquardt algorithm for training the system is the best. Transfer function models of the hyperbolic tangent function ANFIS-2 and ANFIS-3 and the linear hyperbolic tangent function ANFIS-4 also delivers the best results-are placing a Gaussian function with the number 4 for the ANFIS-2, 5 for the ANFIS-3 and 5 for the ANFIS-4 best results obtained in the validation phase predict groundwater level Lailakh, a dynamic model of Tuesday factors for each of the neural network models and inference system Nero- phase respectively by ANN-5 and ANFIS-5 was designed.For the extension of the model of depth parameters static level a month ago, the depth level of static two months ago and the depth level of Static three months ago as input and parameter depth static level next month as output in the government. With the use of climate data include average monthly shower, evaporation and temperature models of average monthly salary for different predicted water level underground development and development. For these purpose three models of and two based on the method of artificial neural network and the deduction system Water Fast-phase design. In this research two model ANN-ANFIS- 6 and 6 the showman Static model three Static factors for artificial neural model and three Static factors for a system of Water Fast phase, were developed. In this model, the amount of evaporation, precipitation and temperature forecasts every month to the average amount of water used in the same month. Through the analysis of sensitivity to input parameters in the static model parameter rain Tuesday factors were found to have no significant effect on the predicted water table. The rainfall data set of input data to model and neural network models and systems do not eliminate the static phase and Hybrid was designed based on the monthly average temperature and evaporation data. Then a static two-factor model (ANN-7 and ANFIS-7) based on neural networks and fuzzy systems were designed to go inference. In the model above average temperatures and evaporation average a month as input parameters and depth of groundwater level in the same month as output parameters are introduced to the study of the hybrid two-factor ((ANN-8 and ANFIS-8) and (ANN-9 and ANFIS-9), a hybrid model Three factors (ANN-10 and ANFIS-10) and a hybrid four-factor model (ANN-11 and ANFIS-11) based on artificial neural network method and system Nero was developed fuzzy inference.In this model a combination of the depth of the level of static step in time before and the time step in climate predicted for current level of underground water use. In these research two model two factors Hebrides network based on the nervous system and of the phase deduce Water Fast design. In models of ANN- ANFIS-8 and 8 evaporation average every month and the depth level of static months ago parameters as input and depth level of underground water the same month as the exit parameter model introduced. ANN-9 models and parameters of ANFIS-9 is the average temperature of each month and the month before the water table as input parameters still water depth in the same month as the output of the models considered. For both model selection gradient algorithm married and hyperbolic tangent transfer function maximum correlation coefficient and gives the lowest error. After learning algorithm to determine the number of neurons in the middle layer and repeat the calculation of optimal thresholds were also tested on two-factor model hybrid inference system Takagy Sugeno fuzzy system is best. On the other hand hyperbolic tangent transfer function and conjugate gradient training algorithm selection for both the ANFIS-8 and ANFIS-9 the correlation coefficient and minimum error is achieved. In this study, a hybrid model Tuesday factor for neural networks and fuzzy systems were designed to go inference. ANN-10 models and average temperatures and evaporation parameters of ANFIS-10 average per month and the previous month as input parameters and depth of shallow ground water level in the same month as output parameters for the model were considered. In the last part of the design of neural network models and neural-fuzzy system, hybrid models with four input factors for each of these systems were developed. The four-factor models ANN-11 and ANFIS-11 parameters and depth of water table depth of the water table a month ago, two months ago, the average temperature of each month and each month an average evaporation as input parameters and depth of groundwater level in the same month as the parameter The output of the model is intended to assess the correct fit and function. Several models exist, the coefficient of efficiency (CE) due to its simplicity, it is most useful in evaluating the performance of hydrological models.Based on standard efficiency coefficient of unity between the two is variable and the scope of the changes from a positive to negative is. (14) For comparison of different network and also estimate the amount of each of the superiority of the model compared to the other models of the indexes statistics. In this case the multiplicity the indexes are the, the process of decision making the decision making a few CriteriaMCDM "and by this decision and will not be so easy and in the absence of the standard speed and precision decision reduced. In this situation in order to analyze it more realistic results and principles can be a hierarchy of process analysis (AHP) decision to use. Analytical Hierarchy Process to analyze complex issues and problems, simply convert them and to solve them. This process consists of three stages. The hierarchy, compared Zoojeyo weight matrix is produced. In order weighting and prioritization of proposed models of neural networks and fuzzy systems do not evolve, according to the criteria, the AHP method was used. [29]. Sensitivity analysis process valuable information about the sensitivity of the model to the input variables to the model gives the designer and architect. To identify the effect of input variables on the accuracy of the prediction model, low-impact variables can be removed from the network and the development of the simpler model.

