

Permeability prediction and construction of 3D geological model: application of neural networks and stochastic approaches in an Iranian gas reservoir

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Abstract Determination of petrophysical parameters by using available data has a specific importance in exploration and production studies for oil and gas industries. Modeling of corrected permeability as a petrophysical parameter can help in decision making processes. The objective of this study is to construct a comprehensive and quantitative characterization of a carbonate gas reservoir in marine gas field. Artificial neural network is applied for prediction of permeability in accordance with other petrophysical parameters at well location. Correlation coefficient for this method is 84 %. In the study, the geological reservoir model is developed in two steps: First, the structure skeleton of the field is constructed, and then, reservoir property is distributed within it by applying new stochastic methods. Permeability is modeled by three techniques: kriging, sequential Gaussian simulation (SGS) and collocated co-simulation using modeled effective porosity as 3D secondary variable. This paper enhances the characterization of the reservoir by improving the modeling of permeability through a new algorithm called collocated co-simulation. Kriging is very simple in modeling the reservoir permeability, and also, original distribution of the data changes considerably in this model. In addition, the SGS model is noisy and heterogeneous, but it retains the original distribution of the data. However, the addition

of a 3D secondary variable in third method resulted in a much more reliable model of permeability.

Keywords Reservoir modeling · Permeability prediction · Neural networks · Geostatistical approaches

1 Introduction

Reservoir characterization is a process of describing various reservoir characteristics using all the available data to obtain reliable reservoir models for accurate reservoir performance prediction. Reservoir characterization is applied in reservoir modeling, simulation, and any primary or enhanced recovery design processes at the petroleum and natural gas industry. Characterization of these parameters is one of the main challenges in petroleum engineering [19, 20].

Characterizing rock permeability and its spatial distribution in a heterogeneous reservoir is a problem with no direct solution. Today, there are two generally reliable means of acquiring knowledge on rock permeability. These are laboratory measurement and well test interpretation. Historically, permeability has been estimated using porosity–permeability transforms generated through linear regression of porosity and permeability data [17]. However, this technique is considered adequate for sandstone reservoirs, but it has no good results for predicting permeability in complex carbonates where diagenetic processes introduce a higher degree of heterogeneity [4, 17, 20].

The integration of well data and seismic data has acquired importance in reservoir characterization studies in recent years [2, 29]. In this paper, 3D seismic data, the available core permeability data and conventional petrophysical well logs from four wells drilled in a gas field

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located in Persian Gulf are used to predict and model permeability.

Neural network is used as a nonlinear regression method to develop transformation between the selected well logs and core permeability measurements. Since 1987, neural networks have been applied to study and evaluate reservoirs, due to their ability to solve highly nonlinear problems in an adaptive manner. So, neural networks have been increasingly applied to predict reservoir properties using well log data. Recent studies [3, 31] suggest that neural networks show great potential for generating more accurate predictions.

Finally, best results will be used in three different geostatistical approaches to construct 3D reservoir permeability models for a better perception of the reservoir. A major contribution of geostatistics to reservoir modeling has been addressing the general problem of data integration, proposing algorithms for merging data of different types, reliability, taken at different scales, into a more accurate reservoir numerical model [30].

2 Artificial neural network (ANN)

Neural networks, in mathematical terms, can be thought of as multivariable, nonlinear regression analysis systems. Actually a neural network attempts to imitate the parallel architecture of the mammalian brain. It is composed of a large number of highly interconnected processing elements that are analogous to neurons that are linked together with weighted connections analogous to synapses [5, 25].

The network's architecture or its pattern of connectivity characterizes how much knowledge is stored in it. It also determines the algorithm to be used in updating the weights of each connection. In recent years, several architectures and learning patterns have been developed for neural network algorithm, such as back-propagation error models, generalized regression neural network (GRNN), probabilistic neural network (PNN) and unsupervised neural network [24, 25].

