PREDICTION OF FUTURE GROUNDWATER LEVEL USING ARTIFICIAL NEURAL NETWORK, SOUTHERN RIYADH, KSA (CASE STUDY)

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ABSTRACT

Saudi Arabia is an arid country with very limited water supplies. About 80% of water supplies come from nonrenewable water resources, i.e., ground water. Natural replenishment of the groundwater is far less than the annual extraction. Consequently, groundwater levels have sharply declined over the last two decades. Artificial Neural Networks (ANN) are effective tools for prediction of future variability. Groundwater levels for a reasonable future period of time can be effectively predicted by ANN. The main objective of the current study was to predict groundwater elevations in four wells south of Riyadh City for a future 20-year period. In order to achieve this, a 30-year database of daily groundwater levels was used. A complete analysis of the 30 years database was conducted. About 80% of the data were used for training the network while the rest of the data were used for validating and testing the model. A sigmoid function was used as a hidden layer which consisted of type 1-6-2. Simulation results agreed well with observations. The prediction shows that future reduction in groundwater levels will not exceed 30% of the reduction during the last 30 years.

Keywords: ANN, Groundwater, Prediction, Well, KSA.
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1 INTRODUCTION

Extensive use of non-renewable groundwater are often used to meet the increasing demands especially in arid and semiarid regions. Among these, the USA, Australia, Spain, India, Jordan, Oman, Libya, Bahrain, the United Arab Emirates, Egypt and Saudi Arabia support domestic, agricultural and domestic activities. The impact on the sustainability of groundwater resources and on the economic and social sectors vary among countries (Abderrahman, W. 2005). Countries within the Arab region are heavily depending on irrigation for food production and they are confronted by severe problems due to both climatic conditions and socioeconomic factors (ACSAD, 1999). From an ecoclimatic point of view, most of the region extends across semiarid and arid zones. The semiarid belts have been particularly affected by cycles of droughts and desertification in the past decades. Socioeconomically, the region is characterized by a fast increasing population, which has resulted in a sharp decline of the per capita availability of water during latest decades. At the same time, supplies of good quality irrigation water are expected to sharply decrease in the near future because the development of new water supplies will not keep pace with the increasing water needs of industries and municipalities.

Saudi Arabia is the largest arid country in the Middle East. The average annual rainfall ranges from 25 to 150 mm (Ministry of Agriculture and Water, 1988). The average annual evaporation ranges from 2500 to about 4500 mm. The country has an area of 2.25 million km^2 of which about 40% are desert land. With low annual precipitation and with no lakes, rivers or streams, Saudi Arabia is faced by rising water demand and by increasingly depending on non-sustainable use of groundwater. About 80% of the total water supply comes from groundwater with very limited natural recharge and is, thus classified as fossil or nonrenewable water (Al-Ibrahim, A.A. 1991).

A variety of major problems including fast depletion of groundwater recourses and deterioration of their quality may occur when the rate of water withdrawal exceeds the net recharge. Saudi Arabian authorities follow a new strategy based on controlling aquifer development and demand management when using groundwater resources. Corrective demand management measures including reduction in cultivated areas and modification in agricultural support policies in addition to the augmentation of water supplies by the reuse of treated wastewater have reduced the stress on groundwater (Abderrahman, W. 2005).

ANN's are computational tools that have found extensive application in a wide range of research areas. Building analysis (Rajesh Kumara et al. 2013). Environmental applications of this technique include stream flow, flood and rain- fall forecasting (Ki¸ si 2007; Jain and Kumar 2007; Tiwari and Chatterjee 2010; Valverde Ramírez et al. 2005), processing remote sensing data (Linderman et al. 2004), flow and transport simulations (Morshed and aluarachchi 1998), ground-water table prediction (Coppola et al. 2005 ; Joorabchi et al. 2009) and water quality modelling (Zou et al. 2007; Khalil et al. 2011).

ANN methodology has been applied in almost all branches of science with good results during the last decades. Dibiki et al. 1999a,b and Dibiki and Abbott 1999 explained the basics of ANN and their applications in the field of water engineering. Liriano and Day 2001 applied ANN to predict scour downstream of hydraulic structures. Kheireldin 1999 predicted scour at bridge abutment where Negm et al.2002b predicted scour downstream of sudden expanding stilling basins by using ANN also Elkiki 2008a used the ANN to predict scour downstream skew siphon pipes. Negm and Shouman 2002 and Negm et al.2002a predicted submerged hydraulic jump characteristics using ANN. The characteristics of hydraulic jump in non-prismatic stilling basins was predicted by Negm et al. 2003. Owais et al. 2003 have succeeded to predict the characteristics of free radial H.B.J. formed at sudden drop. Application of ANN to predict discharge below sluice gate under free and submerged flow conditions was made by Negm 2002 and to predict discharge below submerged gate with sill was done by Negm 2001. Application of ANN to predict the drawdown depth due to ship movement was introduced by Elkiki 2008a,b. The mean velocity through open channel with submerged aquatic weeds by using ANN was made by Mirdan 2012.