3. Results and Discussion

Due to lack of priority classification networks and lack of clear that in case of lack of possibility of using a channel next choice what is. With the use of advanced and effective method of analysis a hierarchy model of different ranking and the highest and the weakest models identified. Through calculation criteria weight share of each criterion in determining the priorities and the best network next clear. Based on AHP method to do this a couple of criteria to be compared. After calculating the weighting of criteria for process should be done. in every 21 network must be compared with each of the 4 criteria above are mutually comparing the hierarchical structure and complete comparison matrix test criteria and options, all entries of the Expert Choice prepared and models can weigh each option with respect to each criterion and the final weight of each option calculated in this way to prioritize their options.

See form 1 shows that network with 5 factors of ANN- entrance underground water level a month ago, two months before and three months ago with weight 065/0 in first priority be, the use of the conditions of and the criteria has led to the most accurate results. As it is seen to be of model parameters with 2 ANFIS- entrance underground water level of a month ago and two months before with far less weight and 064/0 the second model predicted for preferably underground water. In this model of the static ANFIS- 6, ANFIS- ANN- 7 and 7 also have the least weight.

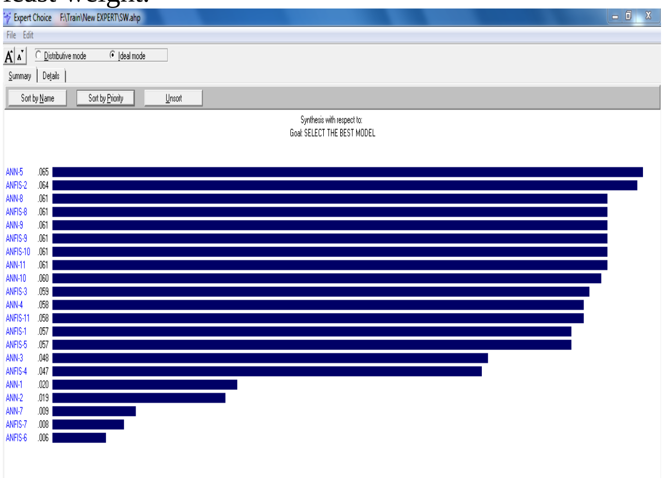

Figure 1: The final weigh their options and rating

Because of this sensitivity analysis of the model relative to the input variables is greater than the threshold value of the coefficient is 1.0, so both are influential input parameters to estimate the depth of water table. Input variables table two months before and three months before the most and the least impact on the accuracy of the prediction model of ANFIS-4 and both parameters have a significant effect on the predicted depth to the water table. The relative values of the coefficient of sensitivity analysis for dynamic parameters Tuesday-factor model (ANN-5 and ANFIS-5) indicates that the input variables of shallow one month before and three months before the most and the least impact on the accuracy Nose Model ANN-5 level. In this model, the coefficient of relative sensitivity analysis for all input variables is greater than 1.0 is the threshold,So every three parameter input of a meaningful influence on the predicted level of depthstatic .That shows that the level of entry variablesstatic a month before and two months before the highest and lowest influence upon the accuracy model nose ANFIS- 5 and all parameter effect entrance means on the predicted level of depthstatic .

Generally the results showed models of ability of Hebrides and more fluctuations for sonstatic level and models ofstatic only considering climatic parameters evaporation temperature and air temperature levels can seawater with an acceptable accuracy estimate .The results of this study showed that the Levenberg Marquardt learning to learn the Laws of higher efficiency in training the neural network is capable of. According to the results of this study do not go for the models based on fuzzy inference systems, system to system Takagy Sugeno T SA Sakoomootv koomotv the proposed models provide better results. What has been observed in practice faster performance than systems Takagy Sakoomootv Sugeno fuzzy systems T and the results were weaker for it. The reason is simpler structure Sakoomootv T models and simplifying assumptions that were applied in the construction of this model.With regard to the results, models nervous network and deduce systemes Water Fast-phase almost weekend performance of simulations in water levels showed. But what is by experience during son achieved, the speed more than son based on the network of the nervous system to the deduce Nero-phase that it was one of the things discussed in the network preference on the nervous system of the deduce Water Fast-phase is considered. The results also showed that neural network models with parameters of entrance underground water level a month ago two months ago three months ago with coefficient of 975/0 squares and the average amount of error 945/0 best model simulator level fluctuations static underground water resources system plain Dehgolan. Model parameters of Water Fast with phase entrance water level mini a few months ago and two months ago with the amount of coefficient 974/0 squares and the average amount of error 022/1 with a far preferable for at least the second model predicted water levels in Underground lailakh plain is considered.

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