3 Geostatistics

Geostatistics is a branch of applied statistical science and a powerful tool in reservoir characterization that studies spatial and/or temporal phenomena and capitalizes on spatial relationship to model possible values of variables at un-sampled locations [6, 26]. Earth science-derived data are characterized by a fundamental feature of spatial variability. Spatial variability includes scales of continuity, or heterogeneity and directionality within the data [9, 16]. Accordingly, these data types are not entirely random, but they are a product of natural geological processes, and they have a component of spatial continuity, correlated over some distance, called regionalized

variables. Unlike other random variables, regionalized variables are distributed in space (and/or time) with location information attached to each measurement. Each measurement is related to nearby observations as a consequence of the physical process or multiple processes that generated them. None of the known classical statistical methods, such as regression methods, are able to address the spatial feature associated with regionalized variables adequately [14, 16, 23].

Geostatistics is often used to estimate the spatial variability in geological properties and other earth science-related properties. Among its different applications, geostatistics is being increasingly used to develop accurate models in petroleum reservoir studies [11, 14].

As mentioned before, the principal objective of reservoir characterization is to develop a spatial understanding of inter-well heterogeneity associated with each reservoir property. This paper studies utilization of geostatistics as a tool in providing accurate reservoir permeability models.

3.1 Kriging

The most popular deterministic algorithm for reservoir static modeling is kriging. Kriging is a linear interpolation technique that estimates each sample by using a linear weighted combination of surrounding sample values. The variogram parameters are used to calculate weights. It can be shown by the following Eq. 1 [7, 13]:

$$Z(x_0) = \sum_{i=1}^n \lambda_i Z(x_i) \quad (1)$$

where $Z(x_0)$ is the unknown value at the position of x_0 , $Z(x_i)$ is sample value at x_i positions, and λ_i are sample weights [9, 10].

Kriging gives the value with the highest probability at each point but this is a smooth result and it is quite wrong to presume that this is the most likely distribution. This is only an average solution and if users carry out many simulations and average them, the result will be similar to those of kriged model [9, 28].

3.2 Co-kriging

This geostatistical technique is a modification of kriging and is based on a weighted linear integration of two

Table 1 Number of data points in each data set for permeability prediction

Data set	Number of data points
Training	760
Validation	253
Testing	253

variables, primary and secondary, unlike kriging, which produces models based on a single variable [21]. Well data are usually considered as primary data because they are exact and sparse. Since seismic data are less exact but dense, they are usually the secondary data. Secondary data

Table 2 Correlation coefficient between core permeability and conventional well logs