Chyan-Deng Jan 2009 investigated the parameters of hydraulic jumps in an inclined rectangular chute contraction. A study on hydraulic jumps due to submerging conditions in blocks was done by Habibzadeh and Rajaratnam 2011. An artificial neural network (ANN) technique was developed to determine the length of the hydraulic jumps in a rectangular section with a horizontal apron by Naseri and Othman 2012. Also, Abbaspour et al. used the ANN to for Estimation of hydraulic jump on corrugated bed.

The hydraulic characteristics of flow over the rectangular weir with three rectangular bottom openings by using ANN was made by Al-Suhaili et al. 2014.

2 METHODOLOGY

2.1 Site Location

The study area is one of the most important agricultural areas in KSA. It is located south of Riyadh City. Around 26% of the crop production of the kingdom comes from this area**.** It contains of four main groundwater wells (Fig (1)). Table (1) shows the longitude and latitude of each well and its distance from the city of Al Kharj (80 km south of Riyadh City).

Table 1. Location of the studied groundwater wells.

Well	Longitude	Latitude	Distance to Al Kharj city (km)
C (5-K-60)	47^o 47’	24^o 15’	45
D (5-K-83)	47^o 00’	24^o 04’	30
E (5-K-84)	47^o 10’	24^o 04’	25
F (5-k-87)	47^o 32’	24^o 14’	20

2.2 Data Collection

The well data used in this paper were obtained by personal communication from the Ministry of water and electricity. The number of water level observations for each well is ranging from 6000 to more than 8000 during 23 years. Table (2) shows the data range and the change in groundwater level during this period.

Table 2. Well data description

Well	Time range	Change in groundwater level
C (5-K-60)	1978-2011	-70.23m to -116.13m
D (5-K-83)	1978-2011	-25.93m to -140.57m
E (5-K-84)	1978-2011	-29.85m to -69.12m
F (5-k-87)	1978-2010	-56.86 m to -106.88 m

2.3 ANN

ANN is useful due to its ability to learn complex patterns and trends in data. By producing systems that learn relationships between data and results, neural networks avoid many of the problems of conventional computing. Given new data, a neural network can make a decision based upon its experience (ElKiki 2008b). The Neural Connection Software (Neural Connections, 1998) is made up of three separate modules. The modules are the graphical user interface, the executive, and the tool modules. The modular design of Neural Connection gives greater flexibility than standard analysis tools, and allows to adapt the application as required, in order to gain the best results from the data.

The graphical user interface provides the Neural Connection workspace, the program window where one builds problem-solving applications. The workspace allows to build, train, and run analysis applications. An application is a method for modeling the problem, which may include inputting the data, processing them in some way, and producing the output in a useful format. Tools are selected as icons from a palette, and moved onto the workspace, where they can be connected to other tools. These connections determine an application’s topology, and the path along which data flows. The workspace has tools for inputting data, statistical analysis, problem modeling, and producing results. Each type of tool performs a specific type of task, and by combining tools in different ways, applications can be built that performs much more sophisticated analysis than any one technique could by itself. A tool which you have placed on the workspace has a series of parameters that can be set independently of other tools, even those of the same type. Initially these parameters are set to default values, which have been carefully chosen to be the optimum values for as many problems as possible. To customize these parameters, one can open each tool. Each tool has a series of simple commands such as Run, Train, and Dialog, which enable it to be used in a straightforward manner.

The executive_is the core component of Neural Connection. It creates instances of the analysis tools, displays them on the graphical user interface, and manages the data flow between them. It also loads, trains, and runs applications developed in the script language.

The tool modules used by Neural Connection consist of neural network and data analysis routines that have been extensively developed. They include tools for data input and output, data manipulation, statistical analysis, classification, and modeling and forecasting. In addition to providing the standard user-defined parameters, the neural network tools contain many advanced features, such as automatic configuration and training. The common characteristics of the analysis tool are:

- Tools store all their data variables in a data body in a computer's memory. This allows different instances of a tool to be created by allocating new data bodies. The software associated with each tool is re-entrant, allowing it to be used by all instances of the tool.

- Tools pass data from one to another via a single logical connection. This connection passes both vector data and control information, such as the names of fields in the vector and their data types. Vector data can contain both input information and target information.

- Tools make no assumptions about which tools are connected in front of, or after them in the topology. If a tool uses the same data set many times (for example in Multi-Layer Perception (MLP) training), then it will automatically hold the data required in memory until it is no longer needed. (ElKiki 2008)

2.4 Building the ANN Models

The following systematic steps are followed to build each of the developed ANN models for the present study:

a – The data set of the specified problem are prepared in a file with the format suitable for the Neural Connection software such as Microsoft excel 5.

b – The Neural Connection is operated and the needed tools from the toolbar are connected together to form general topology of the network.

c – The input tool is used to specify and allocate the input data. In this stage the order of the data is randomized and divided into three subsets, training data (80%), validation data (10%) and test data (10%). All of them are selected randomly.

d – The MLP tool is used to specify the following parameters:

1. A Zero mean unit standard deviation for the normalization method of the input fields.

2. A Sigmoid activation function which is obtained by trail and error.

3. 10 for the number of neurons in hidden layer which is obtained by trail and error so that the best size of the network is 1-6-2.

