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**PETROLEUM EXPLORATION IN SALT DOM USING HOPFIELD NEURAL
NETWORKS AND ITS COMPARISON WITH KOHONEN NEURAL NETWORKS
RESULTS (CASE STUDY: QUM SALT DOME)**

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ABSTRACT

One of the most important methods for geophysics study to obtain subsurface resources and hydrocarbon exploration is gravimetry method. Gravimetry is a method for measuring density changes and identifying different types of underground structures such as salt domes. Since salt as a leakproof material plays an important role in the formation of the traps and studies have shown that most of the salt structures are kind of associated with oil trap so studies on salt domes are essential for hydrocarbon exploration. Since the use of neural networks as a tool in the interpretation of gravity data has found wide use, their progress always along with correct procedures and interpretation of gravity data introduced new path for researchers and engineers in the use of this method. In this study two algorithm were used for interpretation of gravimetry data: Hopfield and Kohonen neural networks and geology and stratigraphy studies.

Keywords: Gravimetry, Hopfield, Kohonen, Salt Dome

INTRODUCTION

The main goal of geophysics researches in oil exploration is finding out about oil traps. Gravimetry is one of geophysical methods that are used for oil and gas exploration. This

method has been created based on non-uniform distribution of the density of subsurface strata. In gravimetry method by eliminating the troublesome forces and adding

the necessary forces, gravity changes is achieved due to changes in the density of the earth formation. Exploration of hydrocarbon resources in the salt dome and large anticline is one of the applications of gravimetry methods in the oil region. Salt domes because of being leakproof are known as one of oil traps. Some structural oil traps as anticlinal in the outcrop but in most cases, these buildings have been completely covered with sediment and the trap just can be realized with geophysical investigations. Meanwhile, the role of gravimetry in determining the oil trap is undeniable because it plays an important role as a method to identify oil trap and salt dome exploration which are covered by sediments that have made important contributions to trap hydrocarbons. The research and studies for the exploration of oil are related to Ministry of Petroleum because the main income of the country is petroleum products. Since most of the world proven oil reserves are salt structures so it is essential to do exploration and geological studies in the areas of diapiric for hydrocarbon exploration. Qom salt dome is one of the areas in which the probability of hydrocarbons is under study. In this Paper, this salt dome was investigated by using gravimetry and the

possibility of hydrocarbon existence will be inspected.

2. Artificial Neural Networks

2.1 Hopfield Neural Networks

Hopfield neural networks (1982 and 1984) are dynamic, recursive and consist of several neurons with delay units that make up a system of feedback polycyclic it means that the output of each neuron to all neurons has feedback. (Lipman 1987) This network can be divided into two categories: continuous and discrete. These networks like middle layer of Hamming network have feedback but the difference is that the ability of the entire Hamming network to solve the identifying problem is patterned. The diagram of Hopfield network block is displayed in Figure (1). This network is kind of network standard of discrete Hopfield. As you can see in the form of network all neurons act like each other and none of neurons are not separate as input or output. First, the neurons by input get initial values and then repeat their network that the final result is network convergence to one of the reference patterns. Equations that explain the behavior of the Hopfield network are:

$$a(k+1) = \text{sat}[\sum w_{ij} a(j) + b_i]$$

$$a(0) = p$$

In which the sstal nonlinear function is a different function that is linear [-1 to 1] and for values less than -1 get -1 value and for values bigger than 1, get +1. Weight matrix design and bias vector for Hopfield network in compare to other networks are more complex.

In this part we give a brief explanation on how to choose the weights for Hopfield network. We start with calculating weight for training a reference group. The purpose is selecting the weights from the reference collection that if one of reference model was applied as input to the network the network converges to that reference pattern.

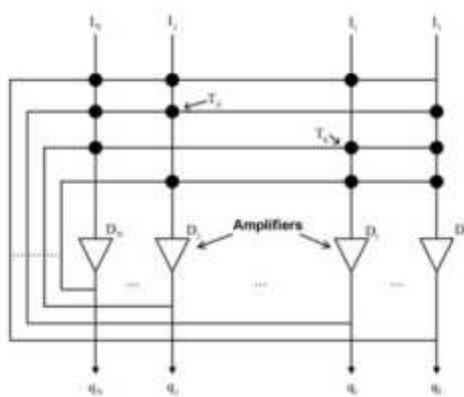


Figure (1) Hopfield discrete neural network (Wang and Mandel 1991)

2.2 Self-Organizing Feature Map Model

2.2.1 Kohonen Model

Kohonen Model is unsupervised. In this model number of nerve cells are arranged together in a flat topology with interact with

one another play self-organizing network task. This task is to estimate a distribution function. Consider $R^n \times \epsilon$ vector that each element of which has a probability density of $p_i(x)$. In this space we choose density of samples frequently and randomly and apply them to network. Based on the location of input vector in R^n space the weight of the cells changes according to an algorithm which will be explained later. This change was done so that in the end, the weight $R^n w_i \epsilon$ vectors of the cells are distributed uniformly in density space of input probability. And thus the network by spreading cells (cells' shapes) probability estimates the input space density. The distribution of cells in space probability input can be considered as data compression because now each cell (with i index) is approximate expression of a specific area in the R^n space. In other words a number of i instead of n is enough for X_i .

2.2.1.1 General algorithm

An input is applied to network (x from R^n space). A cell that has the closest form (w from R^n space) to input vector is identified. The form of the cell and number of its neighboring cells move to the input and again another input and so on.

The process of learning algorithm of Kohonen network is:

- 1- We choose random values for the initial weight vector $w_j(0)$
- 2- We select the vector x randomly from the input space.
- 3- We select that neuron that has the least Euclidean distance with input vector as winning neuron $i(x)$
- 4- We set the synaptic weight of winner neuron and neurons located in the neighborhood of the winner neuron in accordance with the following formula:

$$W_j(n+1) = w_j(n) + \eta(n) h_{j, i(x)}(n) (x - w_j(n))$$

In which $\eta(n)$ is learning rate and is $h_{j, i(x)}(n)$ adjacent function that the winner neuron is in the center.

- 5- Going to step 2 until there are no significant changes in the map view.

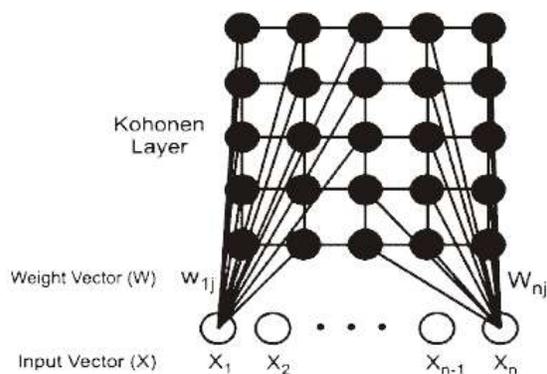


Figure (2): Kohonen network is self-organizing network that number of artificial neurons are put beside each other in a flat topology (Kohonen layer). X is weight vector for network neurons.