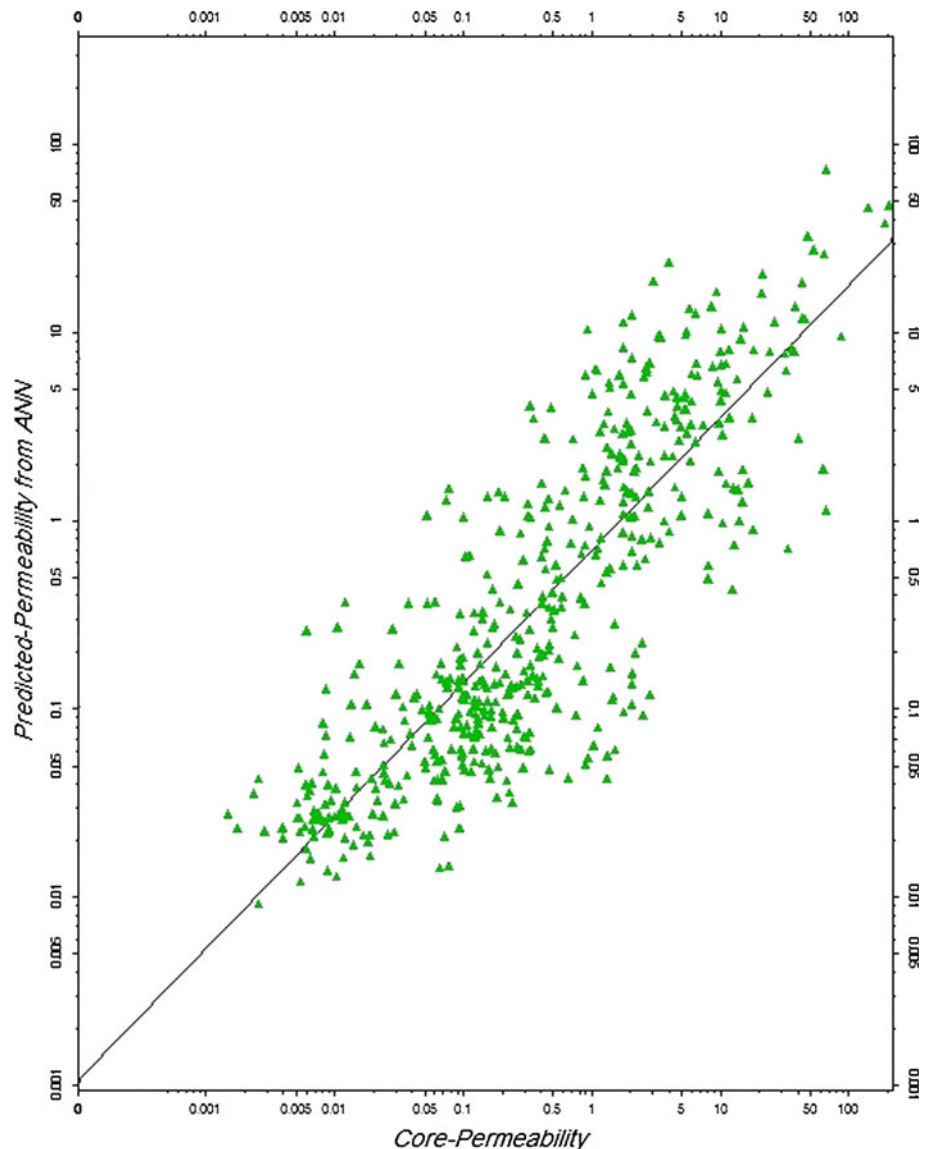
Well log	Permeability
Acoustic impedance	0.60
Density	0.71
Neutron porosity	0.80
P wave	0.65
Effective porosity	0.86
Saturation water	0.61

also can be a modeled variable such as porosity for modeling of permeability [9, 12, 28]. There are two main types of co-kriging: simple co-kriging and collocated co-kriging. First version of co-kriging requires working on data residuals or, in other words, on variables whose means have all been standardized to zero. Second version is a reduced form of co-kriging that consists of retaining only the collocated secondary variable. The co-kriging estimator is written as follows: [12].

$$Z_{\text{cok}}(x_0) = \sum_{i=1}^n \lambda_i Z(x_i) + \mu(x_0) Y(x_0) \tag{2}$$

where $Z_{\text{cok}}(x_0)$ is the unknown value obtained by collocated co-kriging method at the position of x_0 , $Y(x_0)$ is the known value of secondary parameter at the position of x_0 and $\mu(x_0)$ is the sample weight at the position of x_0 .

Fig. 1 Cross-plot between core permeability and permeability obtained from ANN for well C, which is not used in constructing ANN model (permeability is in md and logarithmic scale); correlation coefficient: 84 %



3.3 Sequential Gaussian simulation (SGS)

The most common technique used in reservoir geostatistics is sequential Gaussian simulation [21]. It is called sequential because the same process is repeated to calculate each point, Gaussian because the data set should have Gaussian distribution and simulation because at each un-sampled location a simulated value is drawn from the probability distribution function computed from actual and previously simulated values in the neighborhood of this location. The algorithm starts with a randomly selected location and goes forward sequentially across the grid to be simulated. The order of this progression is not specified by theory, and a random sequence is followed [18, 21].

4 Methodology

Nowadays, the reservoir model building workflow is mainly divided into four steps: (1) definition of the reservoir

boundaries (and especially the top and bottom horizons), (2) building a geologically true structural model (layering, faults, etc.), (3) population of properties (porosity, permeability) by kriging or co-kriging for instance and then (4) upscaling the model in order to obtain a reservoir model [8, 22]. In this study, all steps of the workflow were conducted precisely. In order to improve the constructed model, two new stochastic approaches have been applied in modeling.

