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Application of Neural Network Analysis for Seismic Data to Differentiate Reservoir Units of Yamama Formation in Nasiriya Oilfield A Case Study in Southern Iraq

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Abstract

The EMERGE application from Hampsson-Russell suite programs was used in the present study. It is an interesting domain for seismic attributes that predict some of reservoir three dimensional or two dimensional properties, as well as their combination. The objective of this study is to differentiate reservoir/non reservoir units with well data in the Yamama Formation by using seismic tools. P-impedance volume (density x velocity of P-wave) was used in this research to perform a three dimensional seismic model on the oilfield of Nasiriya by using post-stack data of 5 wells. The data (training and application) were utilized in the EMERGE analysis for estimating the reservoir properties of P-wave velocity, in addition to the neural network analysis and deriving relations between them at well locations. P- wave velocity slices of reservoir units (Yb1, Yb2, and Yc) of Yamama Formation were prepared to determine the enhancement trends within these units. From a general economic point of view, due to good prospecting in Cretaceous rocks, especially in Nasiriya oilfield, , Yamama Formation was found to contain hydrocarbon accumulation and can be considered as one of the most important reservoirs in southern Iraq.

Keywords: Neural Network Analysis, Log and Seismic data relationship, Yamama Formation, Nasiriya oilfield.

تطبيق تحليل الشبكة العصبية للتنبؤ بالمعطيات الزلزالية لتمييز وحدات المكمن لتكوين اليمامة في حقل الناصرية النفطي – دراسة حالة في جنوبي العراق

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الخلاصه

استخدم تطبيق الابراز في برنامج (هامبسون – رسل) والتي تستخدم مجموعة متعددة من الملامح الزلزالية المجسمة والزلزالية ثنائي البعد أو الاثنان معا للتنبؤ لبعض خواص المكمن لهذا الغرض.

إن هذه الدراسة يبين وحدات المكمن النفطي عن وحدات المكمن غير النفطي بالطريقة الزلزالية لتكوين اليمامة، لقد استخدم الممانعة الزلزالية للموجة الطولية في هذا البحث للتأكيد على ما بعد التكديس

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في البيانات الزلزالية المجسمة في حقل الناصرية النفطي، حيث استخدم بيانات خمسة ابار في هذا البحث واستخدم نتائج هذه الابار في تحليل الابراز (التدريب والتطبيق) وذلك لتقدير خواص المكمن لسرعة الموجة الطولية مع تحليل الشبكة العصبية واشتقاق العلاقات بينهم في مواقع الابار.
تم تحضير مقاطع السرع لوحدات المكمن الثلاث لتكوين اليمامة وذلك تمكين سرعة الموجة الطولية وتأكيد تطابق النتائج وتقوية اتجاهات خلال هذه الوحدات، وبسبب الدراسة الجيدة الاحتمالية وجود الهايدروكاربون في صخور عمر الكريتاسي عموما وتكوين اليمامة خصوصا في حقل الناصرية النفطي، لذا فان معظم هذا التكوين هو منتج للنفط في جنوب العراق في هذا العم، فان هذا التكوين لها قيمة اقتصادية بسبب احتوائها على تجمعات الهايدروكاربون التي تعطي اهمية اقتصادية للتكوين في جنوبي العراق.

1. Introduction

The neural network analysis estimates the target log by making use of several attributes chosen from a suite of attributes. The selection of the optimum number of attributes is usually achieved by the linear multi-attribute regression analysis. Also, in order that the seismic data and the target well logs are scaled to the same resolution level, a convolutional approach is used [1]. The application of neural network analysis have been successfully done in the past, through the use of seismic attributes and, consequently, neural networks, with the prediction of the 3-D distribution of physical properties, such as porosity [2-6] and lithology [7,8].
Geophysical applications were used in the beginning of the 1990s in the development of early neural networks for the description and prediction of lithology of wells by using a propagation of Multi-Layer Feed Forward Network (MLFN) [9]. Nevertheless, in Iraq, the current study represents the first work that is performed on Yamama Formation. The estimation of logs using seismic data in neural networks was proposed in geophysical applications for interpretation frameworks [10]. In addition, this field of research was applied for sonic inversion of the content of shale logs using both of seismic data and well logs [11]. Predicting subsurface properties, such as P-wave, has always been a fundamental problem for geologists and geophysicists. For the delineation of the structure of a reservoir, seismic data are always used, but they do not often estimate the distribution of the properties of the reservoir rocks [6]. The two main types of data used , to predict reservoir properties are seismic and well data. In the current study, Probabilistic Neural Network (PNN) analysis was used for predicting P-wave velocity from several 3D seismic attributes.

2. Geological background

The location of Nasiriya oilfield is within Dhi Qar Governorate, at the NW of the city of Nasiriya (Figure- 1). The structure of this field was studied seismically in 1975, as a part of an investigation conducted in southern Iraq by the Iraqi Oil Exploration Company [12]. The current study employed the 3D seismic data collected by a survey that was executed in 2011 [13]. The structural attribute of the field is represented by a gentle NW-SE trending anticline, approximately 35 km long and 21 km wide. The tectonic zone of Iraq shows that the Nasiriya oilfield is located on an unstable shelf of the Mesopotamian basin [14] (Figure-2). This location has an effect directly on the structure of the study area, in terms of intensity of fractures and depositional setting. Yamama basin took its final shape from different tectonic zones, which played an important role in the development of the basin's structure. The tectonism in the study area shows the basin at the western part to be within the Arabian platform of the stable shelf. On the other hand, the basin is located partly within the unstable shelf in the eastern part of the Mesopotamian Foredeep [15]. Stratigraphy of Yamama Formation and its lithological units were determined based on well data, using a core description and a thin section study of core data. The thin sections were selected based on a previous work that had a major role in dividing Yamama Formation. Accordingly, the formation was divided into several units. The first unit is the upper part of Yamama (the contact between the Yamama and Ratawi Formations), which was called as YA-1 and consists of silty sandstone and siltstone [16]. The criteria used to separate the contact by two previous studies [16, 17] were controversial, because the contact is slightly below the YA-1 unit and the top of Yamama Formation was delineated downward, along with the appearance of pure carbonate below the argillaceous limestone and shale of Ratawi Formation. Therefore, this study traced new contacts all over the study area depending on data of five wells. Yamama Formation is conformably grading upward into Ratawi Formation and, hence, the latter is considered as the cap rock of the former [15]. In this study, Yamama Formation is divided based on an earlier work [16] into five reservoir units, including two reservoir units (YA-1 and Ya-2) that are defined in this study as YB-1 and YB-2, respectively [16].