4. A Zero mean unit standard deviation for the normalization method of the target fields.

5. 0.1 for the initial weights with seed of 3 of the links between neurons obtained by trail and error.

6. A conjugate gradient learning algorithm.

7. 200 for the maximum updates.

e – The network is allowed to train and the validation system error is observed. Once the minimum validation system error is reached, the training is stopped. The output tool is used to save the output results for training, validation and test in three separate files.

f – The output files are transferred to the Microsoft Excel software to enable other plotting of results, comparisons and computations of the correlation coefficient (R) and the Root Mean Square Error (RMSE) between the measured and the predicted outputs.

g – The network is allowed to train 5 times at least with different starting point in each time until a global solution is obtained.

The procedure is repeated for each of the developed network. The results of optimal networks are used when comparing the ANN results with the measured and MLR results (ElKiki 2008b).

2.5 Calibration of the ANN Model

2.5.1 Effect of Size of Input Data Set.

The effects of training data input size on the variation of validation RMSE error of the output are shown in Figure (2). Training of the network should be done several times with different tested input data size until a maximum correlation coefficient R for the validation data occurs. The figure shows that a network of percentages 80-10-10 is suitable, i.e. 80% of data set for training the network; 10% for testing, and 10% for validation.

2.5.2 Effect of Number of Neurons of the Hidden Layer.

The optimum number of neurons of the hidden layer was found to be six. To ensure this size, the number of neurons in the hidden layer was changed several times and the error from the network was investigated. Figure (3) shows the variation of R for different output of the ANN versus the number of neurons of the hidden layer. From these figures, it is clear that 6 neurons in the hidden layer yields the maximum R for output variables considering the training, validation, and test errors. This is because, as the number of neurons increases, the errors decrease down to a minimum of 6 neurons and then the errors again start to increase.

2.5.3 Effect of Single Output Neurons versus Multiple Output Neurons.

The effect of using an output layer having one neuron representing one output variable was compared to an output layer having three neurons. Two networks, each of a size 1-6-1 were used to model the two targets of the present study with the same learning parameters used in the network of size 1-6-2. Figures (4) and (5) represent the RMSE and R for the two variables using single and multiple output layers for two computer runs. The figures show that the performance of the network of size 1-6-2, i.e., the two variables taken together is better than those of size 1-6-1 in predicting the different water levels in water wells.

2.5.4 Effect of Activation Function.

The effect of activation function on the resulting error from the best network was studied by performing three computer runs using the best ANN of 1-6-2 and different activation function assuming other parameters unchanged. Figure (6) presents the RMSE for each of the three data sets using three activation functions, hyperbolic tangent (tansh), sigmoid and linear functions. From the figure, it is clear that the sigmoid function is more suitable to predict the outputs of the problem.

2.5.5 Effect of Seed Number (Stability of the Network).

Multiple runs were conducted with training, test and validation sets in order to study the performance and stability of the ANN model. The data sets were chosen randomly. This process was repeated four times. The results in terms of RMSE and R are presented in Figures (7 a,b,c and d). The mean values of the RMSE of the 4 random sets were 1.92 for training, 1.23 for validation and 1.33 for test with standard deviation of 0.039, 0.077 and 0.082, respectively. Also, the mean correlation coefficients were 0.995 for training, 0.997 for validation and 0.993 for test with standard deviation of 0.003, 0.0004 and 0.0042, respectively. Clearly, the RMSE and R are close to the mean values with very small standard deviation. This means that the developed ANN model is stable and hence the results are consistent.

3. RESULTS AND DISCUSSION

3.1 Comparison between ANN results and observations

Output results of the ANN compared to observations are presented in Figures (8,9,10, and 11). The figures show examples of results of training, test and validation data for minimum and maximum reading of the four test wells. An excellent match is observed in all cases indicating good performance of the ANN model in predicting the groundwater depth.

3.2 Prediction

The correlation coefficients between the measured and predicted water depth using the ANN model are presented in Table 3 for training, validation and test data sets. Also, as shown in Figure 12 (a,b) a very good match between training, validation and test data for all four wells is observed which indicates a good performance of the ANN model in predicting the groundwater depth.

Table 3.: Correlation coefficients between measured and predicted water depth for different wells

Well Name	Data Value	Data Type		
		Training	Validation	Test
5 – k – 60	Min.	0.9327	0.8671	0.9654
	Max.	0.9391	0.8787	0.9469
5 – k – 83	Min.	0.9664	0.9553	0.9715
	Max.	0.9658	0.9562	0.9724
5 – k – 84	Min.	0.9924	0.9887	0.9887
	Max.	0.9893	0.9925	0.9919
5 – k – 87	Min.	0.9883	0.9973	0.9969
	Max.	0.9826	0.9976	0.9887

Figure (13) shows the relation between first, last, and estimated readings after 20 years with minimum and maximum water levels. The first readings were collected from about 32 years ago, while the last readings were collected at recent years. Future prediction of well level of well 5-k-87 is about (-119.00) while in wells 5-k-84, 5-k-83, 5-k-60 are (-80.00),(-160.00) and (-126.00) respectively. The percentage of water level reduction after 20 years compared with the reduction during the last 30 years will be only 24, 29, 17, and 23% for wells 5-k-87, 5-k-84, 5-k-83 and 5-k-60, respectively. It means that the future reduction of the well water level in the coming 20 years will not exceed 30% of the reduction done during the last 30 years.