In this paper, an intelligent technique using artificial neural networks (ANN) to determine reservoir permeability from well logs at well locations has been used. Finally, the best results of the first step will be utilized as an input to the different geostatistical approaches through the structural model to construct 3D geological reservoir permeability models.

4.1 Permeability prediction using ANN

First step is the preparation of well logs data and applying ANN on the data. The data sets used in this part of the paper were derived from four wells of the studied gas field

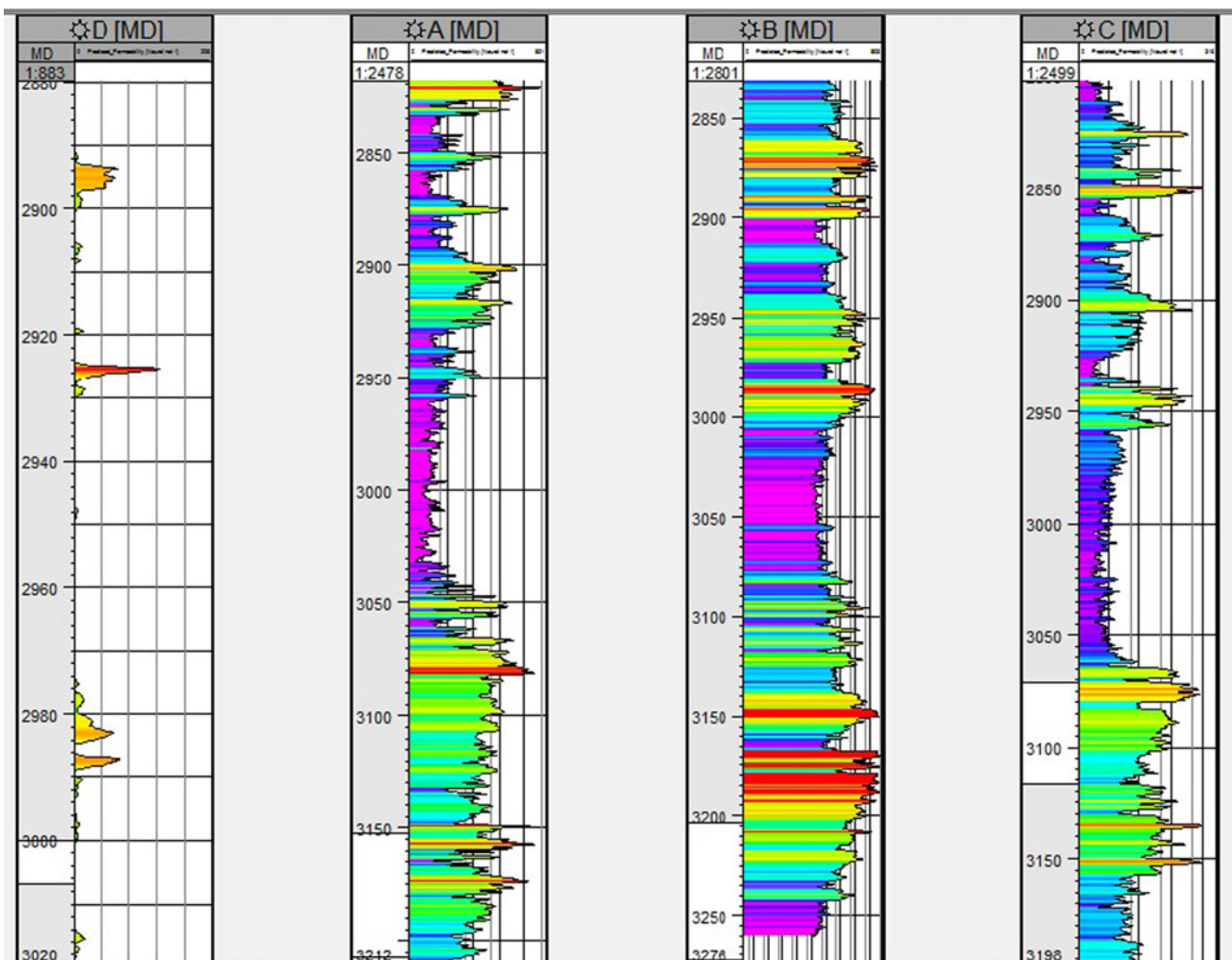


Fig. 2 Permeability logs predicted by ANN at wells (permeability is in md)

