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Hybrid Linear Moments and ANFIS-GA to Predict Groundwater Salinity

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ABSTRACT

There is, unfortunately, a lack of exhaustive qualitative and quantitative information about Iran groundwater resources. That is why various models are used in estimation of qualitative and quantitative groundwater parameters. The present paper presents a comparison of the hybrid of Adaptive Neuro Fuzzy Inference System (ANFIS) with Genetic Algorithm (GA) model and L-moments regarding their power and efficiency in regional and at-site anticipation of salinity of groundwater at Kerman plain. In doing so, electrical conductivity is considered the dependent variable, while, through regression analysis, total cat ions, magnesium ion, sodium percentage, and level of groundwater are assumed to be independent parameters. The correlation coefficient between input values and anticipated ones is the criterion the study takes into account in comparisons as well as in the election of the optimum model. Wells of study area were classified into three homogenous regions. Hass-King Heterogeneity and Incongruity Criterion were calculated for each site. The best result for regional analysis is achieved in well No.17 with correlation coefficient (C.C) 0.9958 whereas the best result for at-site analysis is calculated in well No.2 with C.C 0.9787. Results showed that, in regions with lower heterogeneity criterion, ANFIS-GA regional anticipations were slightly more accurate than at-site anticipations.

Keywords: Salinity, ANFIS-GA, Regional Analysis, At-Site Analysis, Kerman Plain.

INTRODUCTION

Groundwater is the sole dependable source of consumption for drinking water, agriculture, and industry in dry and semi-dry regions. Evidently, quantity and quality of water resources during the next year is important in water resource management. Since 1950, Groundwater simulation has been used vastly for a better management of groundwater resources. Therefore, many researchers have tried to find more accurate models, considering the actual conditions. These models require plenty of information which is difficult and sometimes impossible to gather. And also, considering some execution conditions, reaching a conclusion takes more time if possible at all. On the other hand, there are numerous factors in hydrologic parameters which complicate applying data to the models. Making physical and conceptual models have been poorly noticed for difficulty of gathering more information and the required time for calibration. In addition, nonlinearity of variables makes the problem more challenging. Recently, Artificial Intelligence (AI) models, as new powerful tools, have been used for forecasting hydrologic parameters. These methods act as a black box and do not require lots of physical data and are capable of estimating non-static water quality. Due to short processing time and low input data, AI models can supersede numerical ground water models. These new methods act as powerful estimators without the need for governing equations. For error reduction in regional forecasting, all selected wells must choose from one homogeny cluster. So, it is necessary to define cluster homogeny by some examinations. But one must make sure that these places are available. Because choosing some clusters with some wells inside is not sufficient for homogeny. The L-moments as the new types of statistical methods act for solving such problems. A quick search shows that regional forecasting with ANFIS-GA is a new method for modeling. Nero-fuzzy networks for flood regional analysis were used[1]. Investigation shows that nero-fuzzy model versus artificial neural networks and non-linear correlation, has better ability in modeling of flood estimation in watersheds without hydrometer At-Sites. L-moments was investigated the great supply of four aquifers in Australia[2]. They found that regional analysis increase the accuracy of forecasting. Adaptive neuro fuzzy inference system (ANFIS) have been used to predict water supply in terms of quality and quantity trends in sophisticated systems with acceptable accuracy[3-7]. Methods of AI are nonlinear tools of modeling which do not need any explicit of the physical relationship of the problem. Through recent years, those successful applications for Soft Computing Techniques in the field of water engineering have been published in a great scale[8-10]. This paper attempts forecasting regional salinity of groundwater of kerman plain by ANFIS-GA with L-moments and comparison of between regional and At-Site results.

Study area

This research has been geographically focused in the aquifer of Kerman plain which is a region in Kerman province located in the south-eastern of Iran as illustrated in Figure.3. Reportedly, there is no existence of any permanent river in this plain; therefore, the water supply demands for agricultural, industrial, domestic and municipal consumption in 3200 km2 area around this plain highly depends on groundwater. Droughts and increasing pumping wells in two recent decades have mainly caused major groundwater decline which is happening at a rate of (1-3) meter per year in different wells across the area. Besides, other problems have helped the deterioration of ground water quality[11]. The long-term annual precipitation for this area has noticeably decreased from 150 to 100 (mm/year) in the last 20 years (1993-2013).The local acquired data consists (time series/frequency) of rainfall and ground water levels measured at Kerman airport At-Site (latitude: 30o, 16' N, longitude: 56o, 54' E). The data set was collected by the Iranian Ministry of Energy[8].

