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Salt Dome exploration in oil fields by gravity data using Gravity Data through Fuzzy logic System

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Abstract[1]: In this paper, according to available data, some data are considered as inputs and some as output of Neuro-Fuzzy (ANFIS) and Fuzzy-Logic algorithms and results will be compared and analyzed. Wherever there exist salt dome, Earth's gravity field on top of it is lower than surrounding rocks, but vice versa on top of the buried anticline, Earth's gravity field is more than surrounding rocks. Thus, Artificial Neural Networks are used in this research, therefore the costs will be decreased significantly and results in short time will be gained precisely.

Keywords: Gravity, Fuzzy-Logic, petroleum, ANFIS, Salt dome

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1. Introduction

Neural networks are increasingly popular in geophysics. Because they are universal approximations, these tools can approximate any continuous function with an arbitrary precision.

In the geophysical domain, neural networks have been used for waveform recognition and first-peak picking *(Murat and Rudman , 1992; McCormack et al.,1993);* for electromagnetic interpretation *(Poulton et al , 1992),* magneto telluric *(Zhang and paulson,1997),* and seismic inversion purposes *(Röth and Tarantola,1994; Langer et al ., 1996; Calderon – Maclas et al ., 1998);* neural networks *(Elwadi et al.,2001, Osman et al , 2007 , Hajian 2012);* multi-adaptive neuro – fuzzy interference systems *(Hajian et al , 2011).*

Amongst all of the artificial intelligent methods (e.g. artificial neural network (ANN), fuzzy logic (FL), genetic algorithms (GA), etc), ANN has the most applications due its flexibility and ability to solve non-linear problems. However, most ANNs require a time consuming procedure of architecture design.

In this paper, Fuzzy logic system is used for depth estimation of salt domes from Bouger anomaly data. It is very important to mention that this system does not need to be trained in comparison to other artificial methods. To determine the suitability of the method for application in the real cases, random Gaussian noise was added to the data and the results of fuzzy logic were compared to the results of ANFIS. Furthermore, the method was tested for field data using gravity data over a salt dome site situated in Mors, Denmark.

2. Theoretical background on Fuzzy systems

2.1 Overview of Fuzzy Logic System

Classical logic only permits propositions having a value of truth or falsity. The notion of whether 1+1=2 is an absolute, immutable, mathematical truth. However, there exist certain propositions with variable answers, such as asking various people to identify a color. The notion of truth doesn't fall by the wayside, but rather a means of representing and reasoning over partial knowledge is afforded, by aggregating all possible outcomes into a dimensional spectrum. Both degrees of truth and probabilities range between 0 and 1 and hence may seem similar at first. For example, let a 100 ml glass contain 30 ml of water. Then we may consider two concepts: empty and full. The meaning of each of them can be represented by a certain fuzzy set. Then one might define the glass as being 0.7 empty and 0.3 full. Note that the concept of emptiness would be subjective and thus would depend on the observer or designer. Another designer might equally well design a set membership function where the glass would be considered full for all values down to 50 ml. It is essential to realize that fuzzy logic uses truth degrees as a mathematical model of the vagueness phenomenon while probability is a mathematical model of ignorance.

A basic application might characterize sub ranges of a continuous variable. For instance, a temperature measurement for anti-lock brakes might have several separate membership functions defining particular temperature ranges needed to control the brakes properly. Each function maps the same temperature value to a truth value in the 0 to 1 range. These truth values can then be used to determine how the brakes should be controlled.

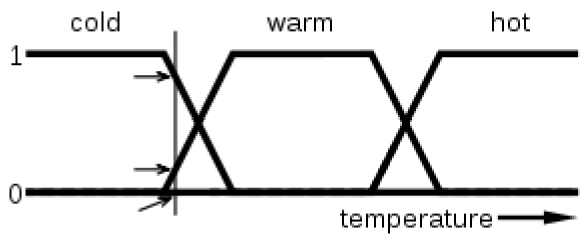


Fig (1): Fuzzy logic temperature

In this image, the meanings of the expressions *cold*, *warm*, and *hot* are represented by functions mapping a temperature scale. A point on that scale has three "truth values"—one for each of the three functions. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this temperature may be interpreted as "not hot". The orange arrow (pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold".