When the algorithm of Kohonen network is converged the map view (that is shown $\{w_j\}$ by the synaptic weight vectors) that is

calculated by this algorithm shows the statistical characteristics of the important input space.

Following parameters have direct effect on Kohonen network function:

- 1- Number of layers
- 2- Number of neurons in Kohonen layer
- 3- Trigger function
- 4- Giving initial values to weight
- 5- Learning rate of n

3. Case Study

3.1 Qum salt dome:

The actual data that are used in this paper are obtained from gravimetry measurements of Qum salt dome. This dome is located in 25km of northwest of Qum, on Qum-Saveh road. Qum salt dome covers area of 6.5 square kilometers and height of 456 cubic kilometers above the surface of earth. In the satellite image (Figure 3) the color of salt hill is darker than other geological features.

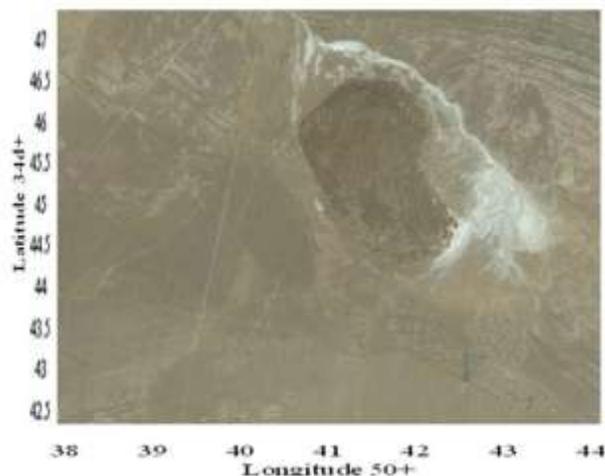


Figure (3) satellite image of area, salt dome is on northeast of picture (west of Qum) East side of dome has rock structure and west side has sedimentary structure. (Alimoradian et al, 2011) The details of the geological structure of under study area, is displayed in the geological map of the area (Figure 4). It should be noted that the latitude and longitude that are shown in the pictures is exactly extracted from existing maps.

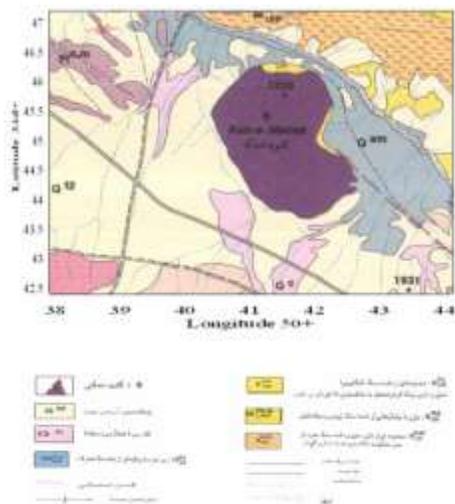


Figure (4): Geological map of the area (Geological organization of Iran)

In general, the geological map and satellite image of region is determined that this region is influenced by two different geological structure. In the eastern part of the dome, the geological structure as rock (sedimentary Miocene Qum Formation) and on the west side there are quaternary sediments. The impact of the geological structure, which increases the amount of gravity from Southwest to Northeast, Bouguer gravity map is visible in figure (5).

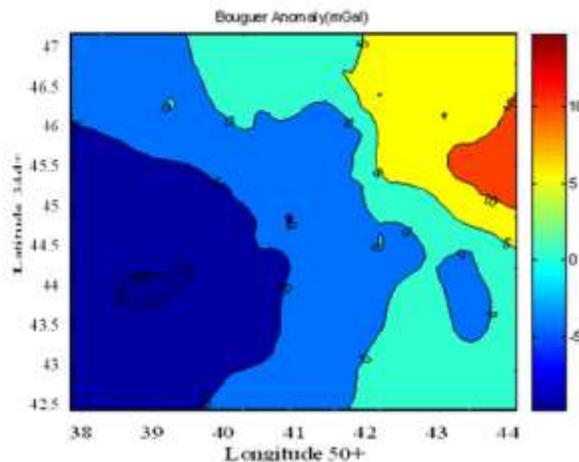


Figure (5): geographical location of area and complete bouguer gravity using Surfer software and based on Talebian (1976) data. (Alimoradian et al 2011) Figure (5) shows the geographical location of the study area with the latitude and longitude. Gravity range is from 10 to 15 minigal in total data.

3.1.1 Analyzing available data related to Qum field

This field contains 288 data for of gravity geophysical data which contains four parameters of longitude, latitude, altitude and residual gravity. Then, using these parameters using artificial neural networks, the point of oil exploration will be evaluated.

3.2 analyzing field using contour and 3D diagrams

In this part, as it is shown in Figure (6), using available data in sorted Excel software, contour diagram is plotted to obtain the dome location. As it is shown in figure, in the center toward the Northeast of contour, the related anomaly is centered that due to the obtained

numbers the salt dome has been shown. Beside contour diagram the two dimensions of this dome were drawn by using software that is easily seen in figure 2.4

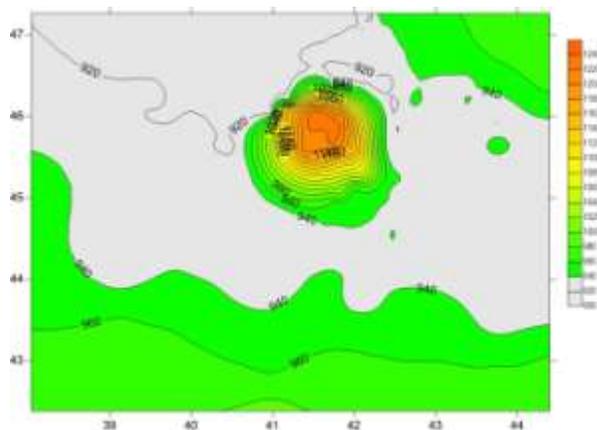


Figure (6): Contour diagram of Qum salt dome (Surfer 11)

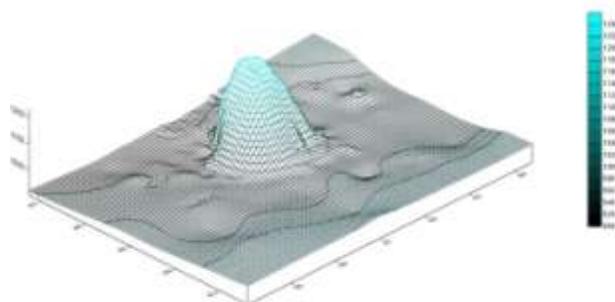


Figure (7): 3D diagram of Qum salt dome (Surfer 11)

3.2.1 Determining 3D diagram of Qum salt dome

Before training, determining and investigating field with the use of Kohonen and Hopfield neural networks, using MATLAB software and other statistical software like DX7 with available data, the 3D diagram of this salt dome was drawn. And by reducing the number of data for better

evaluation, as it is shown in figure (8), 3D diagram of the field was obtained and in following, the data output to train the network and determine the potential for oil exploration will be analyzed.