MATERIALS AND METHODS

L-moments

(Hosking, 1990) has a new definition of L-moments. Based on his studies, L-moments are analogous to traditional moments which are expressible as linear combinations of order statistics. Basically L-moments have linear functions as probability-weighted moments (PWMs)[12]. Alike conventional moments, the primary objective of PWMs and L-moments is to summarize previously-observed samples and theoretical distribution. The theory of PWM was summarized and defined by (Greenwood *et al.*, 1979) as the following[13]:

$$\beta_r = E\{X[F_X(x)]^r\} \qquad ...(1)$$

Where âr is the rth order PWM and FX(x) is the cumulative distribution function of X. Unbiased sample estimators (bi) of the first four PWMs are given as[14].

$$\beta_0 = m = \frac{1}{n}\sum_{j=1}^{n} X_j$$

$$\beta_1 = \sum_{j=1}^{n-1}[\frac{n-j}{n(n-1)}]X_{(j)}$$

$$\beta_2 = \sum_{j=1}^{n-2}[\frac{(n-j)(n-j-2)}{n(n-1)(n-2)}]X_{(j)}$$

$$\beta_3 = \sum_{j=1}^{n-3}[\frac{(n-j)(n-j-1)(n-j-2)}{n(n-1)(n-2)(n-3)}]X_{(j)} \qquad ...(2)$$

Where x(j) represents the ranked AMS with x(1) being the highest value and x(n) the lowest value, respectively. The first four L-moment are given as follow

$$\lambda_1 = \beta_0$$

$$\lambda_2 = 2\beta_1 - \beta_0$$

$$\lambda_3 = 6\beta_2 - 6\beta_1 + \beta_0$$

$$\lambda_4 = 20\beta_3 - 30\beta_2 + 12\beta_1 - \beta_0 \qquad ...(3)$$

Non-biased sample estimators in the first four L-moments are resulted by the substitution of the PWM sample estimators from Eq. (2) and Eq. (3). The first L-moment ë$_0$ and the mean value of *X* are equal. At the end, the L-moment ratios are calculated as:

$$L-C_V=\tau_2=\frac{\lambda_2}{\lambda_1}$$
$$L-\gamma=\tau_3=\frac{\lambda_3}{\lambda_2}$$
$$L-k=\tau_4=\frac{\lambda_4}{\lambda_2} \quad ...(4)$$

Sample estimates of L-moment ratios are obtained by substituting the L-moments in Eq. (4) with sample L-moments.

Heterogeneity Measure

Heterogeneity measure is used for identification of homogeneous regions based on observed and simulated dispersion of L-moments for a group of sites under consideration. This can be computed from[15]:

$$H=\frac{(V_1-\mu_{V1})}{\delta_{V1}} \quad ...(5)$$

Where *V* = weighted standard deviation of τ_2 values, μ_{V1}, δ_{V1} = the mean and standard deviation of N_{sim} values of , and N_{sim} = number of simulations.

A region is declared 'acceptably homogeneous' if H<1; 'possibly heterogeneous' if 1<H<2; and 'definitely heterogeneous' if He" 2. To avoid committing to a particular 2 or 3 parameter distribution, simulation is undertaken using a 4 parameter Kappa distribution and the number of simulation is kept at least at 500 to arrive at reliable estimates of μ_{V1} and δ_{V1}. In addition to the above, two additional measures H1 and H2 based on LCV/LCS and LCS/LCK distances respectively are also considered. The measure H1 indicates whether at-site and regional estimates will be close to each other, while H2 indicates whether the at-site and regional estimates will be in agreement. A large value of H1 usually indicates a large deviation between regional and at-site estimates, whereas a large value of H2 indicates a large deviation between at-site estimates and observed data.

Discordance Measure

Discordance measure, ZDIST, is used to screen out the data from unusual sites, i.e. sites whose at-site sample l-moments are markedly different from other sites and is defined as [16]:

$$D_i=\frac{1}{3}(u_i-\overline{u})^T\cdot S^{-1}\cdot(u_i-\overline{u}) \quad ...(6)$$

Where Ui = vector of LCV, LCS and LCK for a site i; S = covariance matrix of V; $\overline{u}$ = mean of vector Ui.