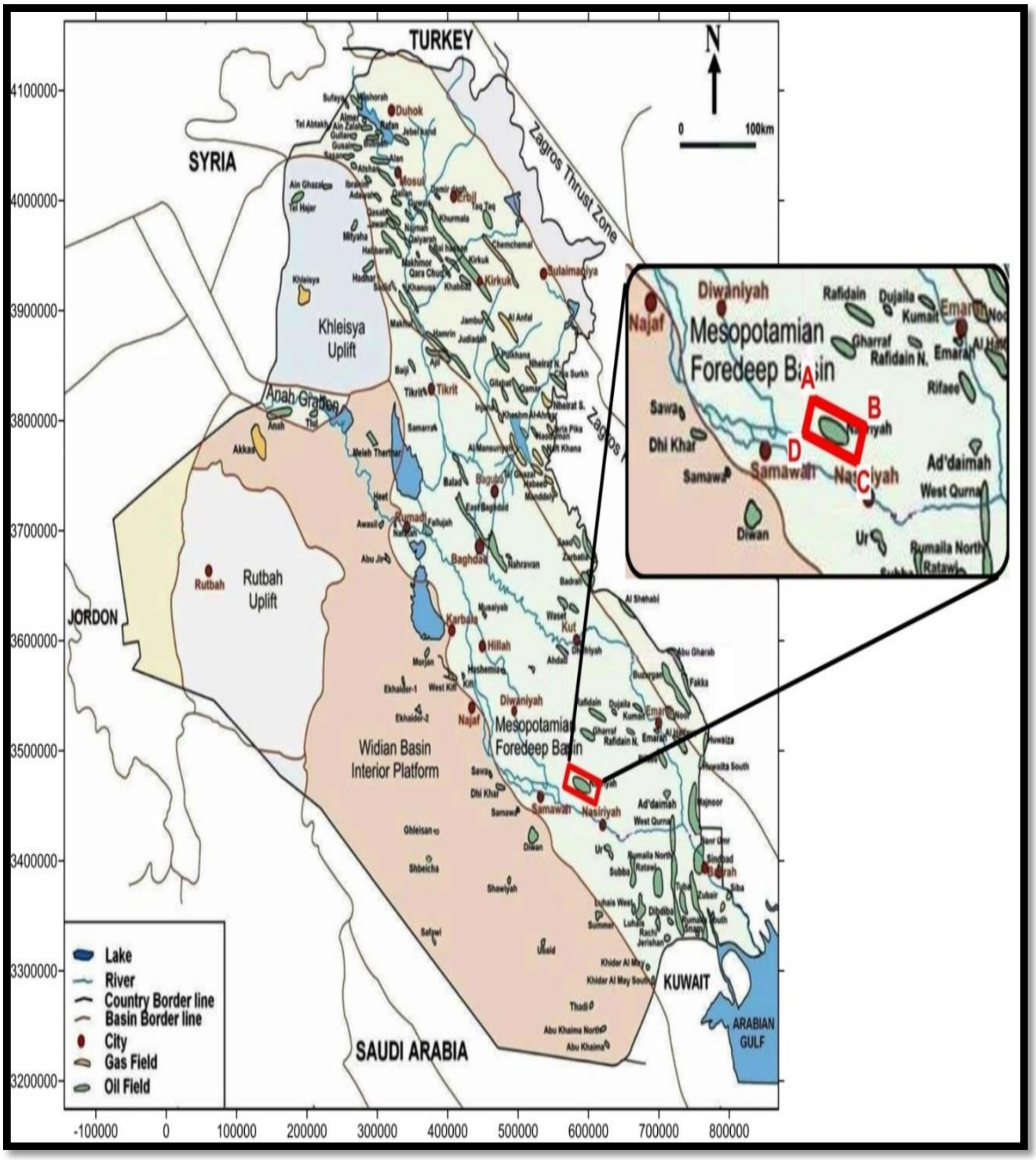

Figure 1- Location map of the study area, modified from Al-Ameri (2010) [18]

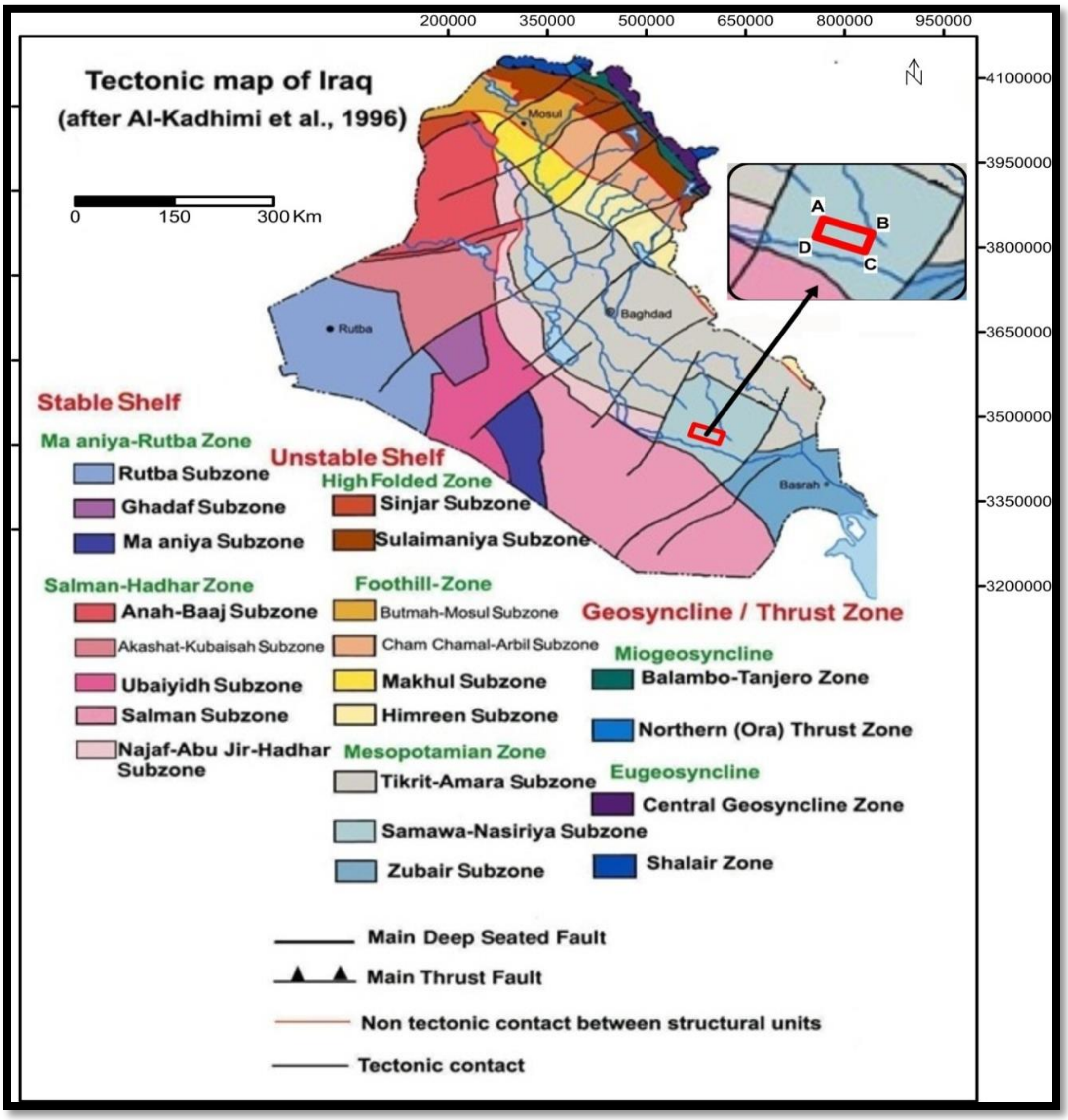

Figure 2- The location map of Nasiriya oilfield on the tectonic map of Iraq, modified after [14].