4 SUMMARY AND CONCLUSION

A groundwater level prediction model study was conducted by using ANN. The ANN was used to develop a network of size 1-6-2 to predict the future water level around 2035. Daily data of water levels for a period of more than 30 years were used for the prediction. The data were collected from four wells located south of Riyadh City. A complete analysis of the 30 years data base was conducted. Results of the prediction show that the reduction of the groundwater level at about 2035 will be no more than 30% of the reduction made during the last 30 years. However, results still show that local authorities need to conduct a reliable strategy in order to reduce the future consumption of groundwater.

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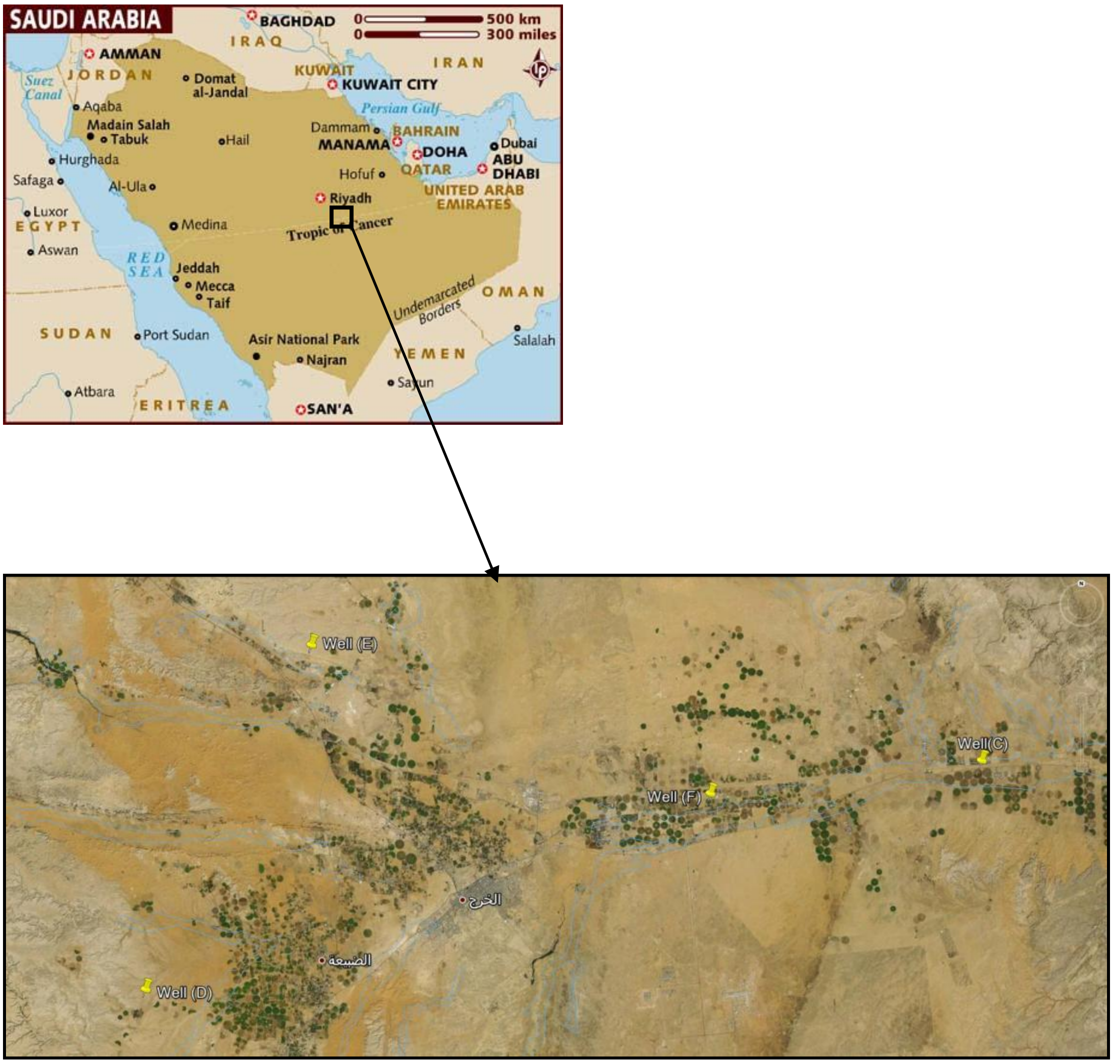
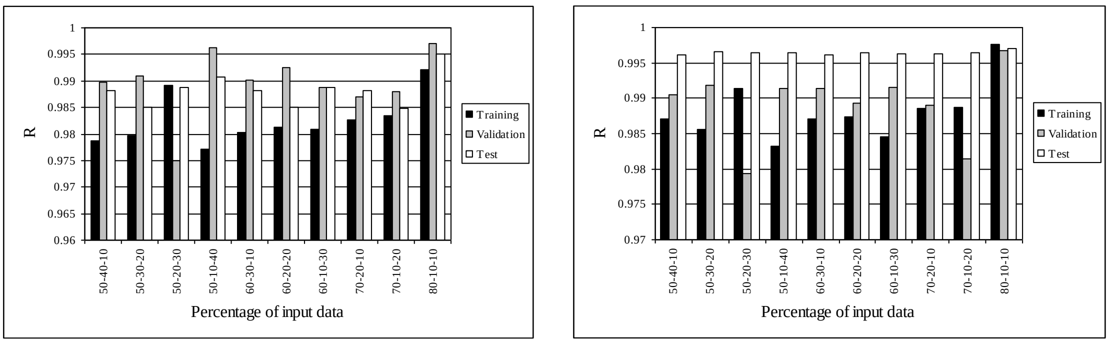
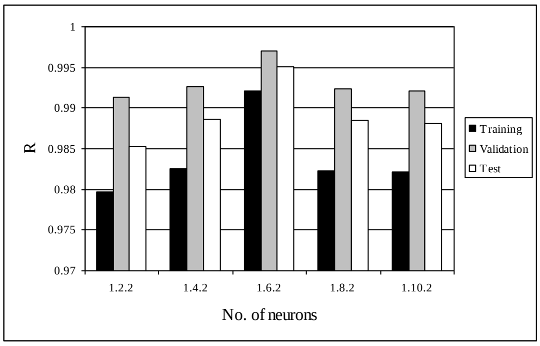