A given site is declared discordant if Did"3. Critical value of ZDIST defines as [14]:

$$D_i\le(n-1)/3 \quad ...(7)$$

Where n is number of At-Sites in studied region.

The neuro-fuzzy structure

The ANFIS , the multilayer feed-forward network, maps inputs into an output using neural network learning algorithms and fuzzy reasoning. It is certain that a fuzzy interference system (FIS) is implemented in the framework of adaptive neural networks. Fig.1 illustrates the architecture of a typical ANFIS with five layers:

For simplicity, a typical ANFIS architecture with only two inputs leading to four rules and one output for the first order Sugeno fuzzy model is expressed[17,18]. It is also assumed that each input has two associated membership functions (MFs). It is clear that this architecture can be easily generalized to our preferred dimensions. The detailed algorithm and mathematical background of the hybrid learning algorithm can be found in the Reference[19].

ANFIS-GA method

There is a hybrid of canonical real-coded GA, subtractive clustering and ANFIS, designed and finalized for the purpose of producing suitable approximate fuzzy models for the sake of accuracy and parsimony. The primary procedure of modeling is an optimization task executed by GA where both the accuracy and compactness of fuzzy models are the subjects of simultaneous optimization. The whole process of optimization by GA is based on four steps respectively, 1- Fitness assignment 2- Selection 3- Crossover 4- Mutation. Generating a fuzzy model based on subtractive clustering method is completed in the fitness assignment part of GA. The flow chart of modeling procedure is illustrated in Fig.2.

Subtractive clustering method can be used to generate a fuzzy model of TSK in which the number certain rules (i.e. the number of clusters) is determined through radii parameters dedicated into dimensions. These radii are mainly used for the purpose of cluster generation. Each cluster is meant to represent a rule and according to the fact that clustering is completed in multidimensional space, and fuzzy sets for each rule must be achieved. By projecting the center of each cluster

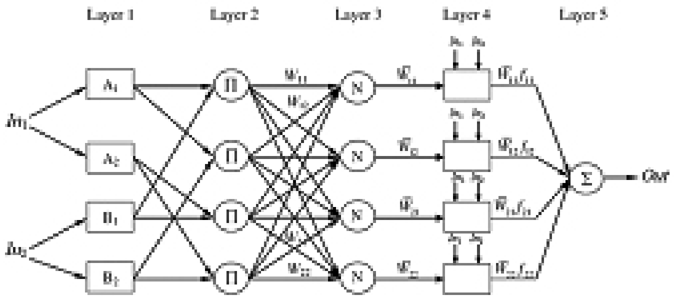

Fig. 1: A typical ANFIS architecture for a two-input Sugeno model with four rules

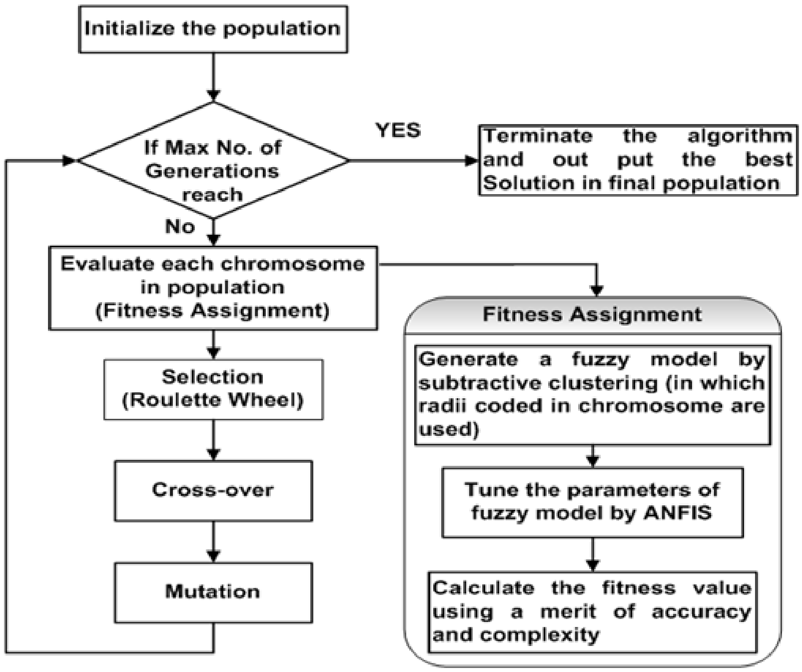

Fig. 2: Steps of modeling procedure

in the corresponding dimension, the centers of MFs are obtained. The widths of MFs for a single dimension are obtained on the basis of radius r_a which is particularly considered for that dimension. Therefore, each chromosome in this study acts as radii values encoder for all dimensions inputs and outputs of a fuzzy model. These radii of fuzzy model are then used by subtractive clustering to generate a TSK FIS.