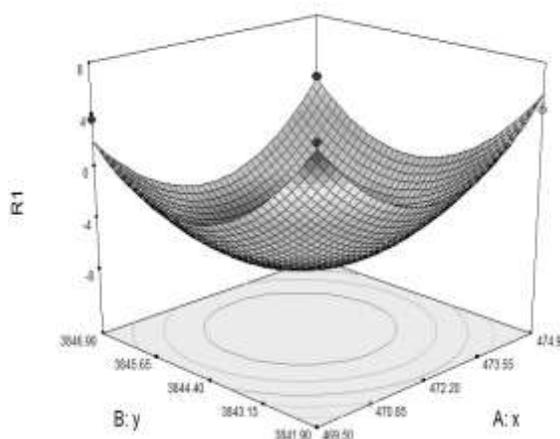


Figure (8): 3D diagram of Qum salt dome

As shown in the figure, X axis is longitude, Y axis is latitude, Z axis in the third dimension of altitude and R1 is residual gravity for measured points. In following, salt dome contour that is obtained from this anomaly is also drawn.

4. RESULTS AND DISCUSSION

4.1 Designing Kohonen neural networks

4.1.1 Unsupervised networks

As it was mentioned before, designing unsupervised Kohonen neural networks is done in MATLAB software. As we know, there are different categories for unsupervised networks that can be based on methods such as clustering, feature extraction and artificial

neural network like SOM. Therefore before networking of clustering algorithm, the method of that is being analyzed in next part.

4.1.2 Networking and clustering

First step for designing Kohonen neural network before using tool box in MATLAB software is determining effective parameters in clustering. So for this important issue parameters of latitude and longitude and altitude on which they are considered by gravity, were chosen. Designing via Kohonen neural network as in second season it was also fully discussed, selecting neuron numbers in hidden layer and obtaining competitive layer is very important. The competitive layer is usually compared to set of points which are the central points. For example if we consider X point and compare it to C_1 central point with determining the distance + or - and to obtain an exit point and min of that point and repeating this for other points until C_n , the min point of min index is considered as competitive pint or layer. The competitive layer will be considered as competitive point in the end.

4.1.3 Clustering using SOM in MATLAB software

Here are the steps for clustering of parameter numbers that are examined in Qum field. For doing this using MATLAB R2013b software

and using Toolbox of this algorithm, clustering was done. In the first phase, the data was given to the network as matrix and in this clustering 288 inputs were given for four elements. Since the goal of this clustering is separating number of parameters according to latitude and longitude so this input number was introduced to network with Matrix rows and had better results.

Networking via Kohonen neural network are taken through following steps:

4.1.3.1 Using nctool

As it was mentioned before, MATLAB toolbox has a panel for clustering parameters that is nctool and using this we can cluster the number of available parameters in terms of characteristics and the effect point. In this study MATLAB 2013 was used. So this part of toolbox can be seen in graphic and directly or typing nctool in Command Window. As it is shown in figure (4.4) the window for SOM algorithm is selected and opened.

As it shown in figure (9) a Kohonen algorithm has a number of input and output and the weighted layers in hidden layer. In next phase input (existed parameter) will be given to network for training.

4.1.3.2 Select Data

In this section, before selecting neurons data should include parameters for the clustering

are given to network. As a result, the data classified in Excel and collected as Matrix and after that as is shown in figure (10), inputs were given to network as Matrix and naming 288 inputs for four parameters. It needs to be mentioned they can be done as Import data in xlsread code.

As it was shown in summary, data were categorizing based on 288*4 Matrix

4.1.3.2.1 Selecting Neurons numbers

4.1.3.1.1.1 Training with 3 neurons

After introducing data to network, as in figure (11), the number of neurons should be introduced for the network size that considering that the size of the network and thus clustering model can be obtained. In this part the network is been trained by 3 neurons and results are given in figures (12, 13, 14, 15, 16 and 17).

In figure (12) weights of clustering network were shown. This is exactly the 3*3 structure that is shown in 9 neurons network. Given the number of parameters involved in the training by neurons can be observed that the number of central neurons have more absorption than their surrounding parameters. So the created weights in 41-42 central points have more effects considering the residual gravity of that point.

Figure (13) shows the retrieved data in compare to adjacent neurons. Of 9 neurons of 3*3 structures and 288 samples, a neuron that has 68 in it means that Kohonen neural network could absorb 68 data of 288. And a neuron with number 7 has the minimum absorption in compare to other neurons. In fact neuron 68 covered more data that other neurons could not.

Based on figure (14), 4 inputs were applied to network that via using them the excitability of neurons in the Kohonen network can assessed. Those neurons that are black means they have the minimum excitability in compare to input and given weight. Considering different inputs it can be concluded that first the first input or the longitude and then latitude or second input and then 4th input or residual gravity and in the end the third input that is the altitude have direct effect on clustering via Kohonen artificial neural network. In other parts weight intervals among neurons and connections were given in figures (15 and 16)

Figure (16) shows the adjacent connections among neurons that is in fact next figure which shows neurons connections with adjacent neurons

As it can be seen, Kohonen network was trained with 3 neurons. Each one of these

hexagons represents a neuron that has been defined before training for artificial neural networks.