Figure1. Wells Locations

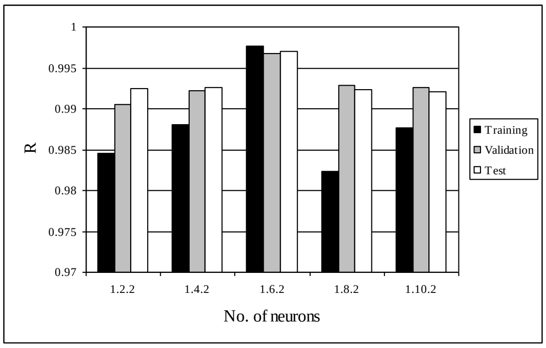


a - max. b – min.

Figure 2. Effect of percent input data on R for the training, validation and test data outputs for max. and min. readings.

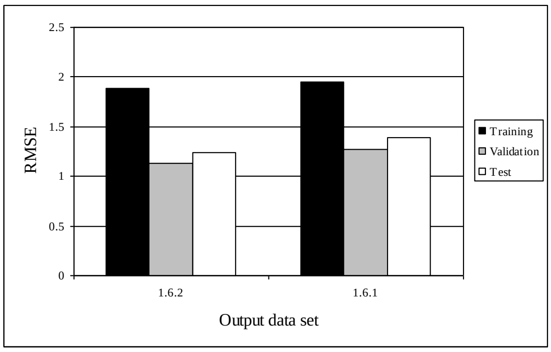


a - max.

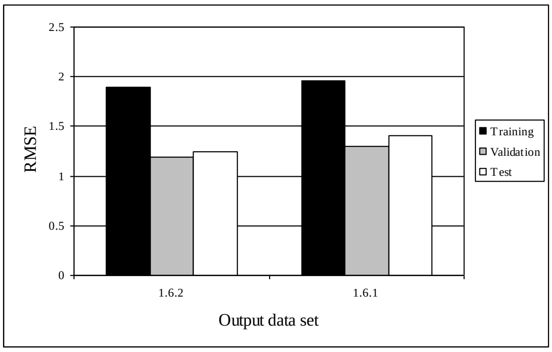


b – min.

Figure 3. Effect of no. of neurons of the hidden layer on R of the ANN outputs for max. and min. readings.

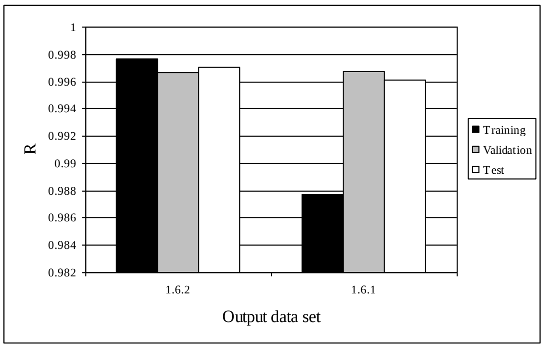


a - max.

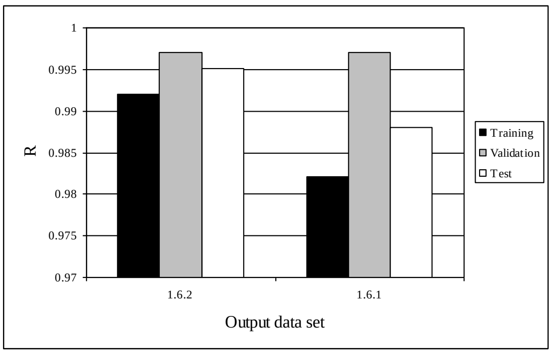


b – min.