Simulation setup

The population size (PZ) and generation numbers (G) for GA are set to PZ = 100 and G = 50, respectively. The 1-point crossover with the probability of 0.7 is employed. Classical mutation with probability 0.02 is used and selection method is the roulette wheel. Number of epochs and learning rate are set to 100 and 0.2 for ANFIS. Ranges of radii are considered to be in interval [0.1, 2].

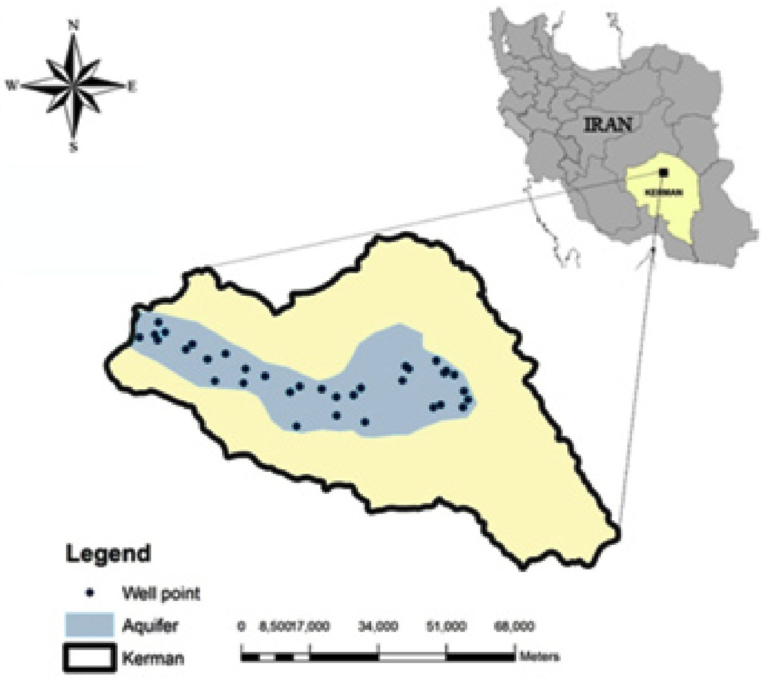

Fig. 3: Location of wells in Kerman plain

Table 1: Correlation coefficient for different parameters in multiple linear equations

C.C	Parameter	Equation
0.998	Sum of Cations	1
0.951	Sum of Cations	2
0.066	Mg	
0.926	Sum of Cations	3
0.08	Mg	
0.031	Na%	
0.928	Sum of Cations	4
0.069	Mg	
0.04	Na%	
0.023	L	

RESULTS AND DISCUSSIONS

First step to define a homogenous region is choosing the most important clustering parameters. Choosing all important parameters to define a homogeny cluster for a phenomena, increase calculating time and errors, so, choosing the most important parameters would make the calculation simpler, without resulting in any major differences. In this paper, out of effective parameters (time series parameters recorded) more important parameters were selected through regression analysis. Results showed that all of the cations, magnesium ions, sodium percentage, and groundwater level have more effect on salinity as they are shown in the following equations.

$$EC = 154.446 + 87.852\, sumCation \quad ...(8)$$

$$EC = 68.539 + 83.78 sumCation + 36.094 Mg \quad ...(9)$$

$$EC = -143.368 + 81.572\, sumCation + 43.985\, Mg + 4.031\, Na\% \quad ...(10)$$

$$EC = -306.097 + 81.705\, sumCation + 38.178\, Mg + 5.253\, Na\% + 1.732\, L \quad ...(11)$$

Where L = groundwater level, the most accurate one is equation No.11 with C.C = 0.97. Moreover, the C.C of each parameter is shown in Table.1

Therefore, these parameters are used for electrical conductivity in clustering and also input parameters for forecasting. In this paper, with K-Means method and Ward hierarchical, the region was divided into 2, 3, and 4 sectors, respectively. And then, the incompatibility and non-homogeny criteria