in which two wells have core permeability data. One of the cored wells is utilized for constructing the ANN model, and the second well is used for evaluating the reliability of the ANN model. Then, the model is applied to predict permeability at the other un-cored wells and intervals.

Table 1 summarizes the number of data points that are used for prediction of permeability. Obviously, it can be seen that the number of training data points (60 % of all data points) is more than the number of other data point sets which is because of the fact that the ANN is built based on the training data set; therefore, it should be representative of all data, and as much as the number of training data points increases this possibility will be increased.

Selection of suitable inputs plays a crucial role in ANN model, because the inputs that have stronger relationships with output can present more accurate prediction than weaker ones. Table 2 illustrates the correlation coefficients between core permeability and conventional well logs used in the prediction.

Learning method is a supervised algorithm in which the error limit and maximum number of iteration were set to 10 % and 150, respectively. After constructing the ANN model using well A of available two wells with core data, the reliability of the model is evaluated by the second well (well C). Figure 1 shows cross-plot between core permeability and permeability obtained from ANN for well C. The final step is to generalize the results of work by applying the ANN model on the other remained wells of the studied area to estimate permeability at un-cored wells. Figure 2 shows predicted permeability logs obtained from ANN at wells. These values are in milli Darcy.

4.2 Structural modeling

Structural modeling is the process of building the reservoir skeleton structure or the reservoir 3D grid. The properties will be distributed in it. The reservoir grid can be constructed in time or depth scale [1, 15].