Figure 4. Effect of single and multiple output neurons on RMSE of the ANN outputs for max. and min. readings.

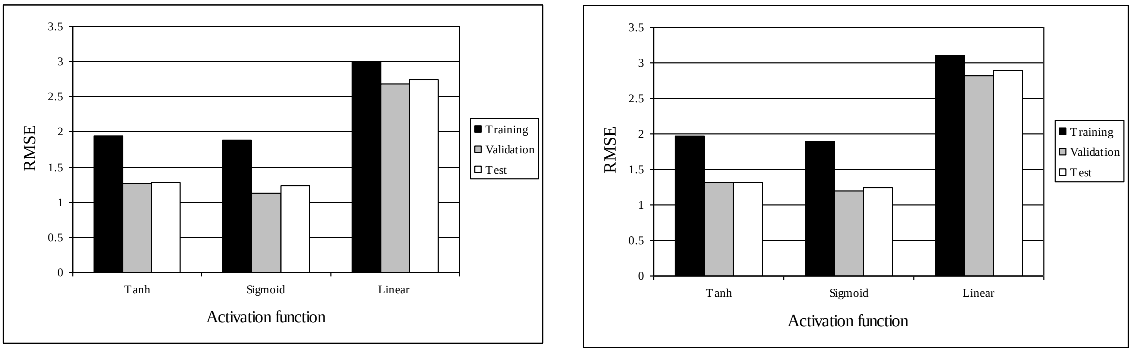


a - max.



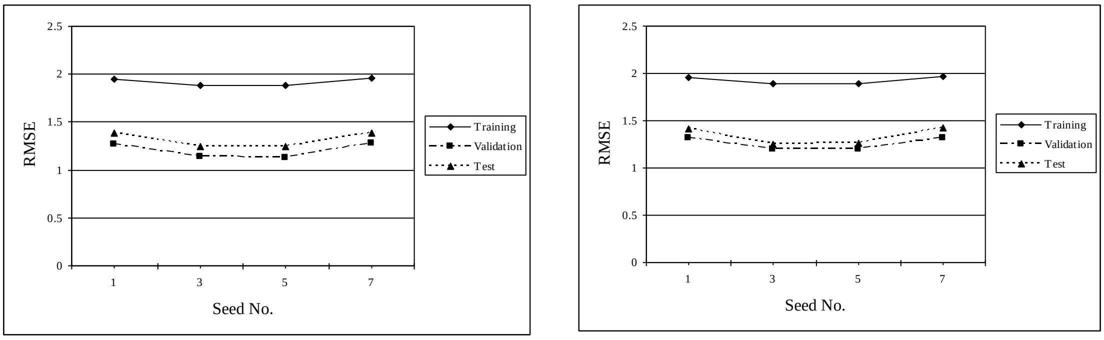
b – min.

Figure 5. Effect of single and multiple output neurons on R of the ANN outputs for max. and min. readings.

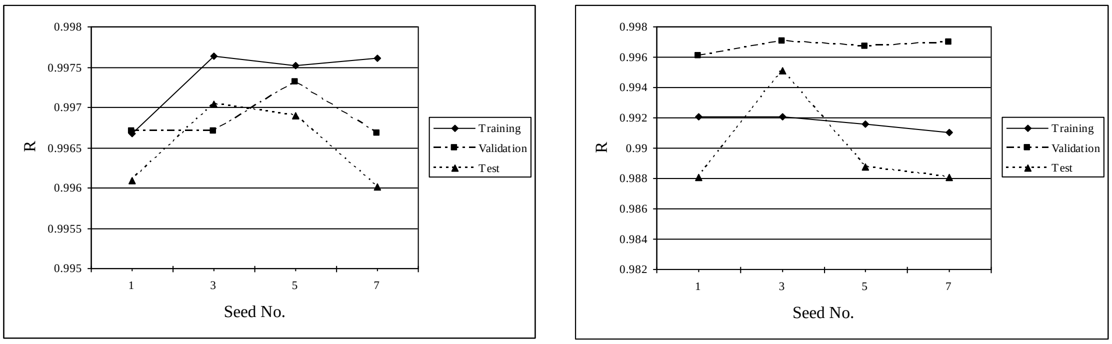


a - max. b – min.

Figure 6. Effect of activation function of hidden layer on RMSE of the ANN outputs for max/ and min. readings.



a - max. b – min.



c - max. d – min.

Figure 7. Results of studying the stability of the network, (a,b) RMSE and (c,d) R of the ANN outputs for max. and min. readings.