3. The EMERGE Module

EMERGE is a module developed by Hampson-Russell Software Ltd. The data that are collected from the seismic reflection with well logs near the well locations is the objective of the module, using a various combination of single attribute, multiple attributes, and neural network. The module finds a relationship between the well log and seismic data at the well locations to estimate and mapping seismic attributes of wells and reservoirs, using three dimensional seismic reflection and well data. These two parameters predict particularly rock volumes, which depend on the effectiveness of the selection of attributes that can estimate the log property and the accuracy of the training of the neural network [19].

Although this relationship is concluded between these attributes with the parameters of the reservoir, it shows no clear physical fundamentals for deriving a statistical relationship as compared to the deterministic one. This procedure, called as data- driven methodology, is summarized in the flow-chart illustrated in Figure -3 [10].

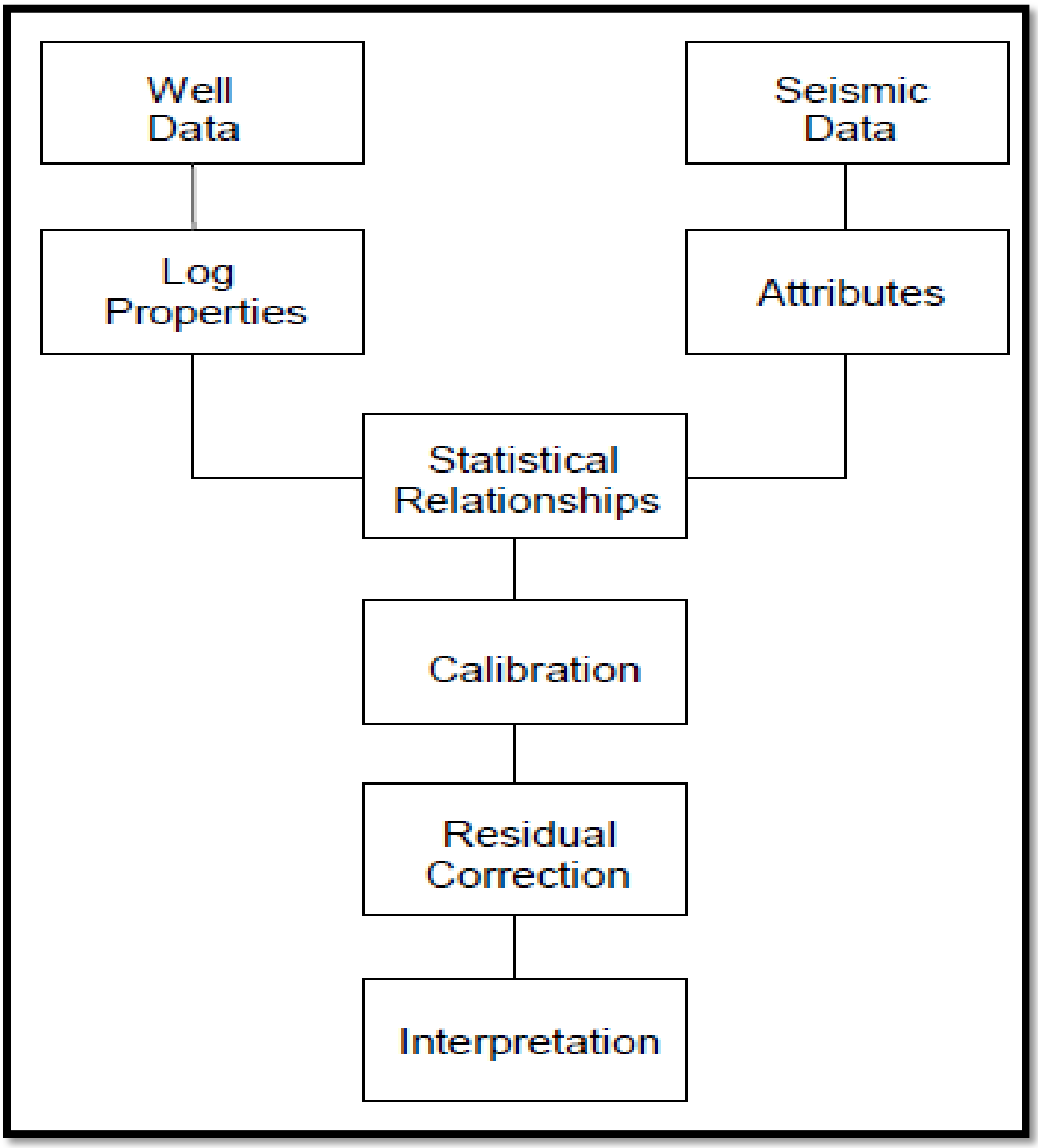

Figure 3- The Flow chart of data driven to statistical interpretation [10].

3-1. The EMERGE training

The EMRGE model has two steps. The first step is the training and the second is the application in the testing stage, by using EMERGE module as an integration tool, which includes three steps: single attribute, multiple attributes, and neural network. The module analyzes and explains the seismic reflection data at the locations of wells to derive a statistical relationship between them (Figure -4). This relation will be used later to predict the sonic log properties over the 3D seismic volume. The loaded data in the current study are necessary to estimate the property of P-wave velocity over the seismic study area. The P-wave velocity data included seismic data, computed P-wave, and inverted volume (Figure -5).