Fig. 3 Cross section of the horizons along with well A in this study

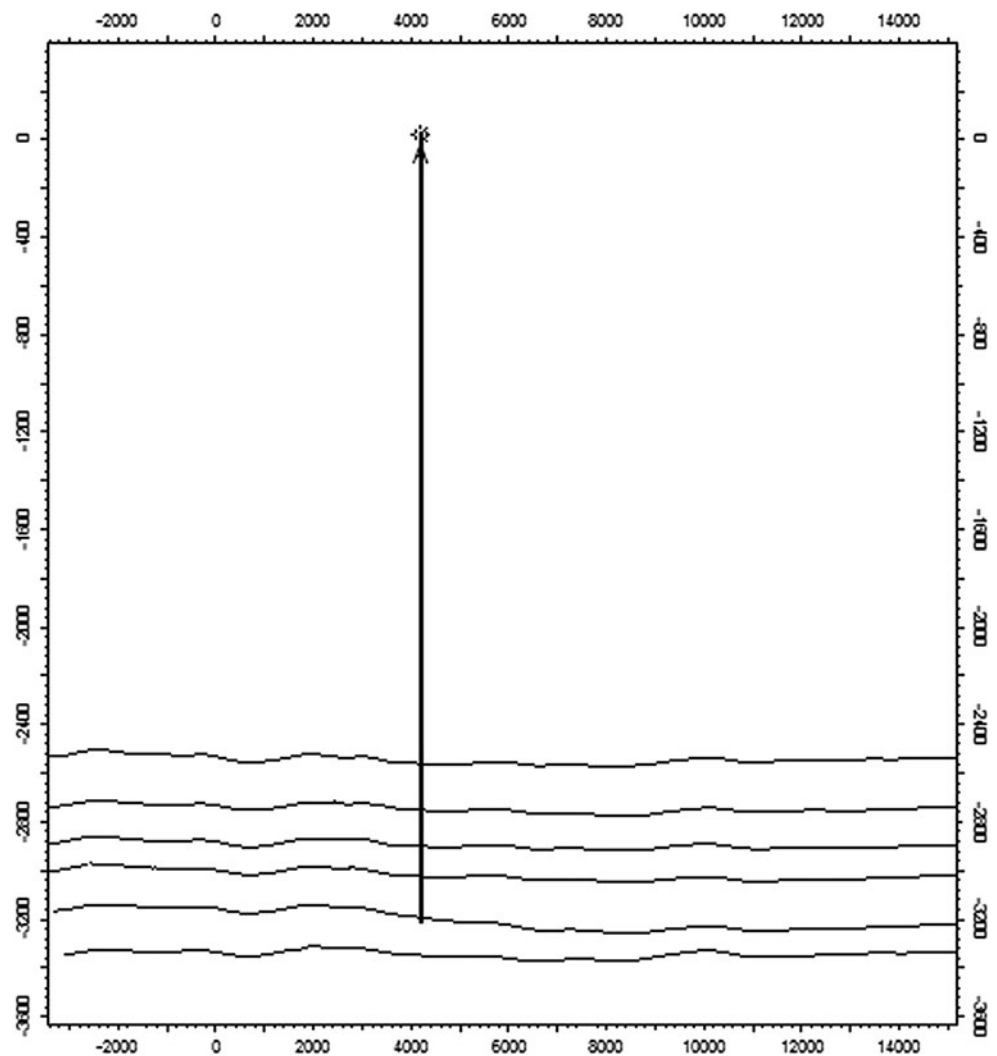


Fig. 4 A view of modeled permeability using kriging algorithm (permeability is in md)

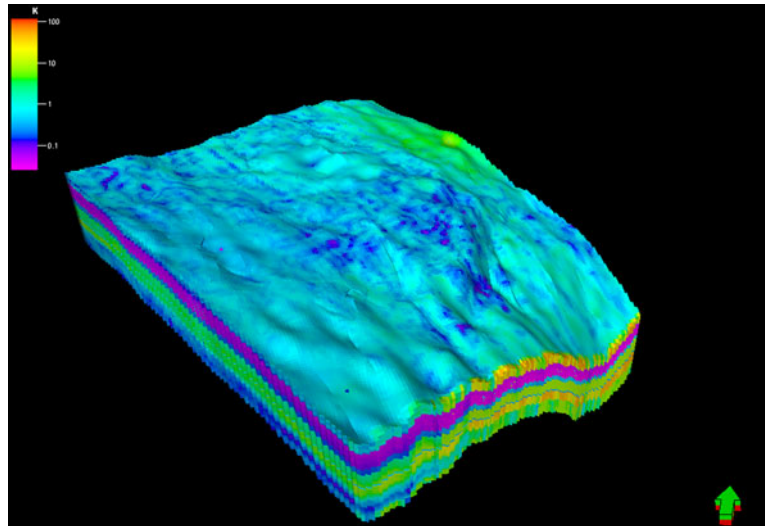


Fig. 5 A view of simulated realization of modeled permeability using SGS algorithm (permeability is in md)