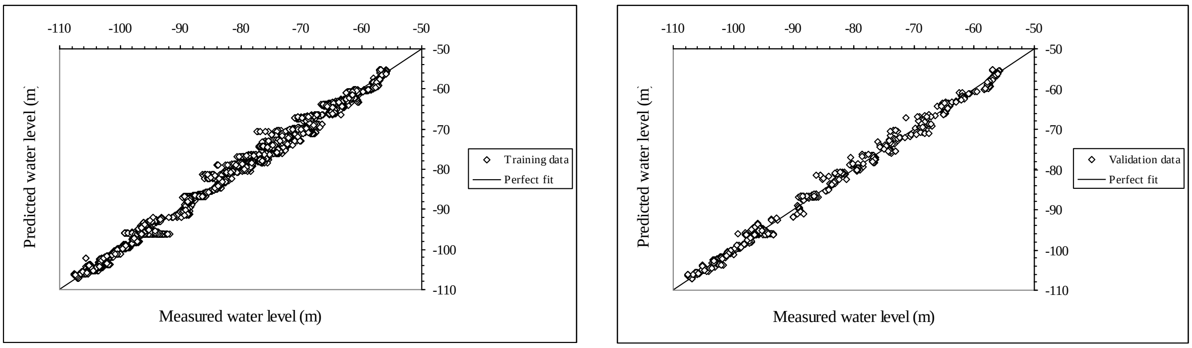


Figure 8. Examples of results of the predicted ANN model as compared with measured water level for different (training, validation) data sets for min readings. (5-k-87)

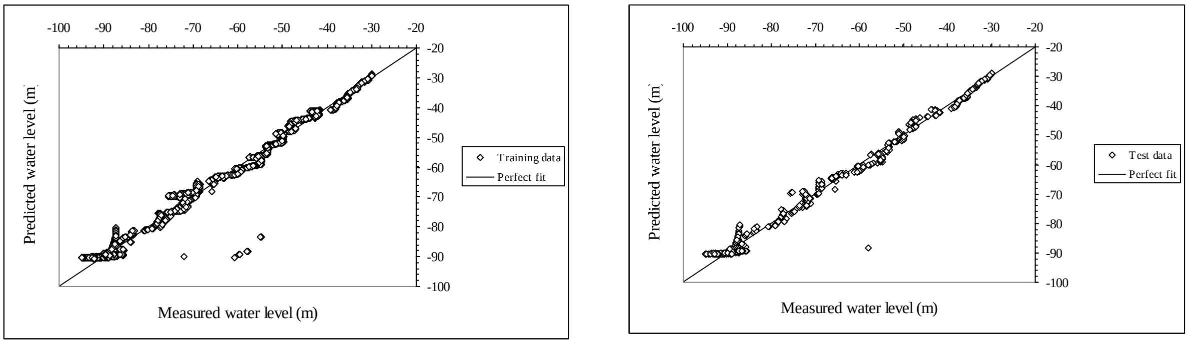


Figure 9. Examples of results of the predicted ANN model as compared with measured water level for different (training, test) data sets for max. readings. (5-k-84)

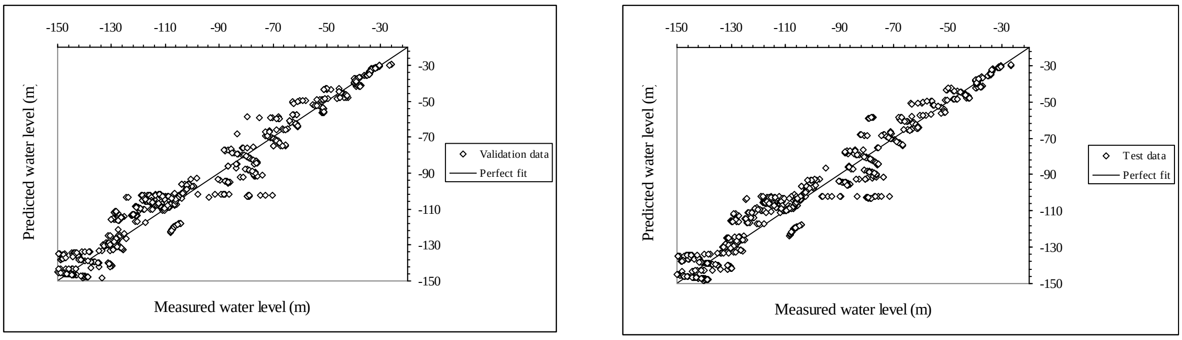


Figure 10. Examples of results of the predicted ANN model as compared with measured water level for different (validation, test) data sets for min. readings. (5-k-83)