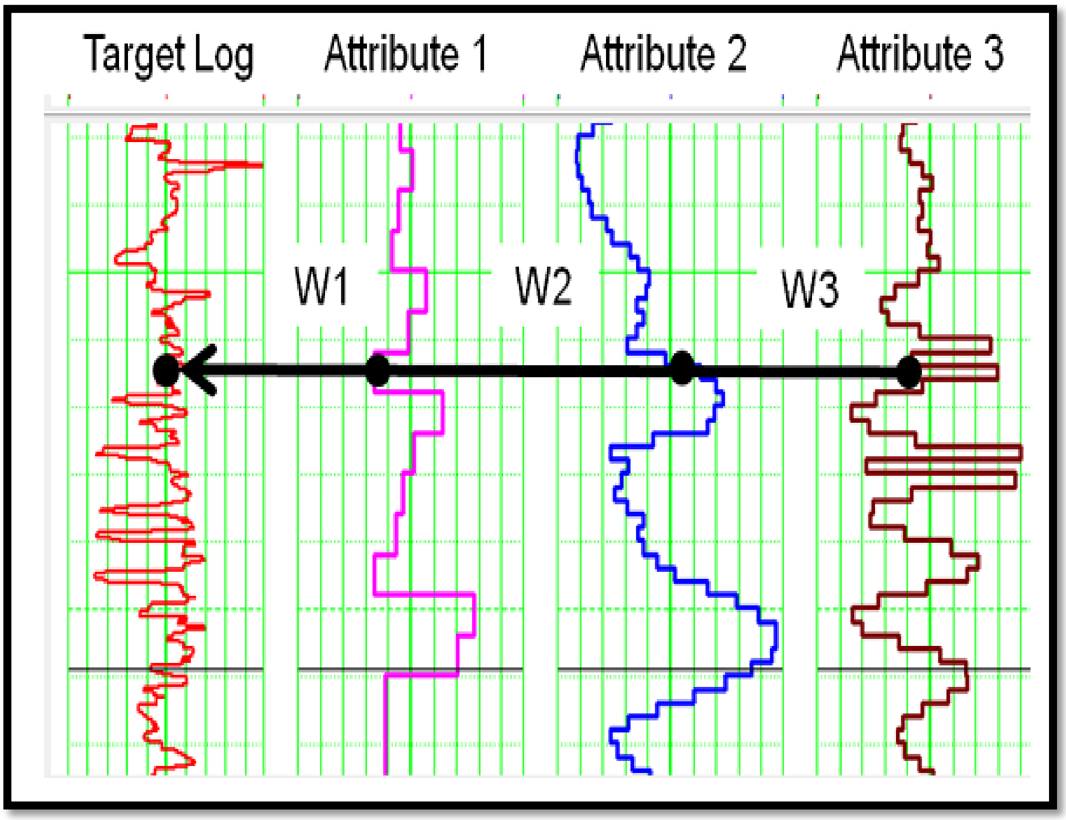

Figure 4- An analytical window for the attributes and target logs at each point [19].

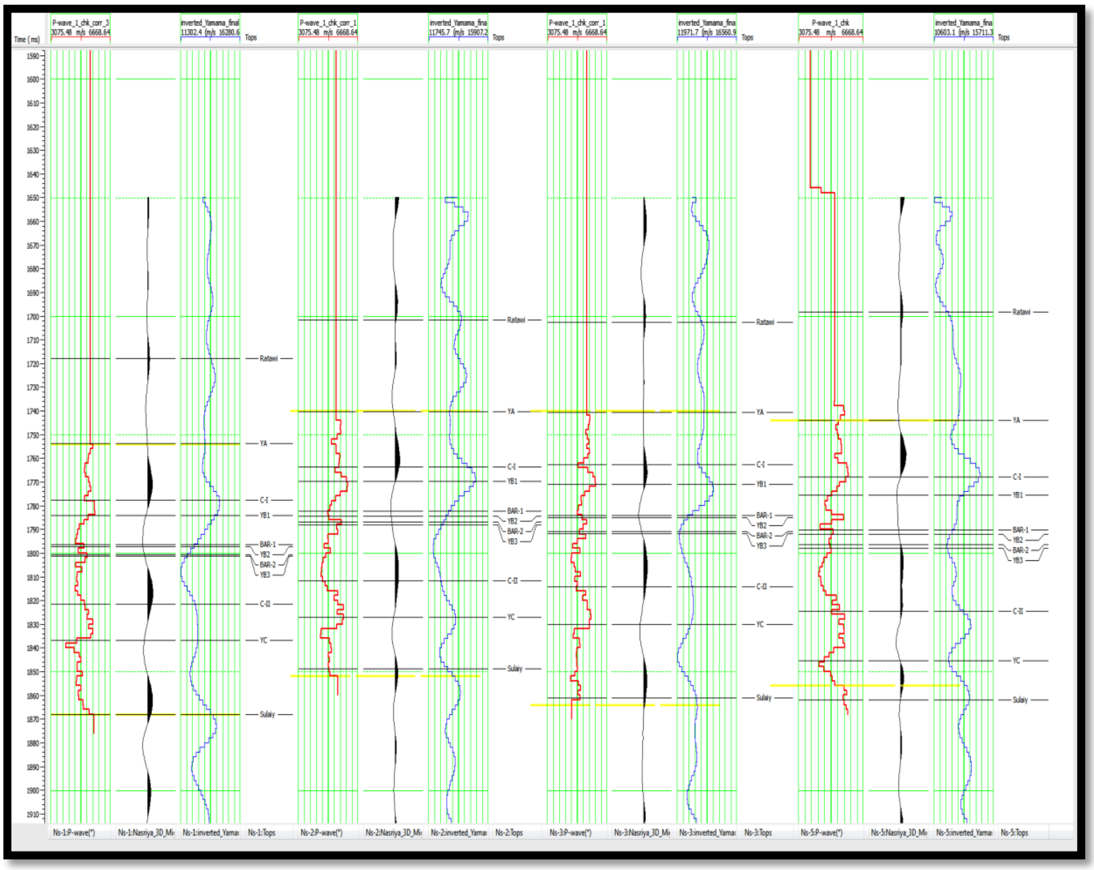

Figure 5- The required Data to estimate P-wave velocity property. P-wave velocity log in red, seismic trace in black, inverted in blue to the four wells in the study area (the data of well-5 are not mentioned here because of lack of information).

4. The P- Wave Prediction Using Neural network

The neural network process of well data is the main key to establish the relationship between logs and seismic data, thus generating a non-seismic 3-D cube from seismic 3-D data. This technique was used for predicting P-wave velocity log from seismic attributes. Two types of attributes are used here, namely the internal attribute and external attribute. This network was distributed by using a parallel processor that has a natural tendency for strong empirical knowledge that made it available to use. The knowledge is achieved by the network along with the training process and interneuron connection. This connection is known as the synaptic weight and used to store this knowledge [20]. Figure-6 shows architecture of many interconnected processing units that organize the operations to feed-forward multilayers of the neural network, which are the pattern layer and input layer, as well as the summation of layers and its output. In the current study, the reservoir properties of the Yamama Formation were determined using the neural network in the EMERGE application. In addition, the internal attribute and target log of P-wave velocity were utilized to extract the volume for these properties.