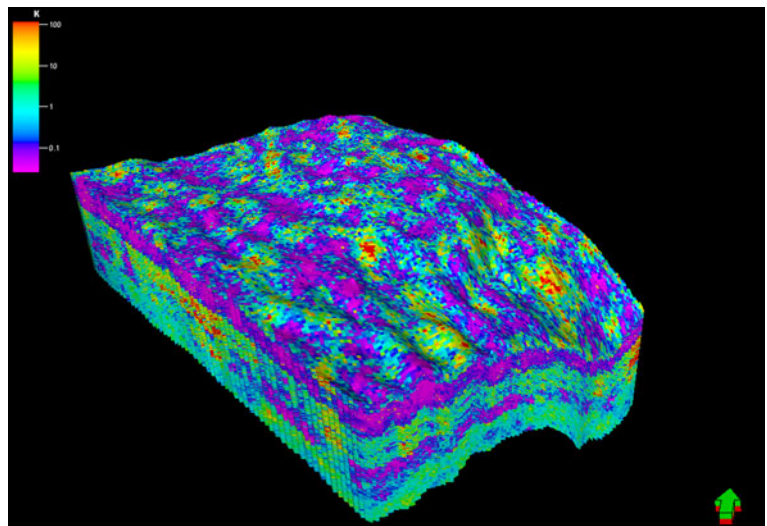
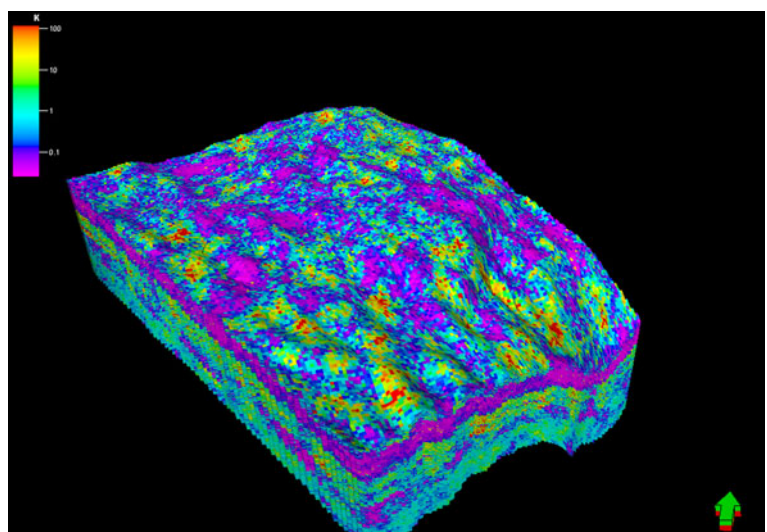


Fig. 6 A view of simulated realization of modeled permeability using collocated co-simulation algorithm (permeability is in md)



Dashtak, Nar, K1, K4, Upper Dalan and lower Dalan horizons are used in this paper. Figure 3 shows a cross section of available horizons. Studied horizons encompass 15 zones. In the making zone process, the vertical division can be added to the model based on the geological information such as isochors or well markers. For making zones in the studied gas field, a finer stratigraphic vertical resolution is defined based on the well information.

Finally after making zones, layering is done in order to model permeability by using geostatistical approaches. This process is performed from finest grids to optimum sizes. Although fine grids cause no data lose after upscaling, they produces a great number of cells, which increases the error of estimation. On the other hand, the coarse cells generate low number of grids, but they cause loss of small-scale variations after the upscaling [15, 27].

4.3 Applying geostatistical approaches

In this paper, permeability is modeled utilizing three techniques: kriging, sequential Gaussian simulation (SGS) and collocated co-simulation using modeled effective porosity as the secondary variable. Kriging is the first method applied to estimate the permeability model. But this method is very simple in modeling the reservoir permeability. So, the sequential Gaussian simulation (SGS), which is the most commonly used method of simulation, is also applied in petrophysical modeling.

Collocated co-simulation is the third alternative to perform petrophysical modeling. Co-kriging method is introduced to solve the problem of insufficient well data by incorporating a secondary variable that is densely sampled and shows a good correlation with the primary well data. Collocated co-kriging is more exact and faster than the simple co-kriging. This new method is used to conduct the simulation using the spatial distribution of a secondary variable with a correlation coefficient.

5 Result and discussion

Figure 4 shows a 3D view of modeled permeability using kriging algorithm. As can be seen, the kriged permeability model could not accurately show permeability variation, and instead, spatially smooth simplistic permeability model is obtained. This kind of inefficiency could be predicted due to insufficient data points utilized in this study. Another reason that could be mentioned is that kriging does not retain the histograms and considerably changes the distribution of original data (Fig. 7a).

