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Original article

# Combining Voronoi Triangulation Discrete Fracture Network (DFN) Models with Fractal Dimension Analysis of Complex Sequences for Predicting Porosity and Permeability

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***Abstract***

Optimizing reservoir performance in fractured reservoirs relies heavily on understanding and harnessing fracture connectivity at the reservoir scale. Voroni triangulation Discrete Fracture Network (DFN) models offer a unique depiction of fractures and their connectivity compared to other methods. Petrophysical property modeling involves various algorithms, with DFN emerging as a novel mathematical approach. This study centers on a segment of Khangiran's hydrocarbon formations, analyzing reservoir porosity and permeability. Among the plethora of available methods, fractal geometry, particularly through the box counting method, proves apt for estimating these properties. By increasing the box size to explore point distribution in the background space, the method calculates fractal dimensions, aiding in porosity and permeability estimation. Applied in modeling, this technique presents a new ellipsoid-based prediction model, providing a comprehensive description of petrophysical properties in reservoir-prone areas. The results, aligned with geological features, mud loss data, and production outcomes, demonstrate remarkable compatibility with lower uncertainty, presenting a promising avenue for enhanced reservoir characterization and performance optimization. The three-dimensional block model estimations derived from the Integrated Discrete Fracture Network (DFN) algorithm with a fractal dimension of complex sequences distribution align with well test analysis and production data results. The iterative application and refinement of the DFN algorithm and fractal dimension modeling process hold potential for further enhancement across the Khangiran reservoir or other hydrocarbon fields. The findings indicate that well 11 is optimally configured and likely exhibits superior performance in terms of hydrocarbon production within the reservoir.

## 1. Introduction

Shurijeh-D, an onshore gas reservoir, constitutes one segment of the larger Khangiran field reservoirs, alongside Shurijeh-B and Mozdoran. Situated approximately 25 kilometers from Sarakhs and 150 kilometers east of Mashhad, the Khangiran field is positioned amidst the Gonbadly and Dowlat Abad structures of the Turkmanesten gas fields [1]. Comprehensive analyses encompassing petrologic, sedimentologic, and geohistory assessments unveil the impact of depositional settings and subsequent subsidence on the petroleum reservoir properties of Shurijeh sandstones within the Kopet-Dagh basin. These sandstones, predominantly composed of sublitharenitic red beds, reflect sedimentation during a regressive phase dominated by rapid siliciclastic sediment supply. The lower and middle sections of the interval were shaped by low-sinuosity braided fluvial systems, while the upper part witnessed high-inuosity meandering systems. Correlating the paragenetic sequence with the geohistory unveils the timing of diagenetic processes, both detrimental and beneficial to porosity, aligning them with the

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onset of petroleum generation [1].

The study of fractured reservoirs plays a pivotal role in the efficient extraction of hydrocarbons, necessitating advanced methodologies for accurate analysis [2]. Among these methodologies, the Discrete Fracture Network (DFN) method emerges as a robust approach for comprehending the complex interplay of fractures within reservoir rocks [3]. This method, rooted in numerical modeling, provides a detailed representation of the intricate network of fractures that significantly influences fluid flow within the subsurface. As fractured reservoirs often exhibit non-uniform flow patterns and varying permeabilities, understanding the spatial distribution and connectivity of fractures becomes imperative. The DFN method, distinguished by its ability to simulate realistic fracture geometries and their impact on fluid flow, stands as a valuable tool for reservoir engineers and geoscientists [3]&[4]. This paper delves into the principles of the DFN method, exploring its application in fractured reservoir analysis, and highlighting its significance in enhancing reservoir characterization and management strategies. Through a comprehensive review of literature and case studies, this research aims to contribute to the evolving landscape of fractured reservoir studies, shedding light on the potential of the DFN method in deciphering the complexities inherent in subsurface fluid dynamics [5]. It is essential to note the utilization of ELM and RBF models, as well as RBFN, MLFN, and PNN machines, for the estimation of porosity. [6] & [7] & [8].

The current research emphasizes aspects related to multidisciplinary data integration, or uncertainty quantification. The goal of this study is to characterize the distributions of porosity and permeability in Shurijeh-B reservoir of Khangiran gas field. Among the plethora of available methods, fractal geometry, particularly through the box counting method, proves apt for estimating these properties.