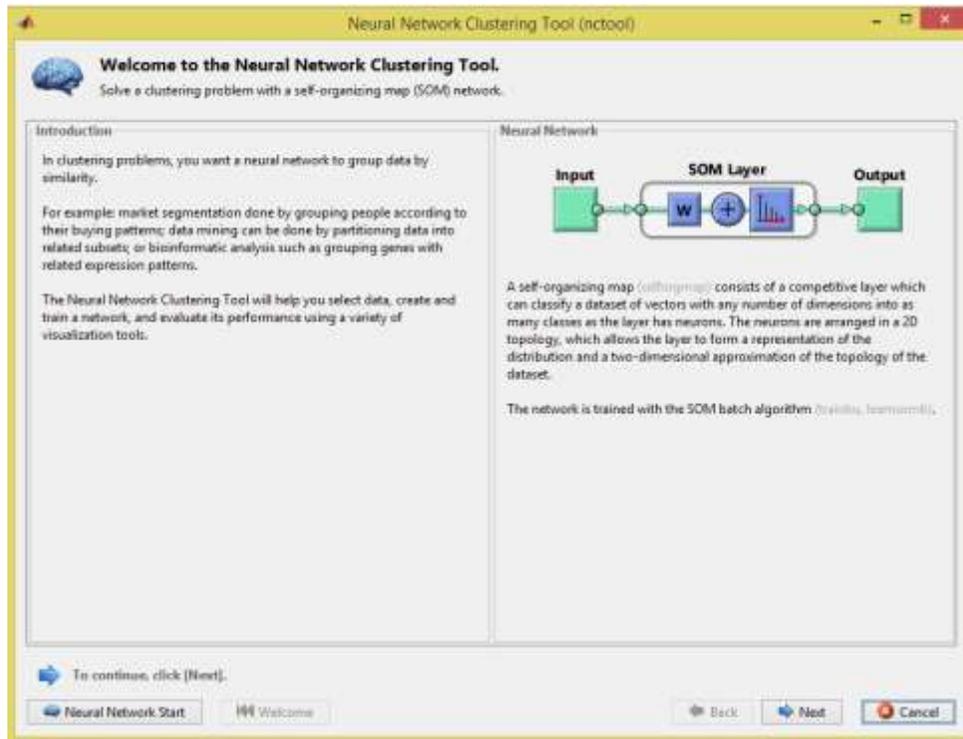


Figure (9): nctool window, SOM, MATLAB R2013b software

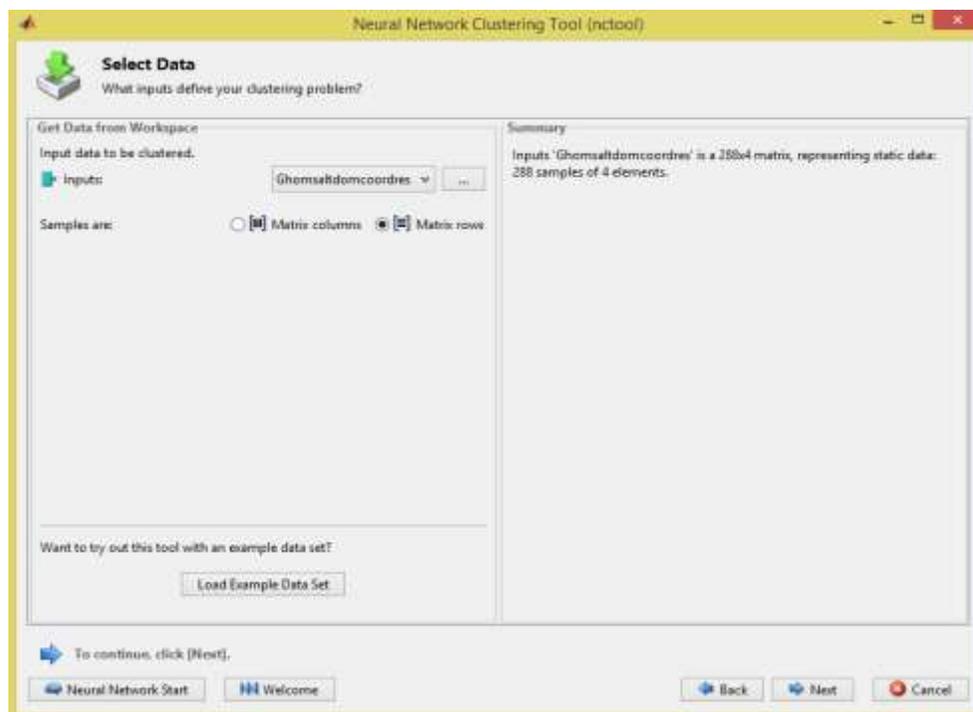


Figure (10): Window for importing data, MATLAB 2013

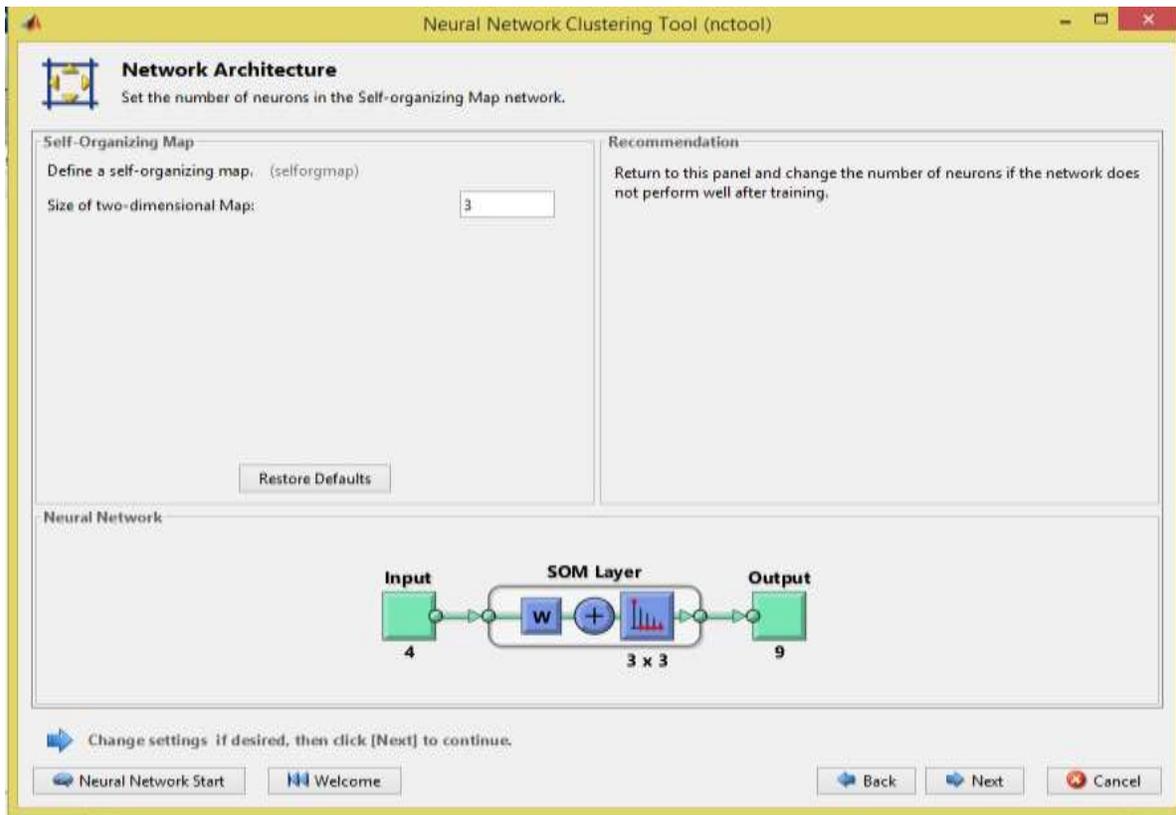


Figure (11): Window for selecting neuron numbers for determining cluster size

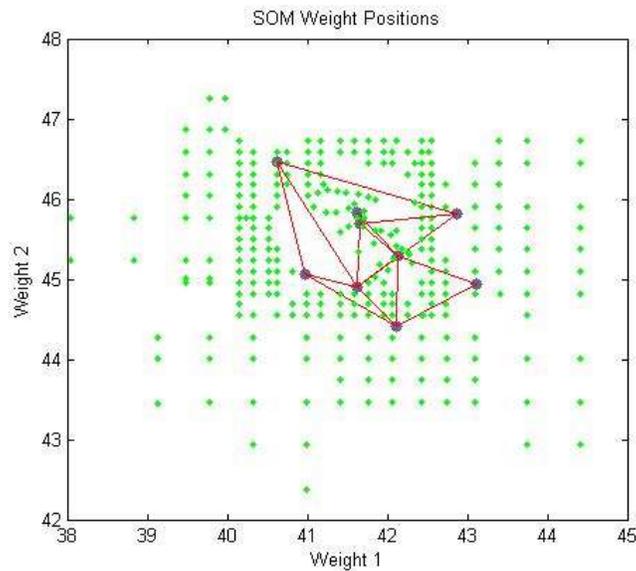


Figure (12): Weight position of clustering network

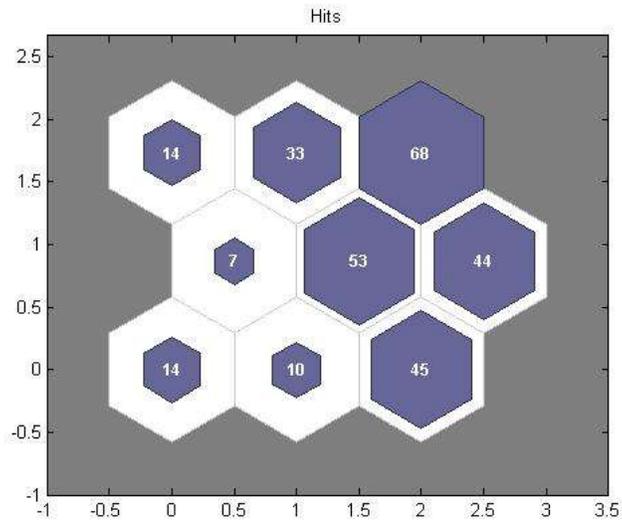


Figure (13): Sample Hits

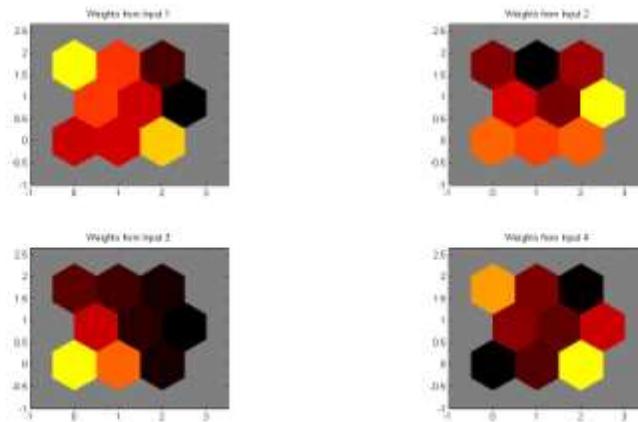


Figure (14): number of applied inputs to network in compare to network weights