Table 2: Non- homogeny criteria for different scenarios

Criteria H_3	Criteria H_2	Criteria H_1	Region	Method
6.77	2.5	1.5	Total	Total wells of a region
1.22	1.01	0.6	A	K-Means
2.5	-0.91	-0.45	B	2 region
1.3	0.65	0.4	A	K-Means
2.28	-0.53	-0.25	B	3 region
3.29	-0.99	-0.45	C	
0.88	0.15	0.1	A	K-Means
1.01	-0.35	-0.25	B	4 region
0.9	-0.22	-0.11	C	
1.8	0.45	0.12	D	
1.22	1.01	0.6	A	Ward
2.5	-0.91	-0.45	B	2 region
1.21	0.59	0.32	A	Ward
2.33	-0.43	-0.31	B	3 region
1.09	-0.71	-0.33	C	
0.92	0.23	0.14	A	Ward
1.17	-0.25	-0.41	B	4 region
1.29	-0.31	-0.14	C	
1.96	0.69	0.45	D	

Table 3: The best topology of ANFIS-GA model for the study areas

Region	Model	No. of input variable	No. of rules	No. of MF	R^2
A	ANFIS-GA	4	5	20	0.9895
B	ANFIS-GA	4	7	28	0.9936
C	ANFIS-GA	4	4	16	0.9929

for the region were defined. For choosing the best clustering mode and optimum number of regions, incompatibility summation of At-Sites, defining the number of incompatible At-Sites with more degree of 1.5, 2 and 3, and also non-homogeny criteria were conducted for each and every region. Results are shown in Table.2

Considering Table.2, when all the At-Sites are considered as one region, only the H_1 criteria are homogeny while H_2 and H_3 are non-homogeny. In general, K-mean method includes 4 regions as the priority and Ward, with 4 regions in the next place. Considering 4 homogeny regions for research area, some wells were scattered in the other areas. To solve this problem, all the following, well No3 in region A, well No_{15} in region B, and well No_{27} in region D were combined together and then the non-homogeny criteria were computed. Relocation of the wells increased the non-homogeny of region A and B and decreased that of region C. To define the increase of non-homogeny, incompatibility of the wells was investigated and it was observed that well No_{14} was incompatible. The well was moved to region B and computation was restarted. The results showed decreased incompatibility for well No_{14}. And finally, with moving to region B and re-computation, better results were achieved. Figures below show the final homogeny regions.

Table 4: The correlation coefficient between observed and predicted data for each well in the area A

R^2	Well number	R^2	Well number
0.9701	8	0.8565	1
0.9018	9	0.9111	2
0.9205	10	0.7825	3
0.9366	11	0.9312	4
0.9912	12	0.9488	5
0.8904	13	0.9726	6
		0.8999	7

Table 5: The correlation coefficient between observed and predicted data for each well in the area B

R^2	Well number	R^2	Well number
0.9024	19	0.9827	14
0.9231	20	0.7903	15
0.9125	21	0.9905	16
0.9259	22	0.9958	17
		0.8592	18

Regional forecasting

First and foremost, for regional forecasting, dimensionless data was computed in each one of the three regions including both selection input data and electrical conductivity. After choosing the best scenario for forecasting, by multiplying average off each well by regional dimensionless data, the dimensionless forecasting data is obtained for each well. Desired periodical statistics are considered on a monthly basis from 2001 to 2013. For analysis, 156 regional dimensionless data were used. In this research, 70 percent of the data was used for teaching, 10 percent for validation, and the remaining 20 percent was used for the testing. Furthermore, for regional forecasting, models constructed with the relation equation are studied. In all models, the momentum training and ANFIS-GA method were used.

Having observed the results of correlation coefficient and non-homogeny criteria, it is obvious that non-homogeny decreased, the correlation coefficient of the observed data and regional forecasted data decreased as well. The reason is that low non-homogeny means incompatibility of the wells with the other wells in the same region. So, this would be able to reduce forecasting error. After implementing the proposed method (ANFIS-GA) for each region, with multiplying the coefficient of each

Table 6: The correlation coefficient between observed and predicted data for each well in the area C

R^2	Well number	R^2	Well number
0.9126	29	0.8512	23
0.9947	30	0.8637	24
0.9458	31	0.9325	25
0.9825	32	0.9238	26
0.8329	33	0.7329	27
0.9917	34	0.9028	28

At-Site for the desired year, by regional forecasting data, electrical conductivity was calculated for each At-Site, and, finally, between the observed and calculated data, the correlation coefficient was calculated. Tables 4 to 6 show the correlation coefficient for each well.