## 2. Material and Methods

### 2.1. Area of Study

The Khangiran gas field is situated approximately 180 km northeast of the city of Mashhad, within the Sarakhs area. Positioned in the Kopet–Dagh basin, as illustrated in Figure 1, the Khangiran structure forms an asymmetric anticline with a prevailing NW–SE trend. The north flank exhibits steeper dips than the south flank, featuring a low dip plunges. Based on the seismic structural contour map, the Khangiran structure extends approximately 20 km in length and 8 km in width near the top of the Mozduran formation. The aerial closure of the structure spans about 115 km², with a vertical closure of approximately 500 m. The Shurijeh gas-bearing zone's thickness is approximately 60 m in well KG-l [1].

The Khangiran gas field, situated in the Kopet–Dagh basin, demonstrates distinctive structural characteristics, with its asymmetric anticline and varying dip angles. The comprehensive analysis of seismic and well data provides valuable insights into the field's dimensions, closures, and the thickness of the gas-bearing zone. Further research and detailed investigations are recommended to enhance our understanding of the Khangiran structure and optimize resource extraction strategies.

### 2.2. Geological Structure

The Khangiran structure manifests as an asymmetrical anticline with a prominent NW–SE trending axis, suggesting that the primary traps are structural in nature. This geological formation has notable implications for the Khangiran shale, partially concealed by diverse alluvial deposits, including loess, sand dunes, and Quaternary Terraces. Analyzing seismic data reveals that the northern flank of the structure exhibits steeper characteristics compared to its southern counterpart. The structure itself presents low plunges, showcasing a vertical closure of approximately 2200 feet and an areal closure spanning about 600 km².

Furthermore, the structural features include a vertical fault oriented parallel to the anticline axis. It's worth noting that this fault, situated in the northern flank of the anticline and distant from its axis, holds minimal impact on the overall trap dynamics, as depicted in Figure 1.

The Khangiran structure's intricate geological composition, characterized by asymmetrical anticlines and fault structures, contributes to its potential as a significant structural trap. The understanding of the structural nuances, plunges, and fault distribution provides valuable insights for further exploration and resource optimization within the Khangiran gas field. Subsequent research endeavors should delve into more detailed assessments to unravel the complexities of this geological formation.