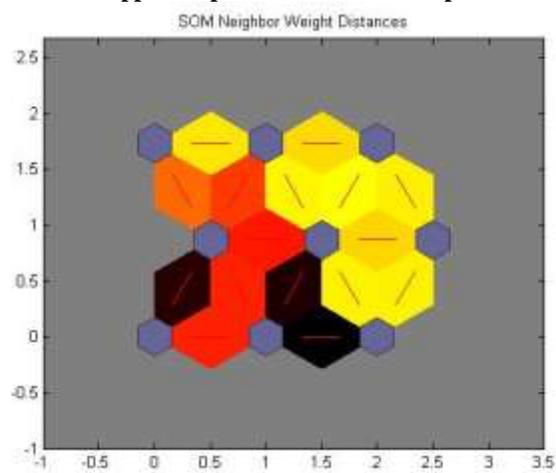


Figure (15): weight intervals between adjacent neurons in clustering network

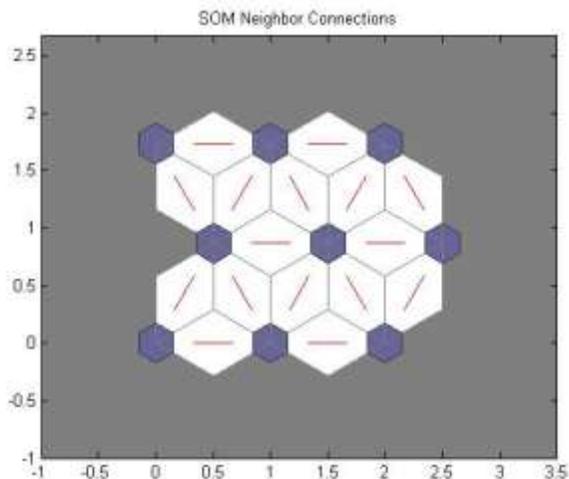


Figure (16): Adjacent connections among neurons

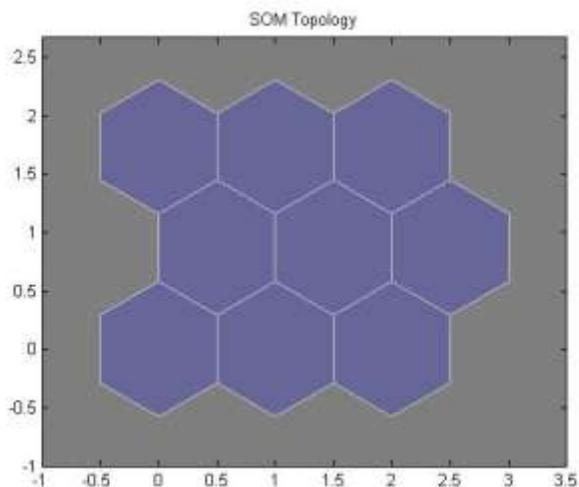


Figure (17): SOM topology of a network with 3 neurons

4.1.3.1.1.2 Training with 4 neurons

Since in engineering projects, usually trial and error has better result, so in this study the existed parameters with 4 and 5 neurons using the Kohonen neural network was trained and tested. Here are the results.

