Intelligent Salt domes depth estimation through General Regression Neural Networks using gravity data, case study: salt dome of Mors oil field in Denmark

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Abstract

Artificial neural network (ANN) is an intelligent tool which mimics the human's brain. Today, this tool has a variety applications in science, engineering, social science, economic and etc. Along with these applications, it has a lot of wide usage in oil industry and geophysics as well. The method of Artificial Neural Network is used as a suitable tool for intelligent interpretation of gravity data in this paper. We aim to model the salt dome in order to get the features of anomaly from gravity data by 2D forward modeling then a Multi-Layer Perceptron (MLP) and a Generalized Regression Neural Network (GRNN) is trained for depth estimation of salt domes from gravity data. The approach was applied to both synthetic and real data. The real data is gravity data over "Mors". Salt dome located in Denmark and the estimated depth is very close to the real depth of the salt dome and also very closes to normal full gradient method results.

Keywords: gravity,Salt dome, GRNN, Neural networks, oil field

Introduction

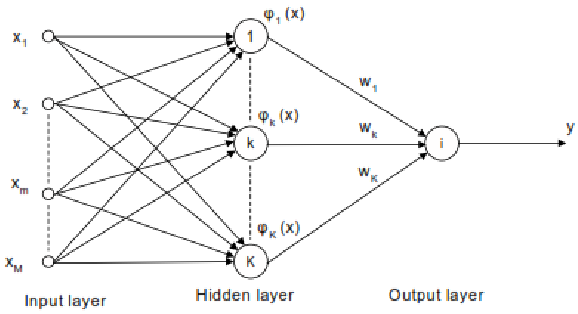
Neural networks are increasingly being used in prediction, estimation and optimization problems. Neural networks have gained popularity in geophysics this last decade (Grêt 2000). Hajian (2008) used Hopfield neural network in order to depth estimation of subsurface cavities. Osman et al. (2007) used forced neural networks for forward modeling of gravity anomaly profiles. Styles and Hajian (2012) used Generalized Regression Neural Networks for cavity depth estimation.
In this paper, GRNN neural networks are used for depth estimation of salt domes from Bouger anomaly data. GRNN flexibility is noticeable in presence of noise .To determine the suitability of the method for application in the real cases, 10% and 20% random Gaussian noise was added to the data and the GRNN was tested with the noisy data. Furthermore, the method was tested for field data using gravity data over a salt dome site situated in Mors, Denmark.

General Regression Neural Network, theory and design

GRNN, as proposed by Donald F. Specht (1991) falls into the category of probabilistic neural networks. This neural network like other probabilistic neural networks needs only a fraction of the training samples which a back propagation neural network would need (Specht 1991).
The Generalized Regression Neural Network is a neural network architecture that can solve any functional approximation problem. The learning process is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for the "best fit" being measured in some statistical sense. The generalization is equivalent to the use of this multidimensional surface to interpolate the test data.
As it can be seen from Figure 1, the Generalized Regression Network consists of three layers of nodes with entirely different roles:

- *The input layer, where the inputs are applied,*
- *The hidden layer, where a nonlinear transformation is applied on the data from the input space to the hidden space; in most applications the hidden space is of high dimensionality.*