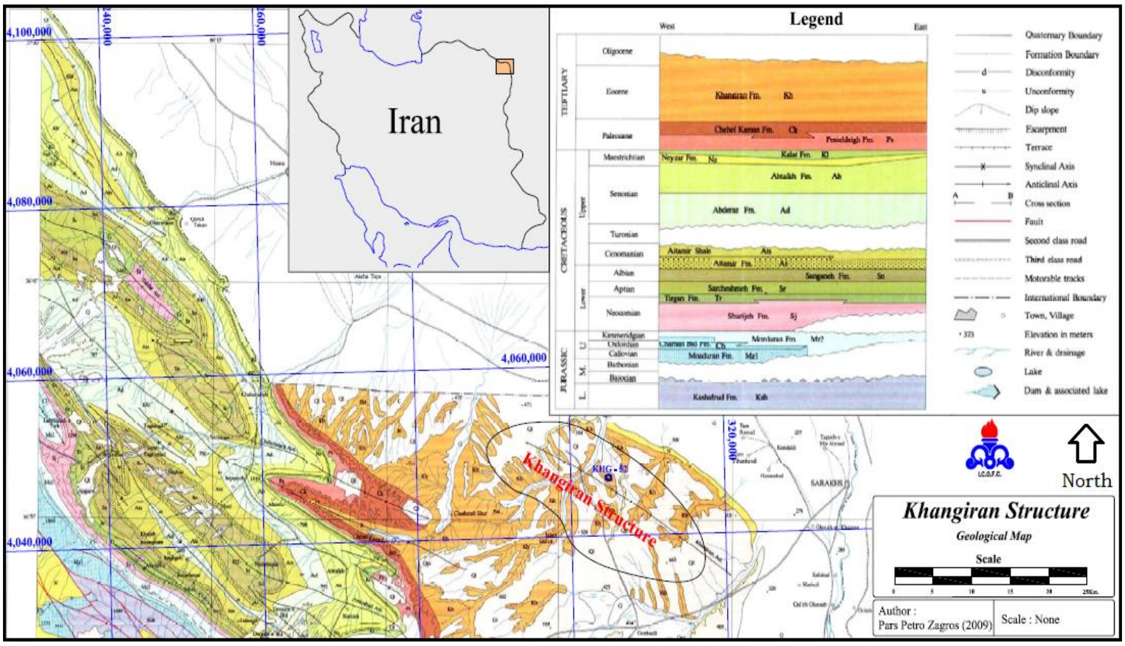


**Fig. 1.** Geological map of Khangiran Structure [1].

## 2.3. DFN Algorithm

The Discrete Fracture Network (DFN) model, employed as a numerical approach, plays a pivotal role in fracture modeling and pattern recognition. However, the movement of hydrocarbons and fluids within fractured reservoirs or conventional reservoirs with significant fracture permeability often deviates from anticipated outcomes. This is evident in early water breakthroughs, diminished tertiary recovery efficiency due to the channeling of injected substances, and dynamic calculations indicating recoverable hydrocarbons substantially less than static mass balance predictions, owing to reservoir compartmentalization. Additionally, production changes of a significant nature occur due to alterations in reservoir pressure as fractures close down, serving as conduits. These issues contribute to reduced ultimate recoveries or escalated production costs [2].

Experience in managing fractured reservoirs underscores the critical role of comprehending and leveraging fracture connectivity at the reservoir scale to optimize performance. DFN models provide a distinct portrayal of fractures and their connectivity compared to other methods. Conventional models representing fracture-dominated reservoirs often fall short in accurately reflecting the geometry of fluid flow pathways. In contrast, DFN models offer a more realistic approach by explicitly modeling the connectivity of faults and joints, contributing to non-continuum flow behavior at both reservoir and well scales.

In the DFN model, each conductive fracture is explicitly represented as one or more 1D, 2D, or 3D elements, with physical and geometrical properties assigned based on measured data or geologically conditioned statistical distributions. DFN models typically combine deterministic fractures directly imaged through seismic or intersected in wells with smaller-scale stochastic fractures generated stochastically. The geometrical and physical properties of stochastic fractures are assigned through Monte Carlo sampling of relevant distributions, often conditioned to both structural geology and depositional framework (figures 2a, b, and 3). One of the notable advantages of the DFN approach lies in its consistent use of a wide variety of geological, geophysical, and production data, incorporating disparate sources conventional dual-porosity models cannot to the same extent. The data used for constructing DFN models can be derived from lineament maps, outcrops, 2D and 3D seismic, various well logs, core samples, single well and multi-well production tests, flow logs, injectivity profiles, as well as structural or depositional conceptual models. Specialized tools have been developed to derive the necessary input data for DFN models from these diverse sources, as illustrated in the presentation [3], [4], & [5].

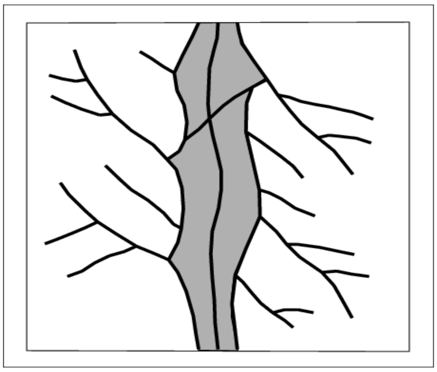
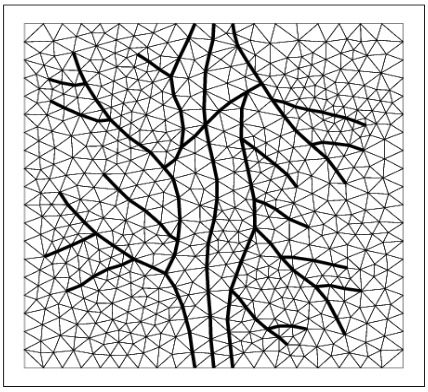


**Fig. 2a (Part 01).** Gridding using the technique of voroni triangulation DFN algorithms [9].



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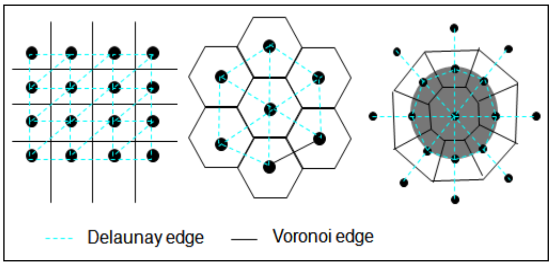


**Fig. 2b.** Distribution points within the inner boundaries system, voronoi and delaunary networking algorithms [9].

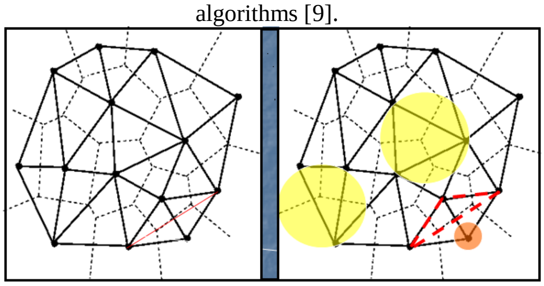

**Fig. 3.** Pattern of Network DFN Model and the ranges that covered by each cell [2].

DFN models have been used for a wide variety of exploration and production purposes over the last decade. The current study represents an extension of DFN technology to improve process modeling in tertiary recovery efforts at Khangiran hydrocarbon field in northeast of Iran.