Considering the results shown in tables 4, 5, and 6 the wells No_3, No_{14}, No_{15} and No_{27} which were moved before, have the least correlation coefficient. Better correlation coefficients are associated with the wells with salinity levels close to that of the regional average. Thus, it follows that regional analysis can forecast with high precision, in case of selection of wells and internal At-Sites. Figures 4, 5, 6, and 7 show forecasting and regional salinity.

The figures 8, 9, 10, and 11 show the salinity of each at-site which is obtained from multiplying the average at-site by regional forecasting data. The horizontal axis is represented EC concentration as it is illustrated in figures 8 to 11 the concentration of

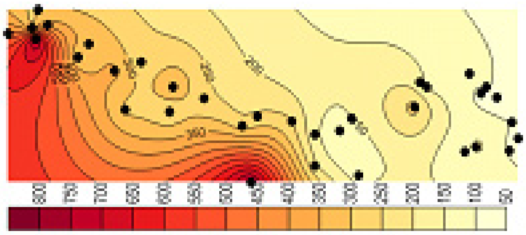

Fig. 4: Regional salinity for September 2001

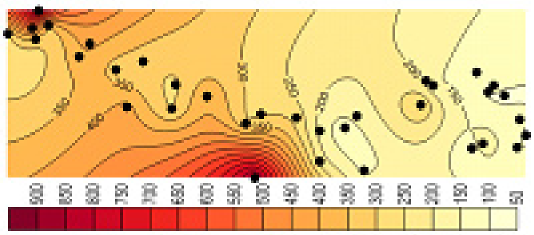

Fig. 5: Regional salinity for September 2007

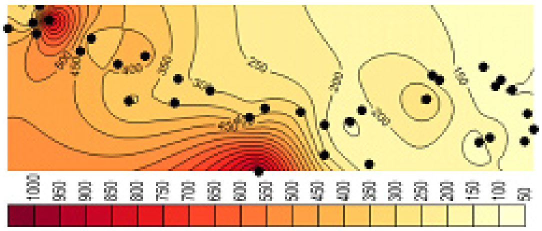

Fig. 6: Regional salinity for September 2011

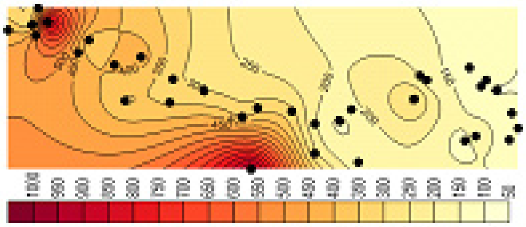

Fig. 7: Regional salinity for September 2013

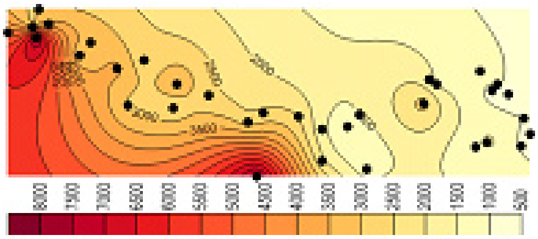

Fig. 8: Predicted salinity for September 2001

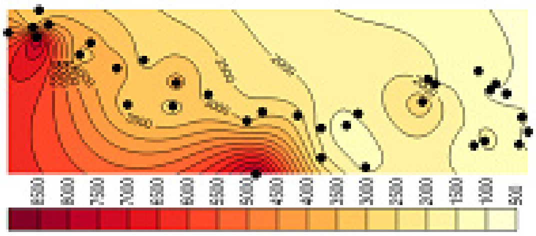

Fig. 9: Predicted salinity for September 2007

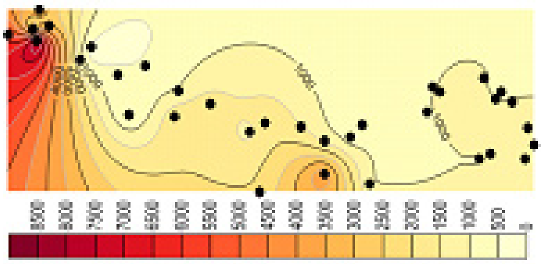

Fig. 10: Predicted salinity for September 2011

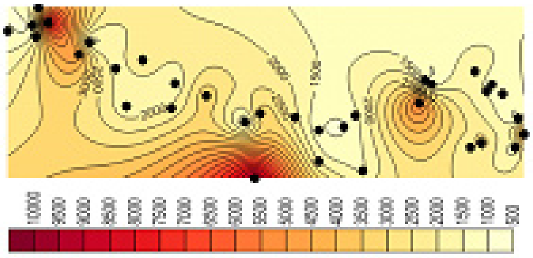

Fig. 11: Predicted salinity for September 2013

EC increase from 8000 micromohs in 2001 to 10000 micromohs in 2013.