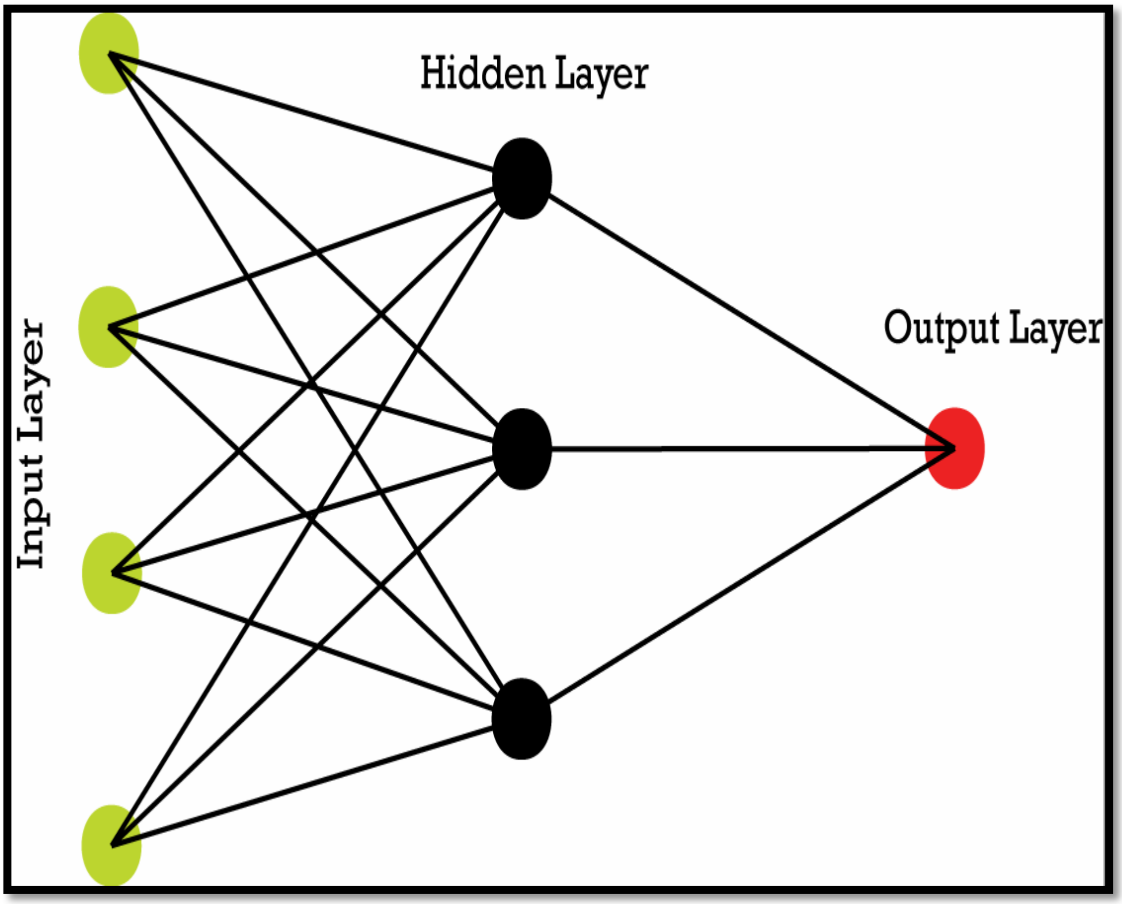

Figure 6- The basic architecture of probabilistic neural network [21].

In the first step of training to build the emerge module, the data used included The 3D seismic volume that was taken as an internal attribute, while the inverted volume was taken as an external attribute. To improve the results, the multi-attribute analysis was carried out for the discrimination of the subtle features on the logs of target. This was achieved via two stages. In the first stage, the logs and seismic reflection data were analyzed for deriving the statistical relation between them . The second stage involved deriving the relation that was applied to the entire volume for the creation of log values throughout the seismic volume. The validation test was carried out to check whether the neural network and the multiple attributes performed well. Theoretically, any type of log property may be used as a target for EMERGE. Practically, the P-wave velocity was predicted successfully.

The assessment of the development of a reservoir and the mapping of its physical properties are very important tools to estimate the rock properties between the drilled wells. This can be achieved through utilizing integration tools for well log properties. These tools predict the seismic data and examine any log property from seismic attributes using multi-attributes or neural networks analysis. One way of measuring the correlation between the target data and any one attribute is to cross-plot them.

Four wells with P-wave logs (the well number 5 log is missing here) were used to perform the statistical analysis, find relations between logs and seismic attributes, and select the most reliable ones, using cross-validation for all logs, to predict the overall volume. The P-wave values were taken as targets for the training and prediction processes, from seismic amplitude and acoustic impedance data, by using the EMERGE module. The inverted three dimensional acoustic impedance data were used in the EMERGE module, which is a good approach for external attributes. Then, this module was compared with the three dimensional and well log data for creating the relations within well locations by using an internal algorithm.

In the current study, the training of properties mentioned above was achieved. The training data were displayed for the P - wave. The training results of the neural network for the P-wave were cross-plot validated for graph error. This approach estimates better algorithms to correlate and predict primary velocity and remove the other training data which might increase error. Figure -7 shows the results that were found to be valid to this analysis.

The cross-plot (Figure-7) has X and Y axes which show the number of the attributes and the prediction error value, respectively, found via neural network analysis by using EMERGE. In the left-hand side of the figure, the black curve shows the total error value, while the red curve shows the error of validation. Only four significant attributes were found to be good in the red color area, because the error is increasing after the fourth attribute (Figure-7). In the right-hand side, a numerical summary of these attributes is tested with the training and validation error.

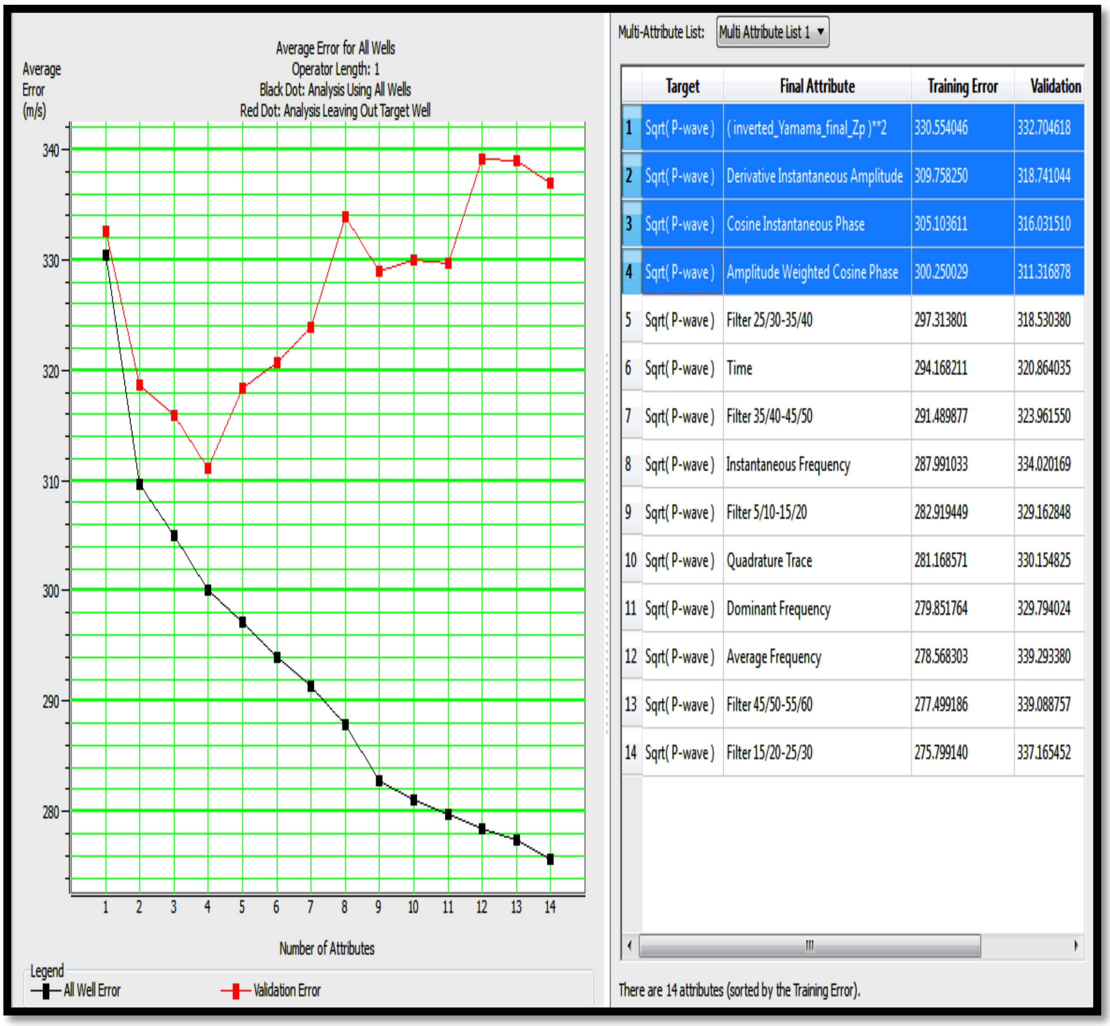

Figure 7- The average error for the best four attributes used for P-wave velocity estimation.