In this study is used DFN algorithm for modeling the distribution of fractures within this study, in the Shurijeh reservoir-Khangiran (figure 4). This model utilizes with OpenFlow V.2.0.3 software that is licensed for one year and has been undertaken by representing the IFP French Company created in the Middle East. This model can be used as a lineament maps, outcrop data, two-dimensional and three-dimensional seismic, borehole logs in all its forms, subsequent tests of a well or several wells, flow logs and injection profiles as a conceptual model of a structure or common cause.

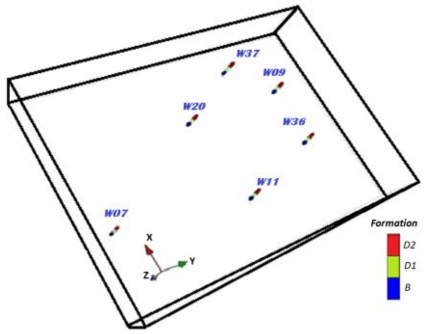


**Fig. 4.** Location of to the wells on the blocks within this study on Shurijeh reservoir.

In this algorithm, ($r_e$) is radius of equivalence and covers the surface of the fracture area ($A_f$) that are called according to equation (1) is calculated as :

$$A_f=\Pi r_e^2 \qquad (1)$$

Where Af is area of fracture, in ($m^2$) or ($ft^2$). And Π is constant, and $r_e^2$ is radius of equivalence in terms of the (m) or (ft). In this model, square surface of fractures is determined by using equation (2):

$$A_f= (\text{Fracture Length})^2 \qquad (2)$$

By combining equations (1) and (2) the size of the fracture can be obtained from equation (3):

$$\text{Length}= \sqrt{\Pi}\, r_e^2 \qquad (3)$$

## 2.4. Fractal Box-Counting Method

Natural objects exhibit scaling symmetry, but only over a limited range of scales. They also tend to be "roughly" self-similar, appearing more or less the same at different scales of measurement. Sometimes this means that they are statistically self-similar; that is to say, they have a distribution of elements that is similar under magnification. In contrast to naturally occurring fractals, mathematical fractals can possess an infinite range of scaling symmetry. The more common constructions also tend to be exactly self-similar.

Fractal behavior has been observed in natural fracture patterns [10] & [11] and fractal geometry provides a quantification of size scaling or scale dependency of the complex fracture systems. Fractal analysis relies on the estimation of a non-integer number, i.e., fractal dimension, D. typically; box-counting technique is applied to measure the fractal dimension of the fracture network [12], [13], [14] & [15].

From an early age, we that learn lines and curves are one-dimensional, planes and surfaces are two-dimensional, solids such as a cube are three dimensional, and so on. More formally, we say a set is n-dimensional if we need n independent variables to describe a neighborhood of any point. This notion of dimension is called the topological dimension. Fractal dimension (DF) is a useful feature for texture segmentation, shape classification, and graphic analysis in many fields. The box-counting approach is one of the frequently used techniques to estimate the DF of an image [10]. The dimension of a fractal-like structure can be measured using a multiresolution approach, as for instance the merging boxes method. Increasing the size of the box used to explore the structure of a distribution of points in a background space, the number of filled boxes, i.e., of the boxes containing points that belong to the given set, decreases according to a power law with the exponent giving the fractal dimension of the set of points [16]:

$$DF = \frac{\log\left(\frac{N_2}{N_1}\right)}{\log\left(\frac{B_2}{B_1}\right)}, \quad (4)$$