- *The linear output layer, where the outputs are produced.*



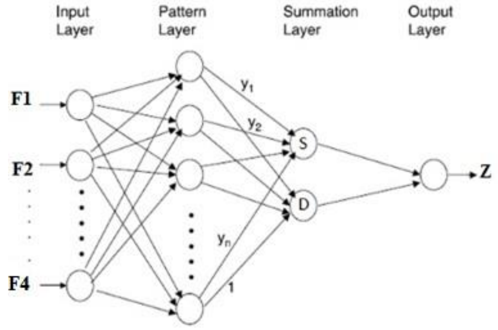
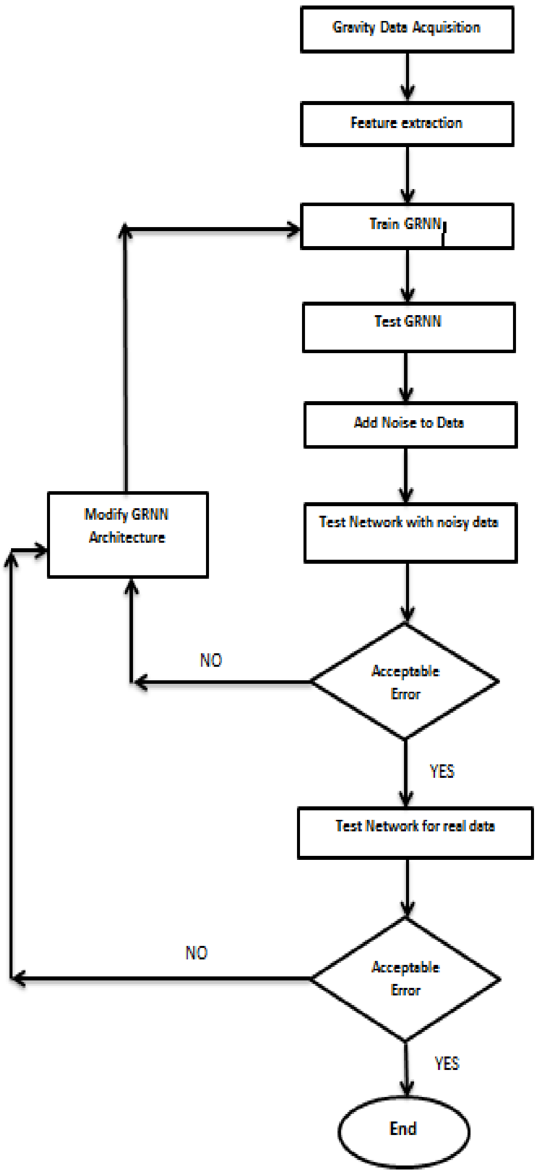


Figure (1). Schematic of a GRNN ***Figure (2).GRNN used for depth estimation of salt dome with inputs***

The probability density function used in GRNN is the Normal Distribution. Each training, sample, Xi, is used as the mean of a Normal Distribution (equations 1, 2):

$$Y(X) = \frac{\sum_{i=1}^{n} Yi \exp(-Di^2/2\sigma^2)}{\sum_{i=1}^{n} \exp(-Di^2/2\sigma^2)} \quad (1) \qquad D_i^2 = (X\text{-}Xi)^T . (X\text{-}Xi) \quad (2)$$

*Where Y(x) is the predicted output for input vector x, n indicated the number of training patterns and σ is the standard deviation, namely "spread" factor. The distance, D_i, between the training sample and the point of prediction, is used as a measure of how well the each training sample can represent the position of prediction, X. To estimate the depth of the salt dome, the inputs of GRNN are (**F_1=g_{Max}، F_2=$X_{g50\%}$ ، F_3=$X_{g75\%}$ ،F_4=X_{gMax})** and output is Z (figure 2), where $X_g n_{\%}$ is the horizontal distance at which the gravity value is n% of its maximum along the selected gravity profile, **X_{gMax}** is the horizontal distance at which the gravity amplitude takes its maximum value and **z is** the depth to top of the salt dome.*
For training the GRNN to estimate the depth, we calculated the mentioned features for different salt domes with different depths to top and fixed density contrast regard to the prior geological information of the region. The salt dome forward model used for producing training data of GRNN is illustrated in figure 5. To find the best value of spread factor we tested the designed GRNN with different values of σ and MSE of the network was plotted versus spread. As it is shown in figure 6, the best value for spread is 0.45 with the minimum value for MSE (Mean Square Error) error.