Beside the acoustic impedance, the following attributes were used: inverted_ Yamama _final _ Zp)**2, Derivative Instantaneous Amplitude, Cosine Instantaneous phase, and Amplitude Weighted Cosine phase. These attributes were determined by the EMERGE module within the neural network analysis. A correlation coefficient value of 0.81 was improved between the actual and predicted P-wave values (Figure -8).

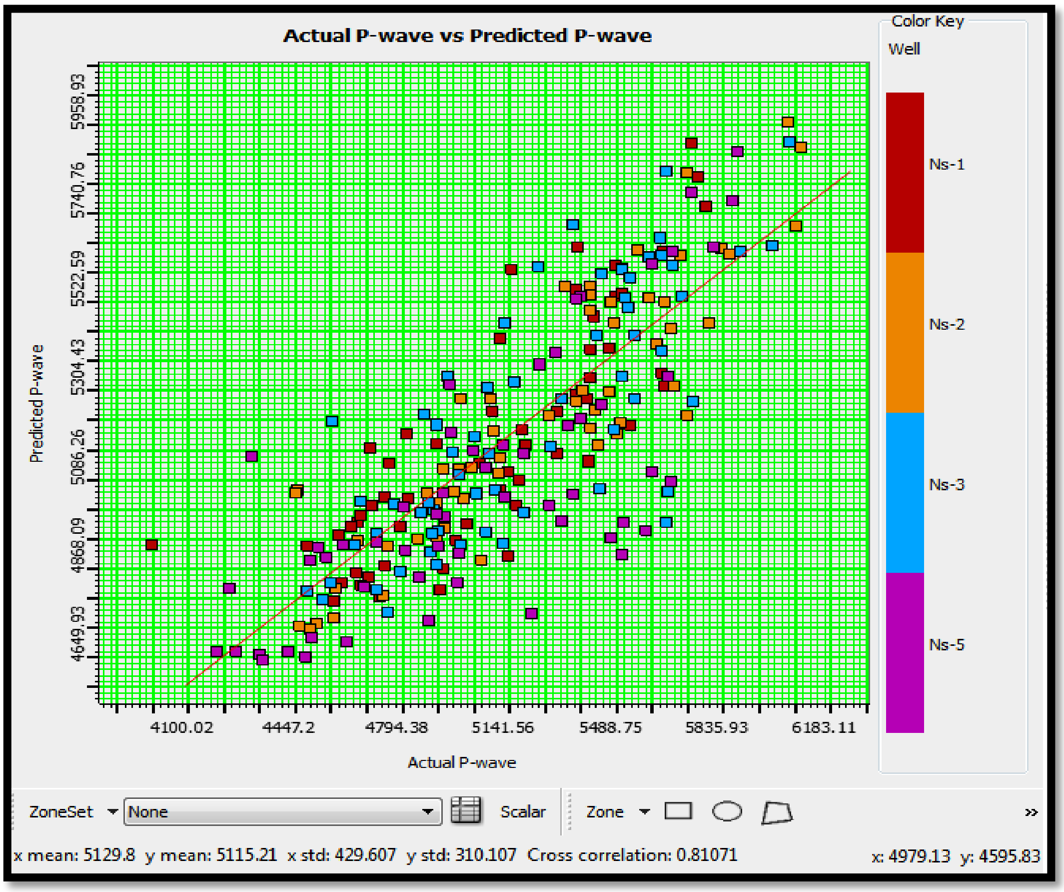

Figure 8- The actual versus the predicted P- wave property for the considered data, the maximum correlation coefficient 0.81 utilizing network analysis.

5. The Result of Application by EMERGE

The application was the second step of EMERGE module, that depends on multiple attribute conversion by the test step for finding best and most obvious results for the reservoir characterization. EMERGE applies the derived relationship to the entire volume to create log values throughout that volume. The 3D seismic for the study area, as shown in Figure -9, is converted to acoustic impedance and used in the analysis of EMERGE to predict any property that is used to predict P-wave velocity (Figure -10).

The P-wave velocity property is predicted by the neural network in the EMERGE analysis using one external attribute of acoustic impedance with internal multi-attributes. In Figure -11, the arbitaray line shows all wells, the green color shows low P-wave velocity and indicates the reservoir units (Yb1, Yb3, and Yc), and the purple color shows high P-wave velocity and indicates the barrier between reservoir units**.** The results of P-wave volume and the cutting of horizon slices within the reservior zones (Yb1, Yb3, and Yc) are shown in Figures- 12, 13, and 14. Figure -12 shows low velocity layers in the crest trending to the NW on the eastern limb of the fold, which indicates a promising area for hydrocarbon. Figure-13 shows that the trending is northwest- southeast on the eastern limb of the anticline, which is also a promising area. Figure- 14 shows the same trending to northwest-southeast on the eastern limb of the anticline and it is a promising area as those demonstrated in the above figures.