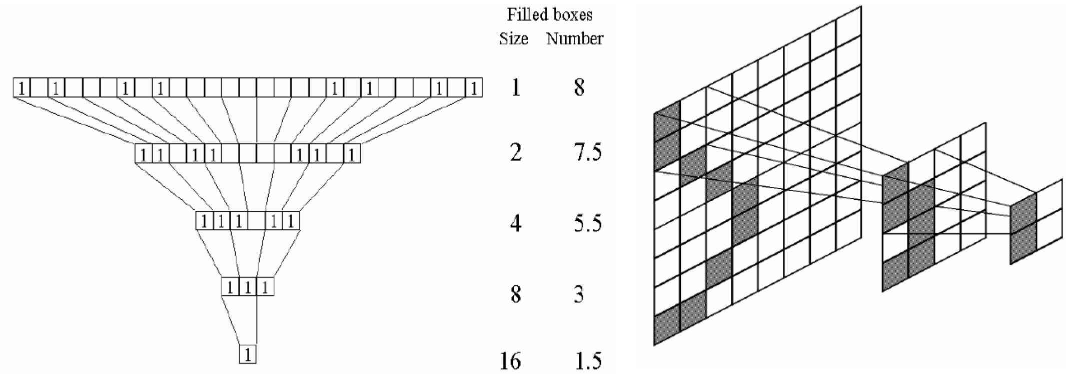


**Fig. 5.** Multiresolution approach to the measurement of the fractal dimension for a signal embedded in a 1D array (a) and a 2D array (b).

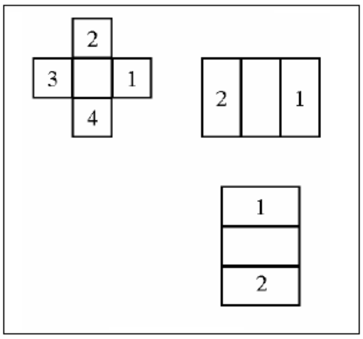


**Figure 6**

**Fig. 6.** Doubling of box size for square and rectangular boxes.

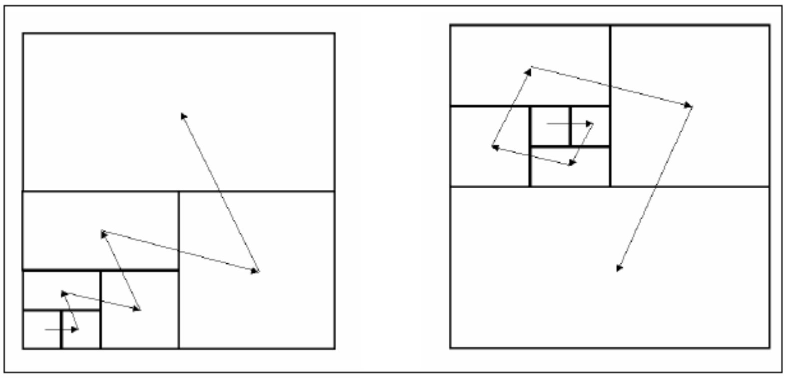

**Figure 7** (a) **Figure 7** (b)

**Fig. 7.** Successive enlargement steps of an elementary box in the (7a) progressive (1-1-1-1-...) and (7b) spiral (1-2-3-1-…) box size doubling [16].

In the given context, N1 and N2 represent the numbers of filled boxes corresponding to sizes B1 and B2, respectively. The identification of a fractal-like structure is facilitated by the linear relationship observed in the plot log (N) vs. log (B), where the slope provides the fractal dimension. The range over which this linearity persists indicates the scales at which the set exhibits the self-similarity property, a characteristic feature of fractals. Figure 5 illustrates the application of this method to both 1D and 2D embedded structures.

To mitigate systematic errors in the system, a fractional correction for the number of filled boxes is introduced, accounting for sets with an odd number of elements. For sets embedded in 2D and higher-dimensional spaces, it is more practical, for implementation reasons, to incrementally enlarge the box size through successive doubling along each dimension, as depicted in Fig. 6. This figure also provides labels for neighbors merged into a square or rectangular box during an elementary step. Various paths for box enlargement are available, as demonstrated in Fig. 7. In the actual implementation, the path illustrated in figure 7a has been employed.

## 3. Result and Discussion

For the cellular gridding in the north-western part of Shurijeh within the Khangiran field, a reservoir-specific study was conducted in a 6700 × 4500 meter square area. Considering the depth of the wells under investigation, a depth of 710 meters was taken into account. The dimensions of each cell for the X-axis are 100 meters, for the Y-axis are 100 meters, and for the Z-axis are 10 meters (100 × 100 × 10 mm^3). This configuration is defined as follows:

$$N = N_X \times N_y \times N_z$$

where N represents the total number of cells, $N_X$ is the total number of cells in the X direction, $N_Y$ is the number of cells in the Y direction, and $N_Z$ is the total number of cells in the Z direction.