2.2 Types of Fuzzy Inference Systems

Two types of fuzzy inference systems in the toolbox can be implemented:

- Mamdani
- Sugeno

These two types of inference systems vary somewhat in the way outputs are determined.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes. Although the inference process described in the next few sections differs somewhat from the methods described in the original paper, the basic idea is much the same.

Mamdani-type inference, as defined for the toolbox, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible, and in many cases much more efficient, to use a single spike as the output membership function rather than a distributed fuzzy set. This type of output is sometimes known as a *singleton* output membership function, and it can be thought of as a pre-defuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function. Rather than integrating across the two-dimensional function to find the centroid, you use the weighted average of a few data points. Sugeno-type systems support this type of model. In general, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant.

Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simply (and ambiguously) fuzzy systems.

2.3 Adaptive neuro fuzzy inference system (ANFIS)

The acronym ANFIS derives its name from *adaptive neuro-fuzzy inference system*. Using a given input/output data set, the toolbox function anfis constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows your fuzzy systems to learn from the data they are modeling. A network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs. Anfis uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation.

3. Case Study

The current case study is located in Denmark, Mors, with the following information:

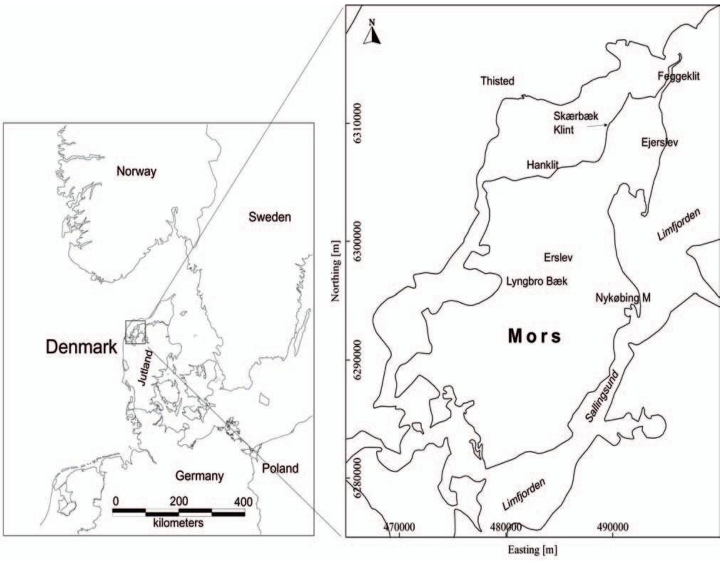
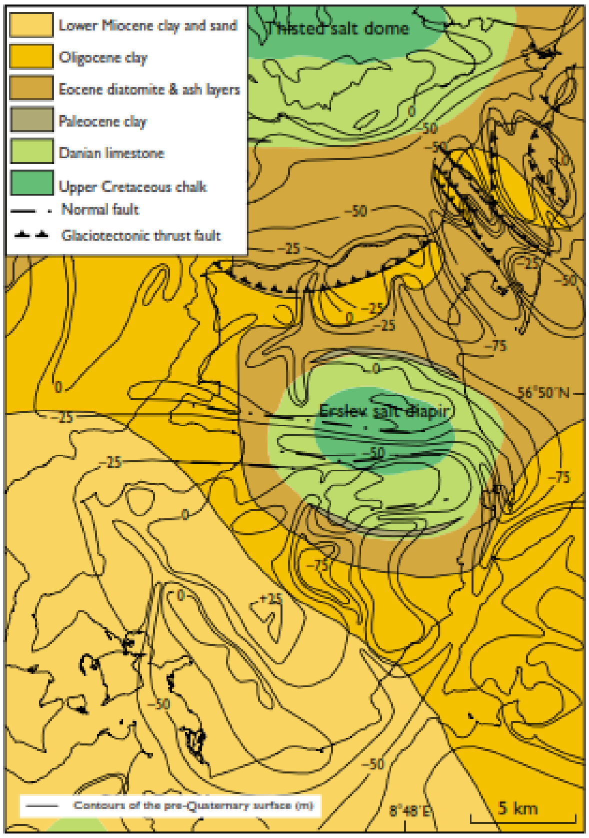


Fig (2). *Location of the Mors Salt Dome* [12].