Figure 5 shows a 3D view of simulated realization of modeled permeability using SGS algorithm. SGS models are more complex, and therefore, they took longer running

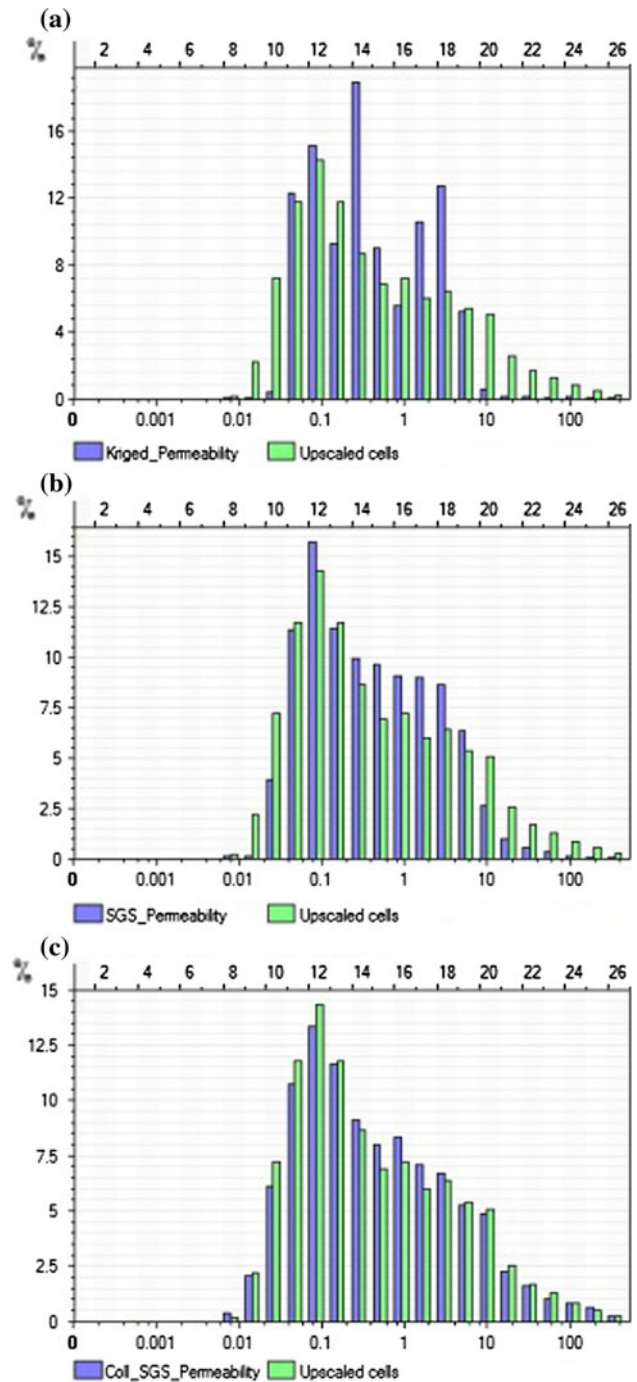


Fig. 7 Histograms of permeability distribution before and after modeling by kriging (a), SGS (b) and collocated co-simulation (c) techniques (permeability is in md and logarithmic scale)

time. Since simulated permeability model could better retain heterogeneity, it has better ability to show the actual reservoir geology (Fig. 7b).

Figure 6 shows a 3D view of simulated realization of modeled permeability using collocated co-simulation algorithm. It can be seen that the randomness of SGS algorithm is much less, and instead, the result has been

affected by the modeled effective porosity trend. Figure 7 shows histogram of data distribution before and after applying different modeling methods. It demonstrates that kriging changes distribution of data and cannot be a suitable method for modeling permeability. Although SGS method does not change original distribution of data, it results in a noisy model. It can be seen from Fig. 7c that original distribution of data does not change in the third method. Also, problems of the second method have been solved by this new method.

6 Conclusion

Applying neural network methods in this paper shows that these methods are suitable for reservoir characterization and similar studies in petroleum engineering. Also, applying geostatistics approaches leads to significant results. The kriged model is smooth, and the original distribution of the data changes considerably in this model. The SGS model is noisy and heterogeneous, but it retains the original distribution of the data. The addition of a 3D secondary variable that is densely sampled and have a reasonable correlation coefficient with primary data resulted in a much more reliable model of permeability. Collocated co-simulation algorithm is a new geostatistical method that provides a reliable model of reservoir permeability.

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