As it can be seen in figure (17), considering the training with clustering network of 4*4, the numbers of neurons that have better weight position are in central part. It needs to

be mentioned above figures are result of network test results with adjacent data.

Figure (20) like previous test shows 4 inputs applied to the network that is based on 4*4 Network and 16 involved neurons was trained. In this figure too, second input or longitude had the best performance, then first input or latitude and after that residual gravity and altitude, fourth and third inputs, have impact their neurons on network clustering.

4.2 Designing Using Hopfield Neural Network

As it was mentioned in chapter 3, Hopfield neural networks are without supervisor. In this network, the output or state variables at any moments depends on the state variables at the past moment. In this part with using available data, a Hopfield neural network using code writing was done in MATLAB 2013.

4.2.1 Designing Using Code Writing

In network design using code writing as it is shown in Appendix, first the index data was extracted from the available data and the code was written. Then using the command of **net=newhop (T)** a Hopfield artificial neural network was designed. As in figure (24), a

network with 288 outputs has been designed with a delay and applies weighted data that has no inputs.

After designing and building a network for better network performance, data were normalized between 0 and 1 that the code was written and applied to network. After data normalization, some matrixes were written to apply to data which plots converge towards the central points. After network functioning numbers of involved neurons in the test network were added to the written code and due to the written circle number of rounds that the designed network should perform and apply and these results were obtained that are coming in following paragraph.

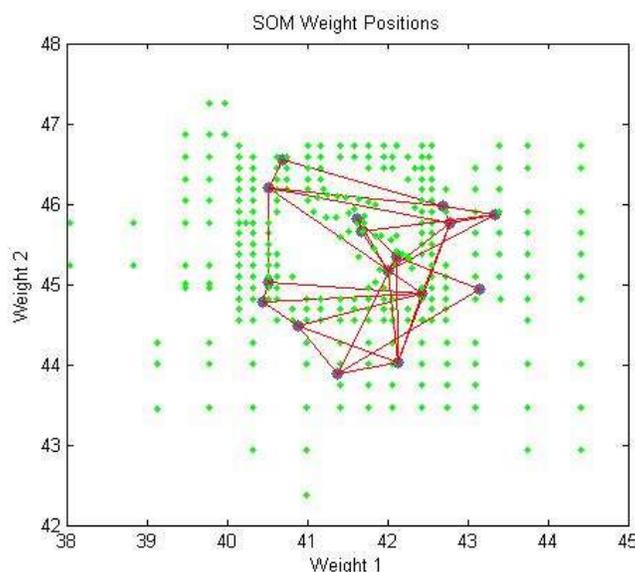


Figure (18): weight positions of neurons with 4*4 networks

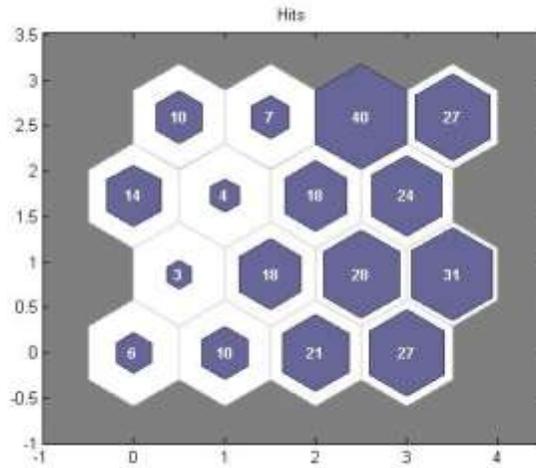


Figure (19): Sample Hits obtained from 4*4 Network

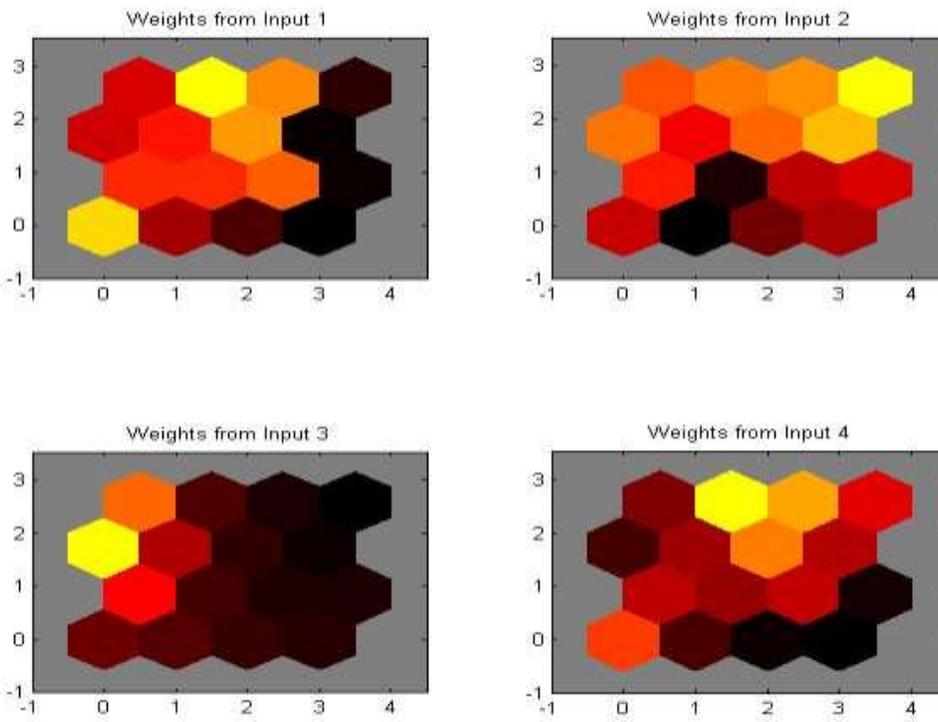


Figure (20): The number of applied inputs to 4*4 Network in compare to network weights