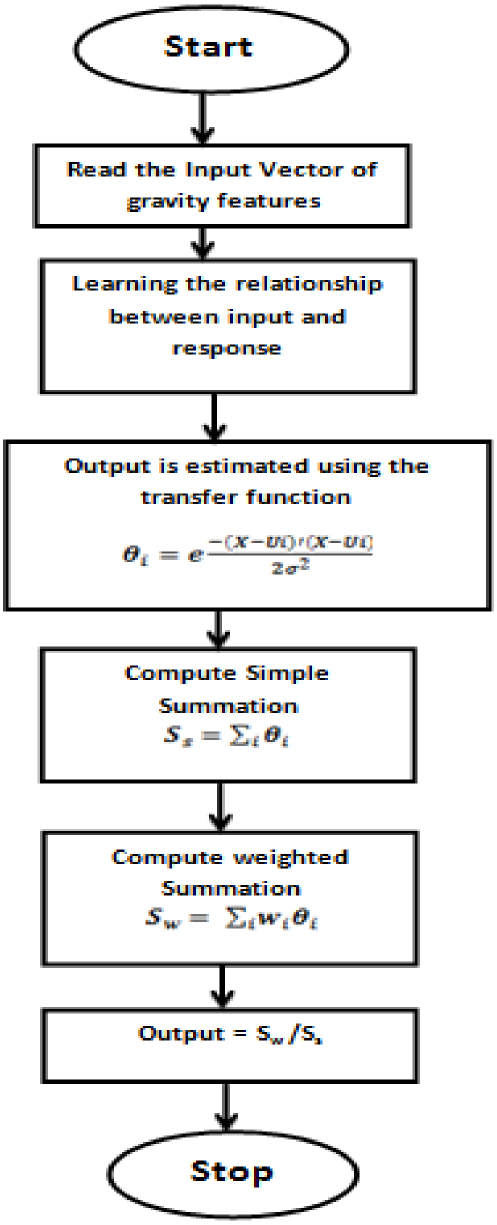
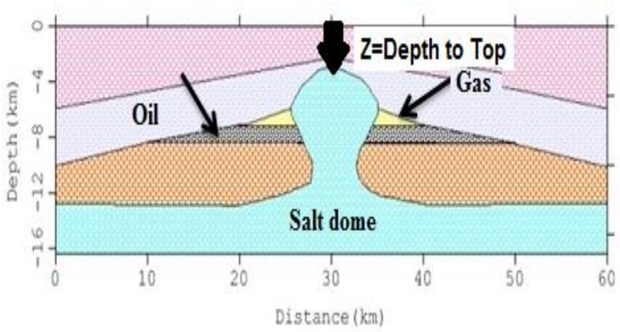
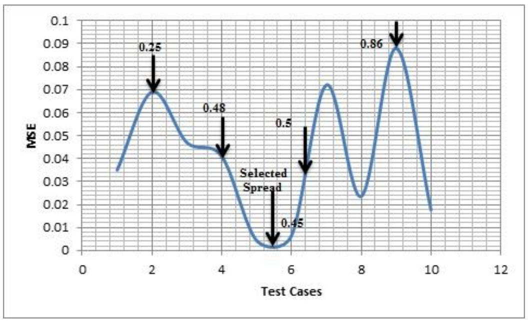


Figure (3). Flowchart for GRNN architecture designing

Figure (4).Flowchart of GRNN training procedure.





Figure(5). Salt dome model used for producing training data

Figure (6). Selecting the optimum value for spread.

Test of GRNN for noisy data

After training the GRNN, it was tested for two different levels of noise added to gravity data 10% and 20% white Gaussian noise. Then the features F_1, F_2, F_3, F_4 *were calculated from the noisy gravity signal and* applied as inputs to the designed GRNN. The results are shown in table 1. The comparison of the real depths and estimated depths showed that the method is robust to 10% and 20% noise.

Table (1). Test of GRNN for 10%, 20% noise added to the gravity effect of salt dome model.

Noise Level	*Real Depth to top of the salt dome(km)*	*Estimated Depth to top of the salt dome with GRNN(km)*
10%	***2.50***	***2.35***
10%	***3.00***	***2.86***
10%	***4.50***	***4.63***
20%	***2.50***	***2.63***
20%	***3.00***	***3.27***
20%	***4.50***	***4.88***

Test of GRNN for real gravity data, Mors Salt Dome

The current case study is located in Denmark, Mors. The study area is confined to the island of Mors, which is situated in the northwestern part of Jutland, Denmark (Figure 7). 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. 2005). 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 (Figure 8a). The Bouger anomaly map of the area is shown in Figure 8b, a principle profile was selected, the features were extracted and applied to the GRNN, and the estimated depth was 4.7 km. The depth to top of the salt dome was estimated 4.82 km via Normal Full Gradient (NFG) method (Aghajani et al.2009) and the result of GRNN compared to this method is valid (Table2).