The study area is confined to the island of Mors, which is situated in the northwestern part of Jutland, Denmark (Fig 2). The island covers an area of about 360 km^2. It is 10-15 km wide and about 35km long with a SSW-NNE trend (Jorgensen et al).

3.1. Geological setting of Mors

The structural contour lines at 25m intervals show the elevation of the pre-Quaternary surface. The dome-like structure on central Mors is made of chalk which covers the top of the Erslev salt diaper. The boundaries between glaciotectonic complexes and their foreland on northern Mors are also shown (Fig 3).



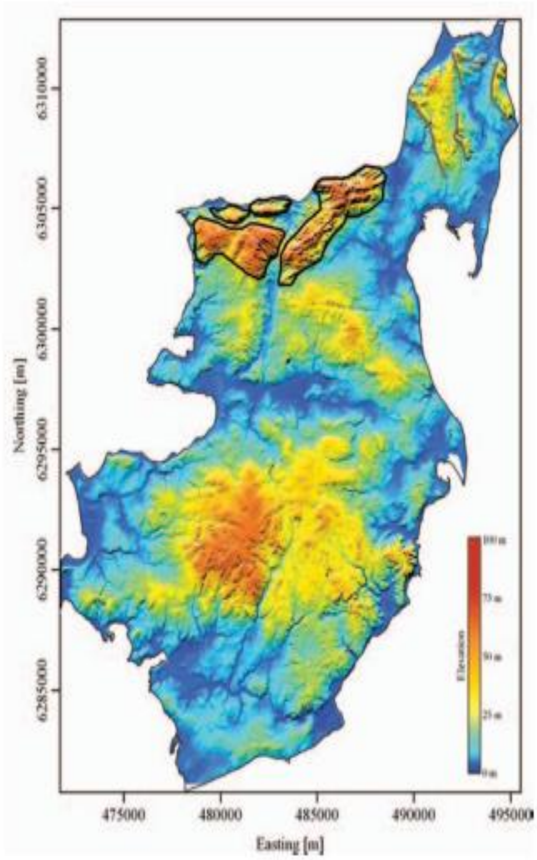


Fig (3). *Bedrock depth map of Mors* [11].
Fig (4). *The topographic Map of Mors* [11].

The sub-Quaternary strata comprise Upper Cretaceous white chalk (Maastrichtian) and Paleocene limestone (Danian) covered by clays and diatomite (Paleocene – Eocene).The diatomite is contained in the Fur Formation (Pedersen & Surlyk 1983). These layers are followed by Oligocene micaceous clay and, to the south, also by Miocene clay, silt and sand (Gravesen 1990, 1993). The Paleogene sediments are in general 50-250m thick, but locally they are thinner or even absent. They commonly been subjected to deformation during the Quaternary glaciations, but the most pronounced impact on the Paleogene topography is by a series of incised Quaternary valleys. These valleys have mainly been filled with thick sequences of glacial deposits. Where no valleys exist, only relatively thin layers of glacial origin cover the Pre-Quaternary formations.

The overall structure of the tertiary and quaternary formations on Mors is mainly controlled by 1) The Mors salt diapir, 2) glaciotectonic deformation during the Quaternary glaciations and 3) Extensive systems of incised buried valleys.