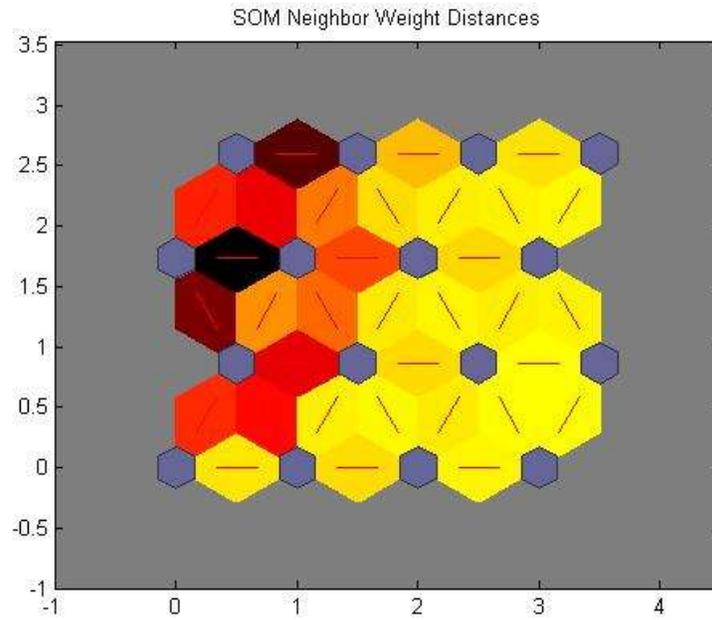


Figure (21): weight intervals among adjacent neurons in a clustering network

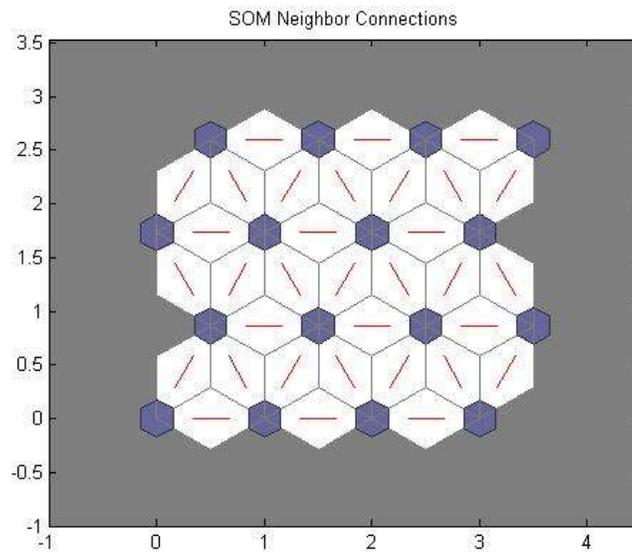


Figure (22): Neighborconnections among neurons

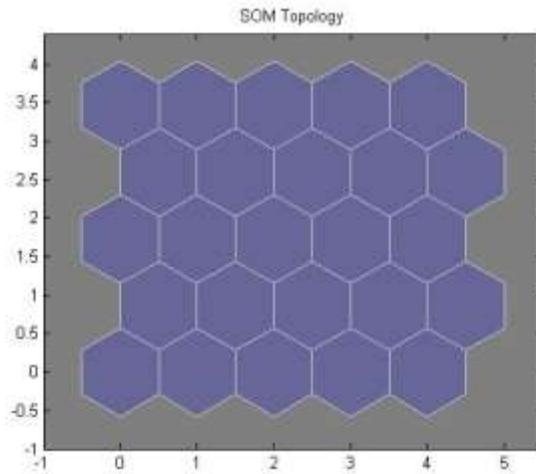


Figure (23): SOM Topology of network with 4 neurons

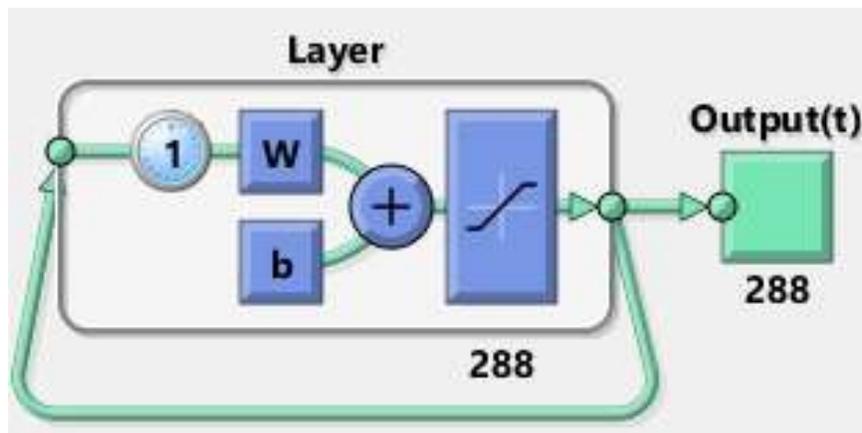


Figure (24): Designed Hopfield neural network

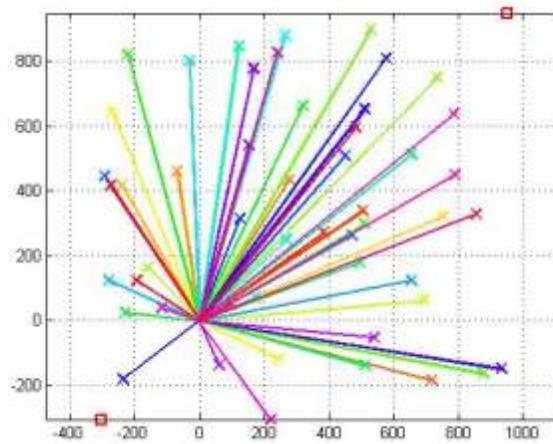


Figure (25) Hopfield output with 50 testing rounds

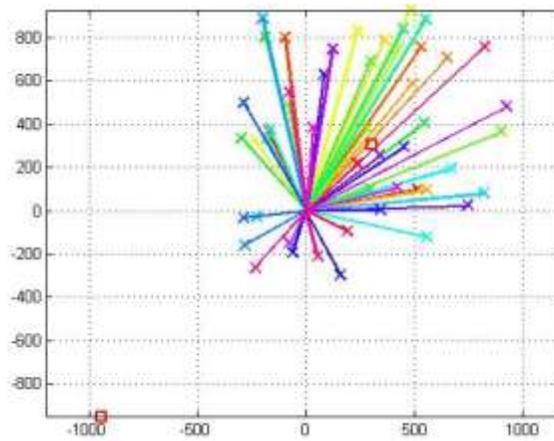


Figure (26) Hopfield output with limited data

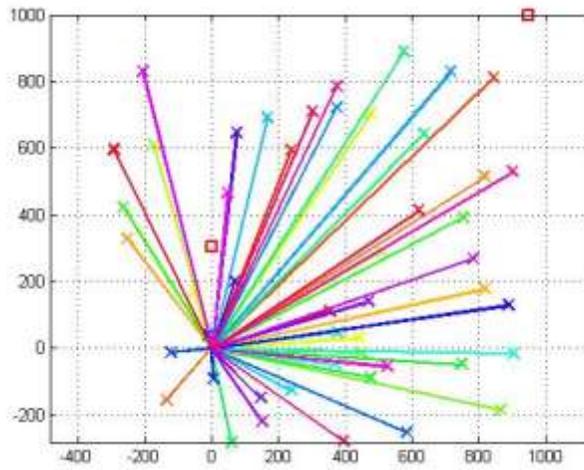


Figure (27): Hopfield outputs with data shift up to 3 times

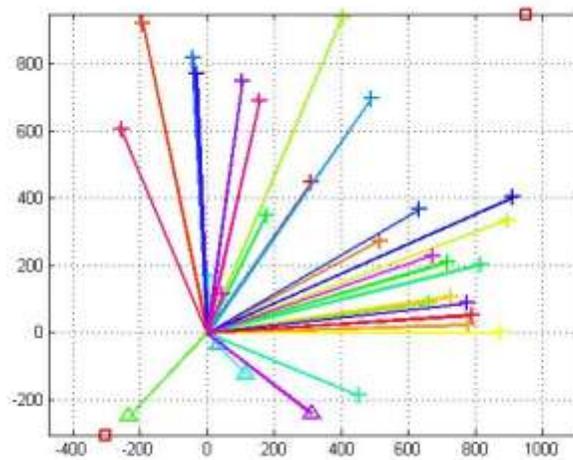


Figure (28): Hopfield convergence output shows the main points to the minor point

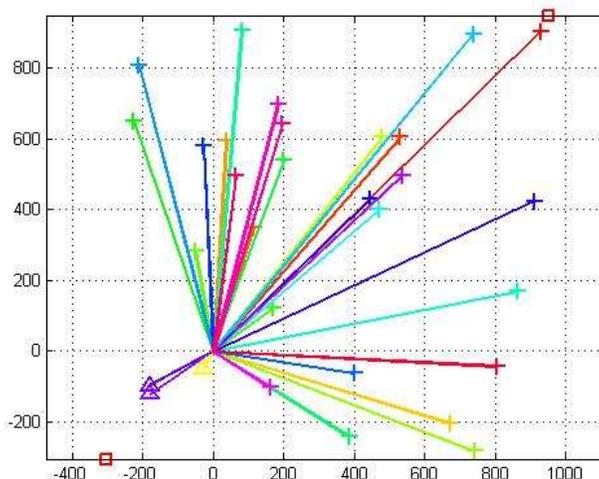


Figure (29): Hopfield convergence output shows the main points to the main point

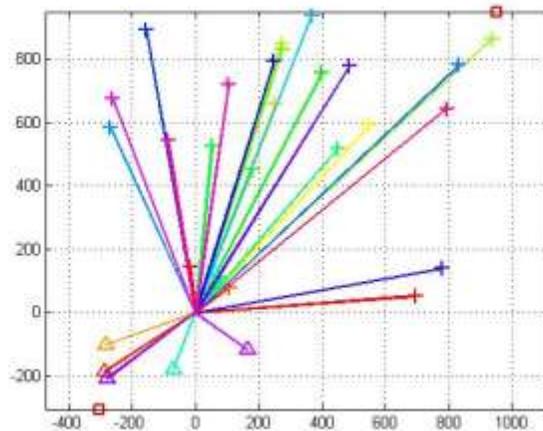


Figure (30): Best performance of Hopfield neural network with 30 times repetitions. Most of the points are converged. As it was shown in figures, in figure (25) data with 50 rounds test converged toward central points that is not reasonable due to geophysics point of view so the repeated network with limiting parameters like residual gravity and test altitude as the result is in figure (26) and it can be seen all data converged toward center that is the direct impact of residual gravity parameters in designing Hopfield neural network. After that as it was shown in other figures, the network was tested for more rounds and the best performance toward more convergence of points to central points. With designing of this network according to the available data the parameters that can have the most impact on the creation of the anomaly and directing toward residual gravity, longitude, latitude and altitude.

4.2.2 Depth estimation using Hopfield neural network

One of other tasks that were done in this paper was depth estimation of anomaly using Hopfield neural network. So first for available data, weight data were identified and with using network coding of design network and for various different locations including latitude and longitude depth was calculated as in table 1 and 2. It is important to mention that this network was not accurate in depth estimation and in following other networks of network category and artificial neural