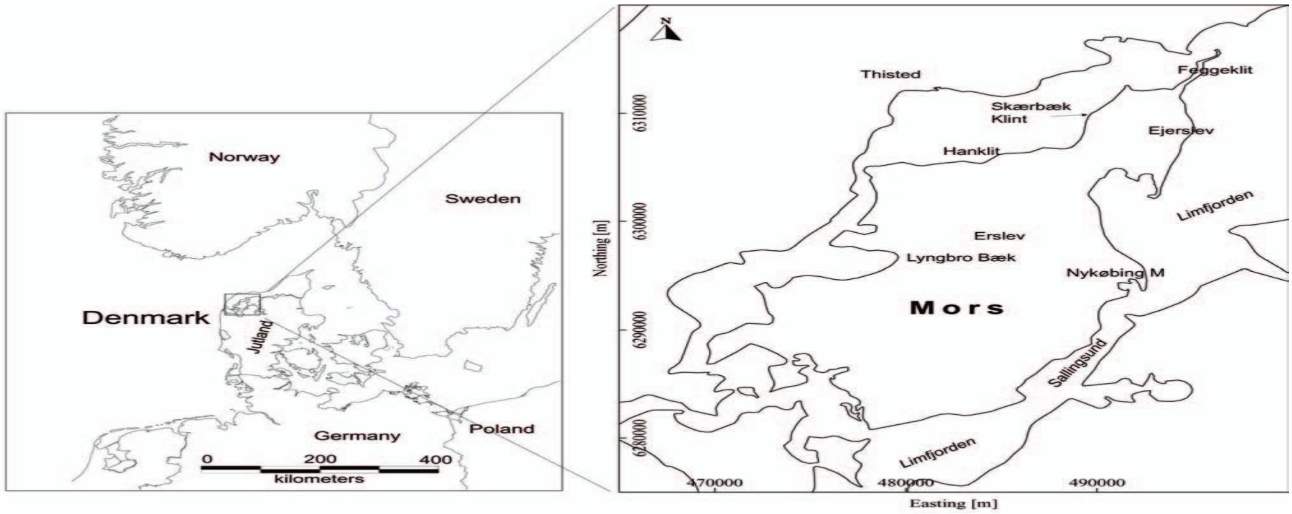
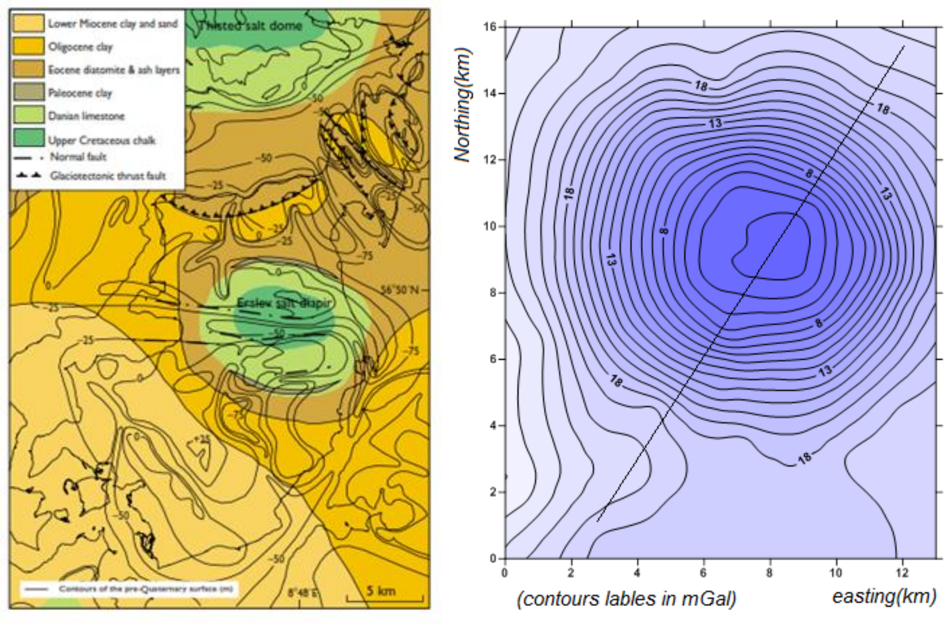


Figure (7).The location map of the Mors Salt dome, Denmark (Jorgensen et al. 2005).

Conclusion

A new method for using artificial neural networks via GRNN was applied to estimate the depth to top of salt domes from gravity data. GRNN network applied for different values of spreads and the optimum was achieved at 0.45.Results for synthetic noisy data implied that this network is robust for noisy gravity data. The method also was tested for the real data from the Mors salt dome in Denmark. The results for estimating the depth of salt domes revealed that GRNN is a suitable intelligent method to estimate the depth to top of the salt dome.



(a) (b)

Figure(8) .(a)Bedrock depth map of Mors(Jorgensen et al. 2005) ,(b)Bouger anomaly map over Mors salt dome with selected principle profile .

Table 2. *The result of GRNN applied for real gravity data over Morst salt dome.*

Value of Spread	*MSE*	*Estimated Depth by GRNN*	*Estimated by NFG Method (Aghajani et al.)*
0.45	***0.0009098***	***4.82 km***	***4.7 km***

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