So that: $N = 67 \times 45 \times 71 = 214065$

Figure 8 illustrates the gridding of the block with fractal dimension using the Influence Radius of Permeability and Porosity (IRPP) method integrated with the DFN algorithm. Consequently, three-dimensional modeling results for porosity and permeability data are presented separately in Figures 9a and 9b.

After establishing a cellular network, three-dimensional block model estimations were derived using the Integrated Discrete Fracture Network (DFN) algorithm with a fractal dimension of complex sequences, investigating a hydrocarbon reservoir in the north-western part of Shurijeh within the Khangiran field. Figure 10 illustrates that the results obtained from this approach reveal a more suitable region compared to conventional porosity and permeability modeling methods.

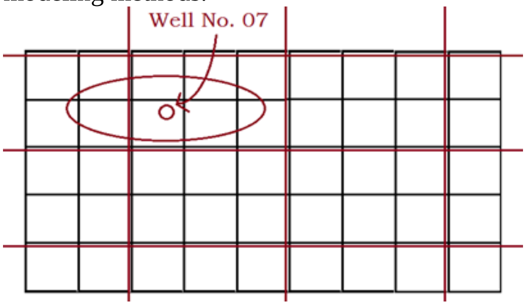


**Fig. 8.** Gridding for calculation of fractal dimension [17].

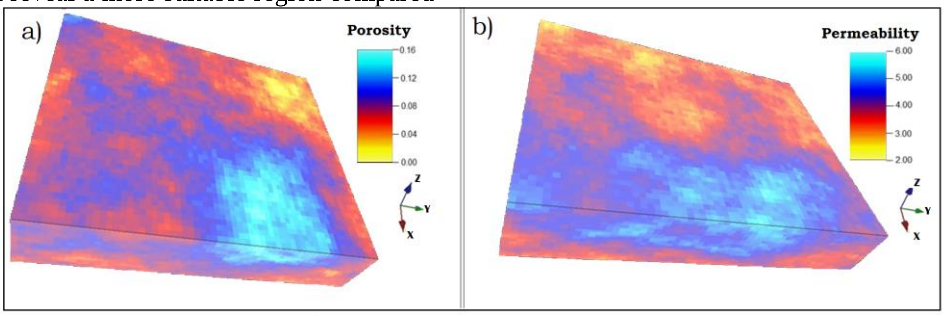


**Fig. 9.** a) Three-dimensional block model estimates from porosity data, b) Three-dimensional block model estimates from permeability data on hydrocarbon reservoir.

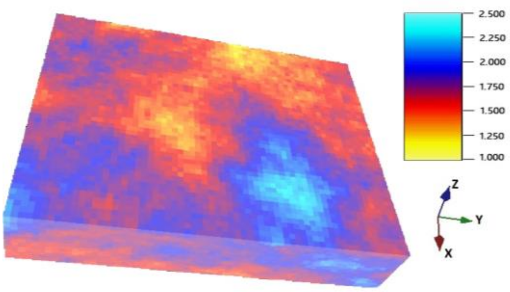


**Fig. 10.** Three-dimensional block model estimates from the Integrated DFN algorithm with fractal dimension of complex sequences studies in hydrocarbon reservoir

## 4. Conclusion

As discussed earlier, a comprehensive case study was conducted over a limited area in the northwest of the Khangiran hydrocarbon reservoir to showcase the efficacy of the proposed research in contrast to simplistic porosity and permeability models based on random point distribution. Initially, the integrated method was employed to estimate fracture density and fractal dimension [18] & [19]. A selection of input data including lithology index, mud loss, porosity, and permeability was made from previously described data sources, prioritizing widely available, reliable, and high-resolution data. A comparative analysis of the integrated model with simple models demonstrated the superior accuracy of the proposed method. In conclusion, the three-dimensional block model estimations derived from the Integrated Discrete Fracture Network (DFN) algorithm with a fractal dimension of complex sequences distribution align with well test analysis and production data results. The iterative application and refinement of the DFN algorithm and fractal dimension modeling process hold potential for further enhancement across the Khangiran reservoir or other hydrocarbon fields. Therefore, the southeastern parts of the study block model, encompassing well No. 11, demonstrate favorable conditions for the extraction and utilization of hydrocarbons.

## 5. Acknowledgment

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