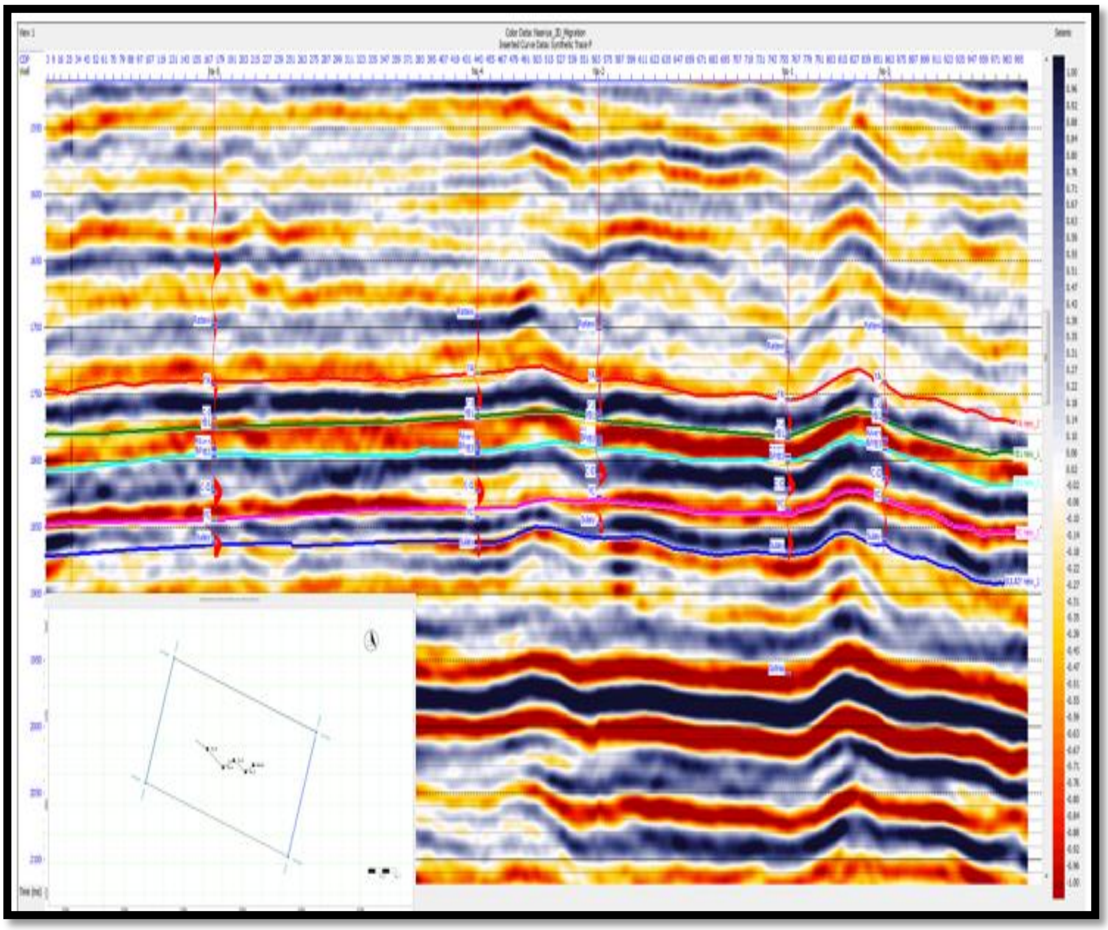

Figure 9- An arbitrary line through wells within 3D seismic data volume.

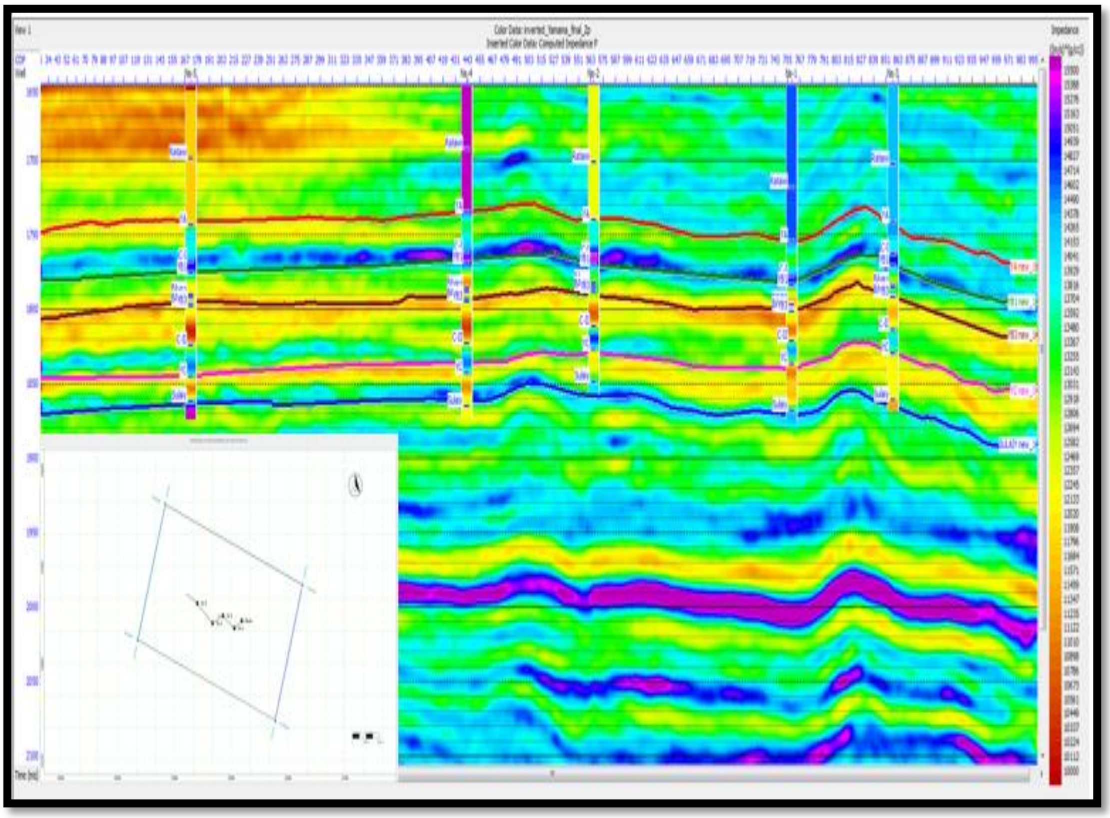

Figure 10- An arbitrary line through wells within 3D acoustic impedance data volume.

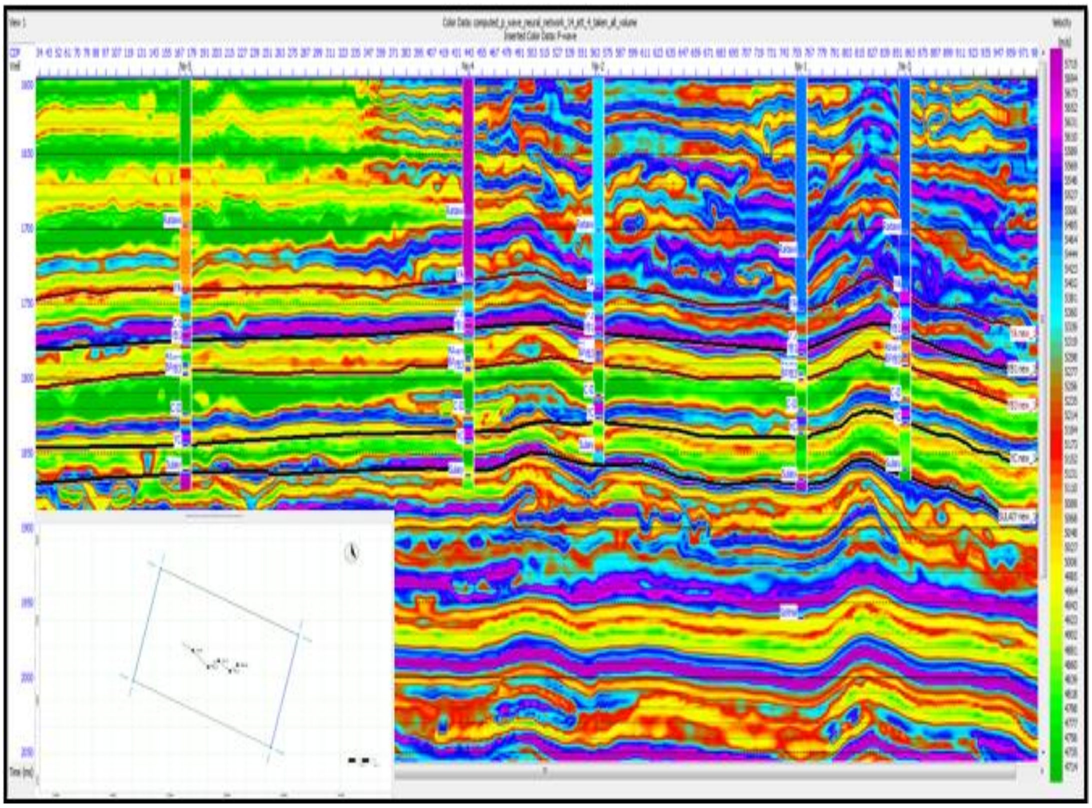

Figure 11-An Arbitrary line through wells within 3D volume of predicted P-wave velocity.