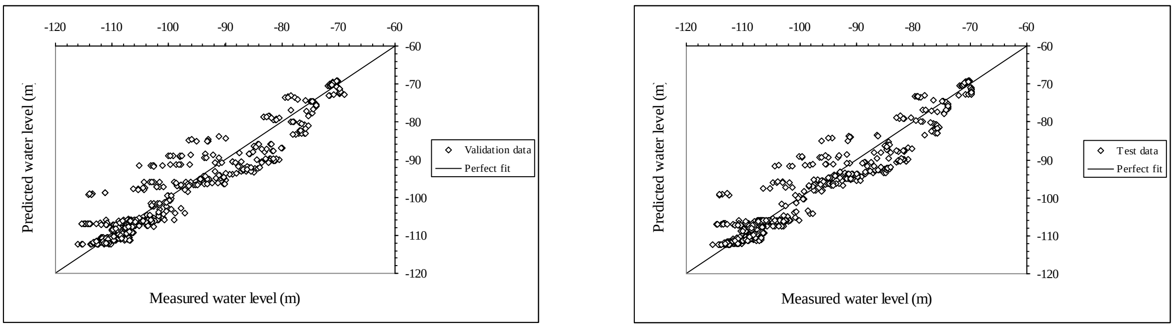
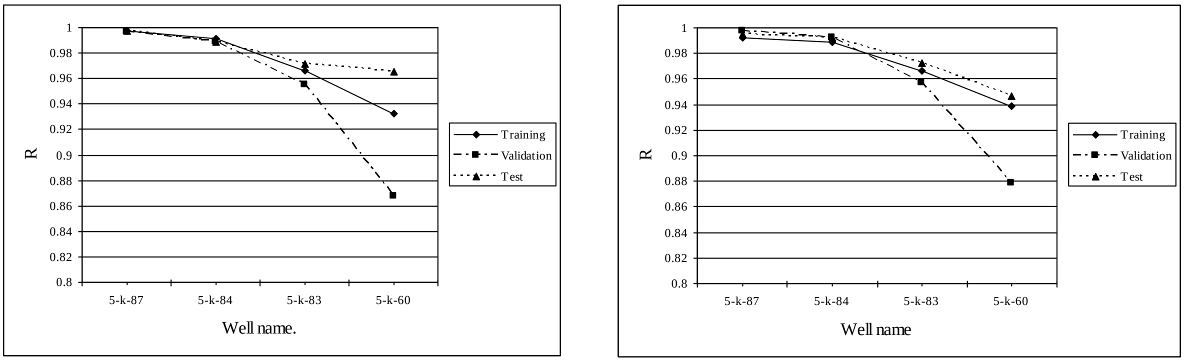


Figure 11. examples of results of the predicted ANN model as compared with measured water level for different (validation, test) data sets for max. readings. (5-k-60)



a - For min. readings a - For max. readings

Figure 12. The value of R of the ANN outputs for the different well name for (a) min. and (b) max. readings.

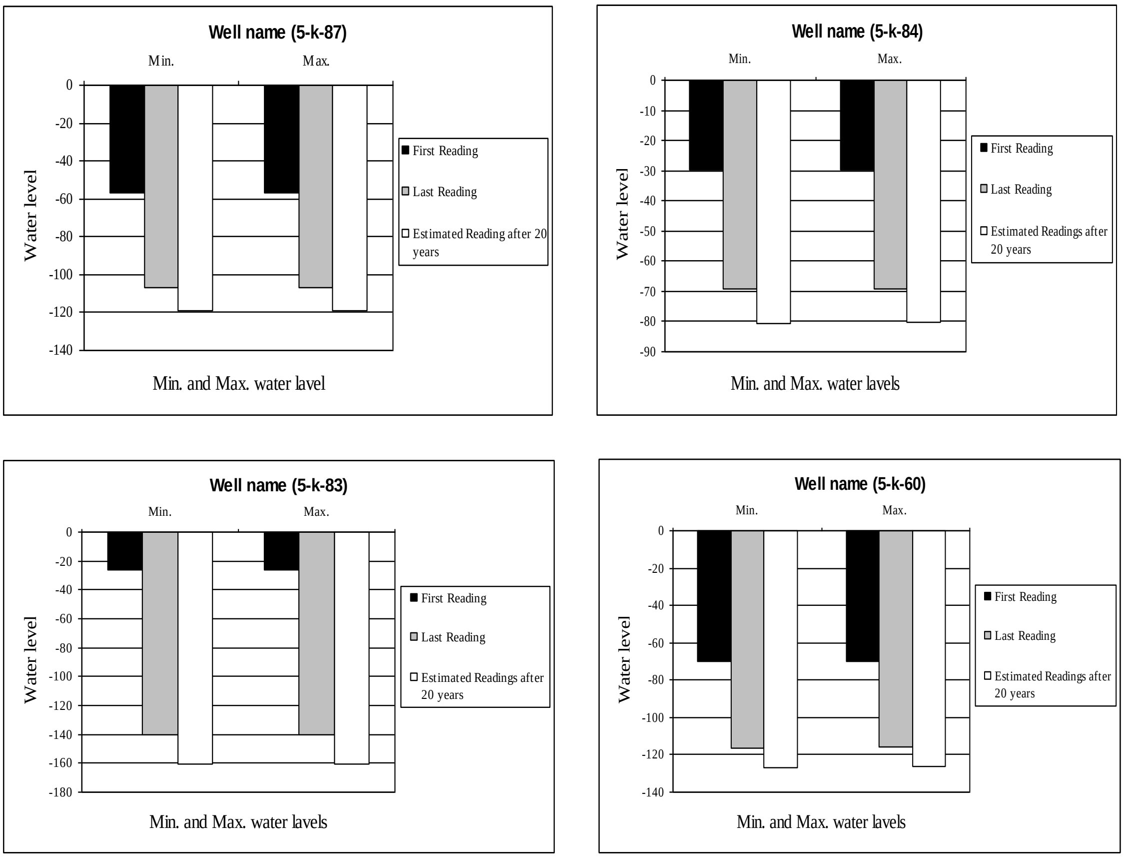


Figure 13. The relation between first, last and estimated readings after 20 years with min. and max. water levels.