4. Results and discussion

4.1. Designing Fuzzy Neural Network

4.1.1 Depth estimation of Salt dome using Fuzzy logic algorithm

As fuzzy logic algorithm defines with if-then rules, so type of mapping which represents the input and output must be defined which in this study, the mapping of the input space (the appropriate characteristics of a gravity signal) to the output (the salt dome) is defined. The changes are defined as input of the network in this characteristics of the signal, with up or down variables data are defined and consider as qualifies descriptions of up and down that the depth of anomaly will be changed based on these changes. Fuzzy inference in this study is based on the interpretation of the input space that includes the appropriate characteristics of the gravity signals, and according to this base, the depth of salt dome has been estimated which is introduced as the input of fuzzy network in this study.

4.1.1.1 Sugeno Fuzzy Model

Suggested fuzzy model used to estimate the depth of salt dome is done through fuzzy inference system of Sugeno. Sugeno model is same as Mamdani for fuzzy modeling. The membership functions of output data is the only difference of these two methods. In the Sugeno method unlike Mamdani method, membership functions of output data are linear or constant and are defined by the clustering method. Depending on the data in one of the above methods used for modeling. Sugeno method is used in this study.

The first step in designing a fuzzy inference system, is designing the FIS which is accessible by using the toolbox of MATLAB software. As shown in Figure (5) is shown FIS Editor Window must be opened through MATLAB >>> Start >>> Toolboxes >> more >> Fuzzy-Logic and then from the File section, the Sugeno model will be selected. After selecting the model, as shown in Figure (6) the number of entries is selected from the Add Variables section and will determine with the output and then the model will be created.

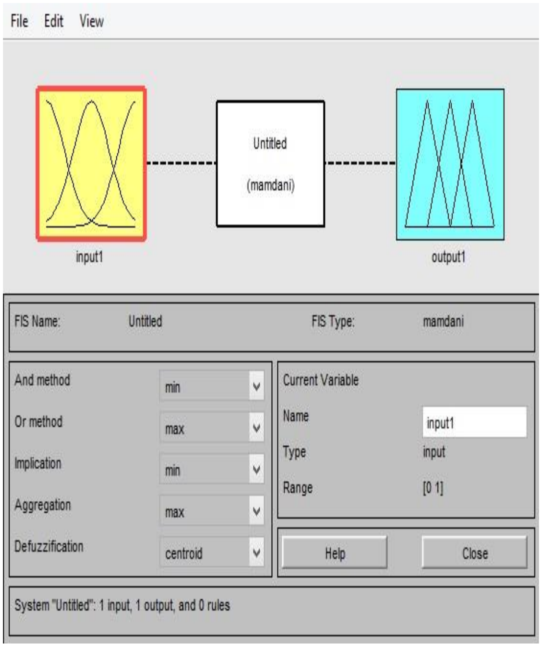


Figure (5): FIS Editor Window from the software MATLAB 2012a.

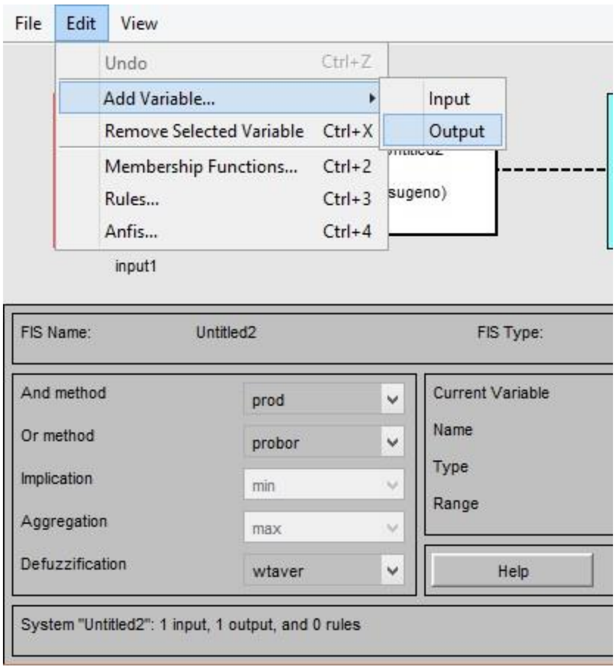


Figure (6): adding input and output in FIS.