At-Site forecasting

For forecasting the salinity of our 34 wells, similar to the regional method, the proposed method ANFIS-GA is applied to each well. For this purpose, the correlation coefficient between the observed data and forecasted data was obtained. After choosing the appropriate model, the forecasting started. Review of the results suggests that the salinity of groundwater for the study area increased during the past years. And also it's clear that ANFIS-GA is capable of forecasting acceptable groundwater salinity.

Table 7: Correlation coefficient for best structures at different Wells

Priority	Correlation Coefficient Regional	At-Site	Well No
At-Site	0.8565	0.9485	1
At-Site	0.9111	0.9787	2
At-Site	0.7825	0.8305	3
At-Site	0.9312	0.9485	4
At-Site	0.9488	0.9598	5
Regional	0.9726	0.9093	6
Regional	0.8999	0.8179	7
Regional	0.9701	0.8902	8
At-Site	0.9018	0.9553	9
Regional	0.9205	0.9134	10
Regional	0.9366	0.8943	11
Regional	0.9912	0.9166	12
Regional	0.8904	0.8029	13
Regional	0.9827	0.8245	14
At-Site	0.7903	0.875	15
Regional	0.9905	0.8971	16
Regional	0.9958	0.9403	17
Regional	0.8592	0.853	18
At-Site	0.9024	0.9584	19
Regional	0.8231	0.8812	20
Regional	0.9125	0.9295	21
At-Site	0.9259	0.9292	22
At-Site	0.8512	0.8139	23
Regional	0.8637	0.9296	24
Regional	0.9325	0.9406	25
Regional	0.9238	0.8911	26
At-Site	0.7329	0.8016	27
At-Site	0.9028	0.8723	28
Regional	0.9126	0.9063	29
Regional	0.9947	0.9551	30
Regional	0.9458	0.9457	31
Regional	0.9825	0.9463	32
At-Site	0.8329	0.9552	33
Regional	0.9917	0.9665	34

Comparison of At-Site and regional forecasting

Priority of regional or At-Site analysis for each studied well of Kerman plain was revealed through the method of correlation of coefficient, and then inserted into Table 7.

According to the results mentioned above, 21 wells with regional analysis and 13 wells with At-Site analysis method maintain good accuracy. The investigation shows that for wells, for which regional analysis shows lower accuracy in comparison to At-Site analysis, the average is above regional average (wells No_1 ,No_5, No_9, No_{15}, No_{19} and No_{22}) or below regional average (wells No_{23}, No_{28} and No_{33}). The rate of incompatibility for these wells is higher than the other regional homogenous wells. Region A has the most priority in At-Site analysis followed by C and D. As a result, the most important regions for analysis are the non-homogenous regions. As a result, in case of proper selection of the at-sites in a homogeneous region and low at-sites incompatibility as well as non-homogeneity criterion, regional analysis is preferable to at-site analysis.

CONCLUSION

According to regression analysis, sum of cat-ions, magnesium ions, percentage of sodium, and groundwater table are the most effective on salinity. Moreover, for defining the number of homogeny clusters, generally, K-Means method, with 4 regions is the first and Ward with 4 regions is the second suitable selection. As the non-homogeny criteria decreased, correlation coefficient between the observed data and regional forecasted data reduced as well. The largest correlation coefficient was associated to the wells with close salinity to the regional average. In case of precise selection of the wells and At-Sites inside the region, the regional analysis can forecast with high accuracy. The most important regions for analysis are the non-homogenous regions. Moreover the ANFIS-

GA model analysis showed an increase in the compactness and accuracy of the mentioned model during the testing stage. Our proposed method aiming to provide us with the best and effective composition of structure in the ANFIS model trade off rise and fall between the accuracy and the number of certain parameters. The maintained results are to show a new hybrid algorithm providing both accuracy and complexity for a Neuro-Fuzzy model.

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