algorithms will be introduced that have more ability for direction estimation. After network designing and preparing data anomaly was considered to be spherical and using spherical formula of data %5 and %10 of noise was applied so the results be more real.

As it was shown in 2, a network with %10 noise had minimum standard deviation that anomaly depth of Qum field 2, 1 kilometer was estimated.

Table 1: The output depth obtained by Hopfield network with 5% noise

| Test Number with %5 noise | Standard deviation values for the anomaly Z Spherical model | Hopfield output for Z Spherical model in kilometers |
|---------------------------|--|--|
| 1 | 0.98 | 2,6 |
| 2 | 0.25 | 2,485 |
| 3 | 0.64 | 3,01 |
| 4 | 0.74 | 2,8701 |
| 5 | 0.556 | 2,289 |

Table 2: The output depth obtained by Hopfield network with 10 % noise

| Test Number with %10 noise | Standard deviation values for the anomaly Z Spherical model | Hopfield output for Z Spherical model in kilometers |
|----------------------------|--|--|
| 1 | 0.47 | 2,3 |
| 2 | 0.875 | 4,1 |
| 3 | 0.12 | 2,1 |
| 4 | 0.664 | 2,777 |
| 5 | 0.748 | 2,87 |

CONCLUSION

In this paper, a new method for using artificial neural networks via Hopfield and Kohonen was applied to estimate the depth of salt domes from gravity data. As it is shown, Kohonen neural network has a good performance in separating and clustering data and geophysical parameters. The software which is used called DX7 is a statistical software for modeling salt dome with gravity

data and has shown good result. Depth of Qom salt dome in obtained coordination with a standard deviation of 0.12 was estimated 2.1 km. The effective parameters of this method are latitude and longitude, and then gravity. Hopfield neural network had poor performance in estimating geophysical parameters. If we have exact geological information then Hopfield network can have better estimation. Finally, Code writing in

MATLAB software for designing Hopfield network in compare to using toolbox has better rate and accuracy

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