After entering the input and output, each of the input variables, including F1 = gMax, F2 = Xg50%, F3 = Xg75% and F4 = XgMax are defined and the output variable in this study which is Z the depth of salt dome defined which is shown in Figure (7).

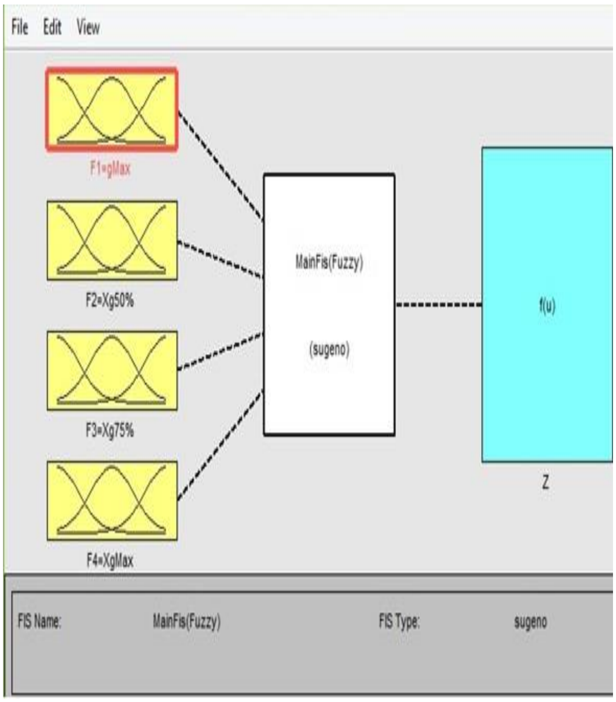


Figure (7): Designed Sugeno model with defined inputs and outputs.

After data preparation the depth of salt dome using Sugeno method fuzzy model will be reported:

4.1.1.1.1 Preparing inputs

After the introducing the input and output variables to the created model, data should be prepared. This means that the data due to the lack of a training fuzzy model and neuro-fuzzy, they must be specified by the range and be introduced to fuzzy systems.
As a result, in this research for data of input space the limits are defined as follows:
F1=gMax= [5.48 6.99]
F2=Xg50%= [25.40 29.27]
F3=Xg75%= [35.32 44.32]
F4=XgMax= [13.67 15.28]

And so the output is the same as the salt dome is defined as follows.
Z=Depth of Salt Dome= [2.11 9.25]

4.1.1.1.2 Membership functions and defuzzification of inputs

After determining the input`s boundary, membership functions for the input must be selected
As a number of possibilities should be considered for the fuzzy inference system, so for presented inputs two membership function defines and probability of estimation in the range of 4 to 5 km called High and depth range of less than 4 km called Low and was defined for inputs.

4.2 Fuzzy system rules

As it has been mentioned in the previous section, in fuzzy logic, system defines with if-then
And on the other hand, a trial and error should be a priority in an engineering project, thus, in this research through various trial and error the following laws were obtained.
if (F1 is High) and (F2 is High) and (F3 is Low) and (F4 is High) **then** (Z is High)
if (F1 is High) and (F2 is Low) and (F3 is High) and (F4 is High) **then** (Z is High)

if (F1 is Low) and (F2 is High) and (F3 is Low) and (F4 is High) **then** (Z is High)

Finally, as shown in Figure (8):
if (F1 is **6.37**) and (F2 is **26.9**) and (F3 is **40.8**) and (F4 is **14**) **then** (Z is **4.88**)

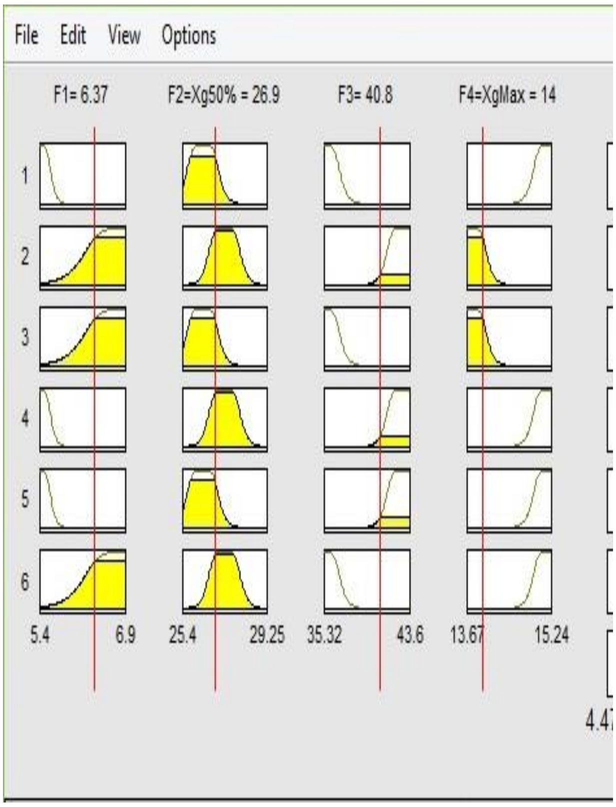


Figure (8): Answer each of the graphs of the input variables and the desired output is obtained according to the relevant laws.

4.3 Applying fuzzy operators

The default internal functions in the toolbox fuzzy logic was used. At this stage, "and" operation is used and minimum (min) method is considered as default (Figure 9).

4.4 Applying the implication method

The default internal functions in the toolbox fuzzy logic was used. Minimum method (min) was used according to the target (Figure 9).

4.5 summing outputs

The default internal functions in the toolbox fuzzy logic was used. Maximum method (max) was used according to the target (Figure 9).

4.6 Defuzzification

The default internal functions in the toolbox fuzzy logic was used. Calculating the area under the curve, considered number specifies the salt dome depth.

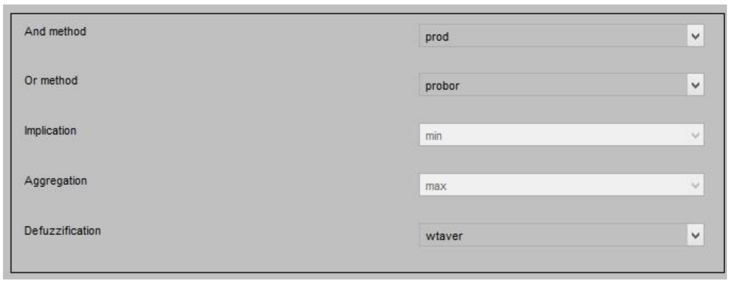


Figure (9): applying the fuzzy operators, application of implications, collates and defuzzification output using fuzzy logic toolbox in MATLAB.

Table (1): Comparison of three methods used to estimate the depth Mors Salt Dome.

Fuzzy Logic (in this study)	(Shirazi et all) GRNN method	(Aghajani et all) NFG method
4.88 Km	**4.82** Km	4.7 **Km**

5. Conclusion

In this paper, a new method for using artificial neural networks via fuzzy logic was applied to estimate the depth of salt domes from gravity data. Results for synthetic data and real data via this method show that this network can have a reasonable performance for noisy gravity data. This system was applied for different numbers of neurons in hidden layers based on the defined laws and also the method tested for the real data from the Mors salt dome in Denmark. The results for estimating the depth of salt domes revealed that fuzzy logic system is accurate and needs less time for training. According to these results, the possible depth of Mors salt dome is **4.88 km**. The depths to the salt dome compare well with those estimated by the NFG method (Aghajani et al, 2009) and with the research done by GRNN method (Shirazi et al, 2014). While we have developed this method for gravity data interpretation in order to simulate and estimate the depth of salt domes anomaly, this method has general applicability for many other complex geophysical interpretation problems, as well.

6.References

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