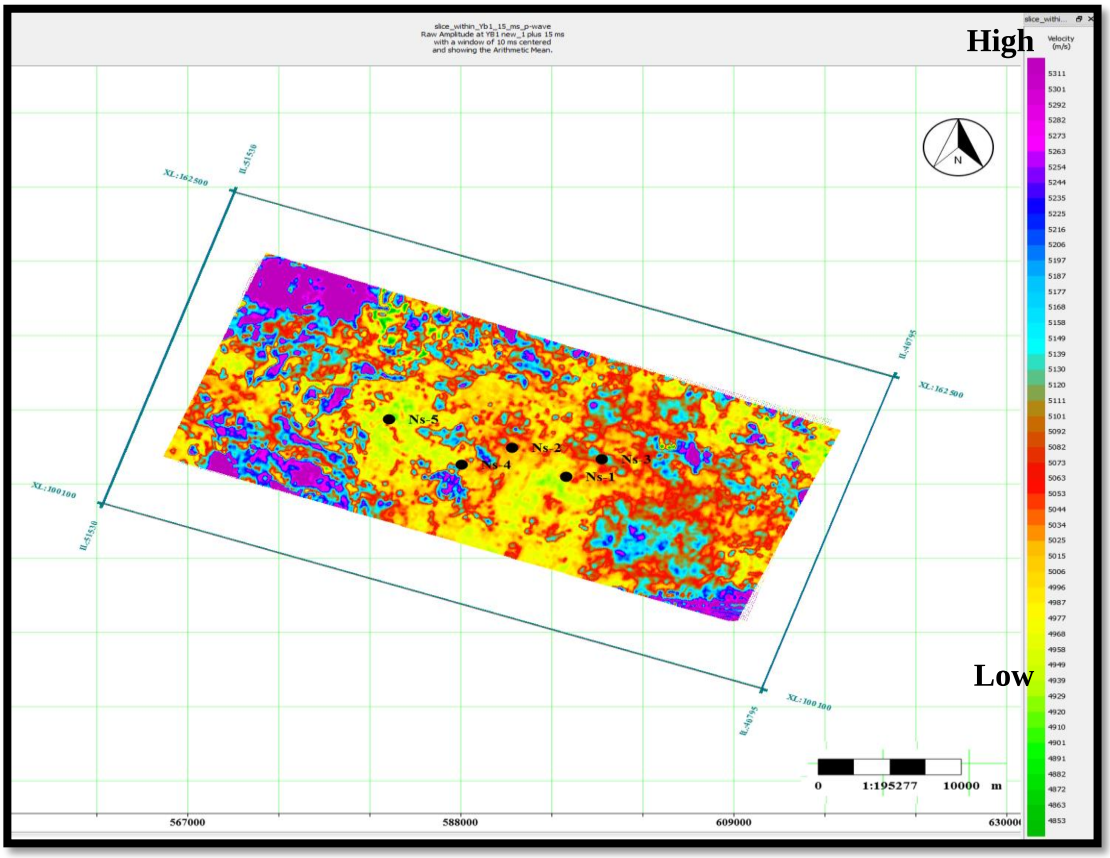

Figure 12- The P- wave horizon slice for unit Yb1 from the velocity of P-wave centered window below Yb1 horizon.

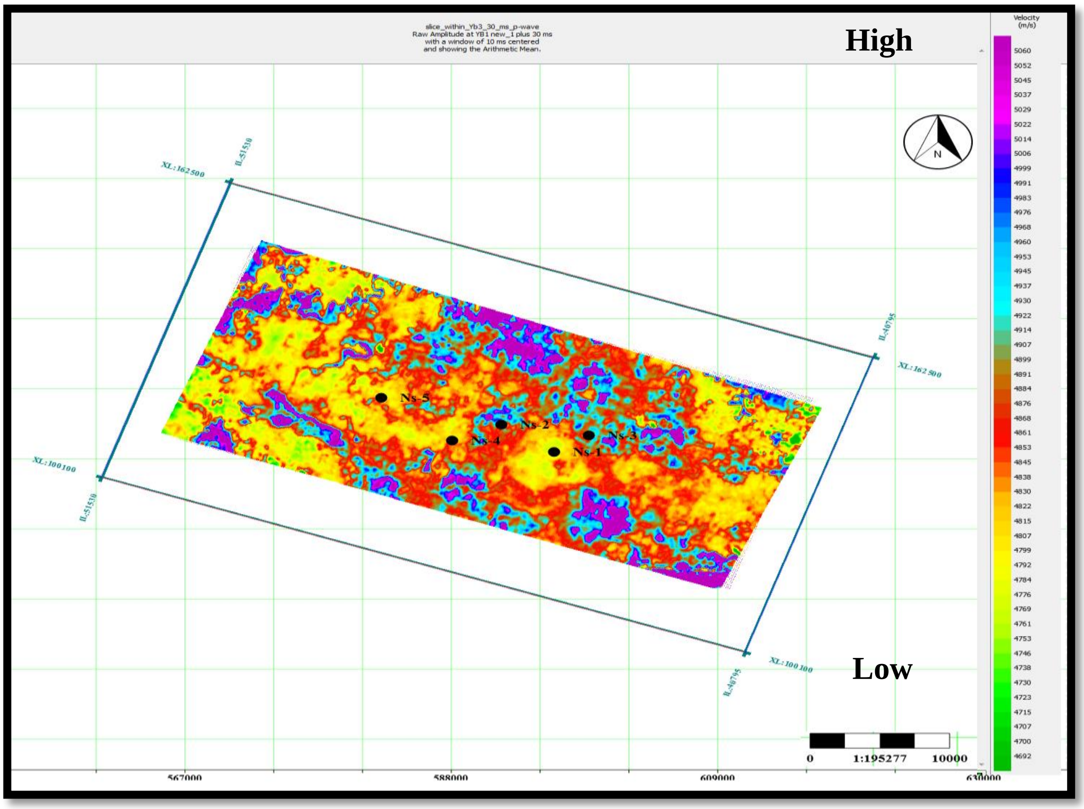

Figure 13- The P- wave horizon slice for unit Yb3 from the velocity of P-wave centered window below Yb3 horizon.

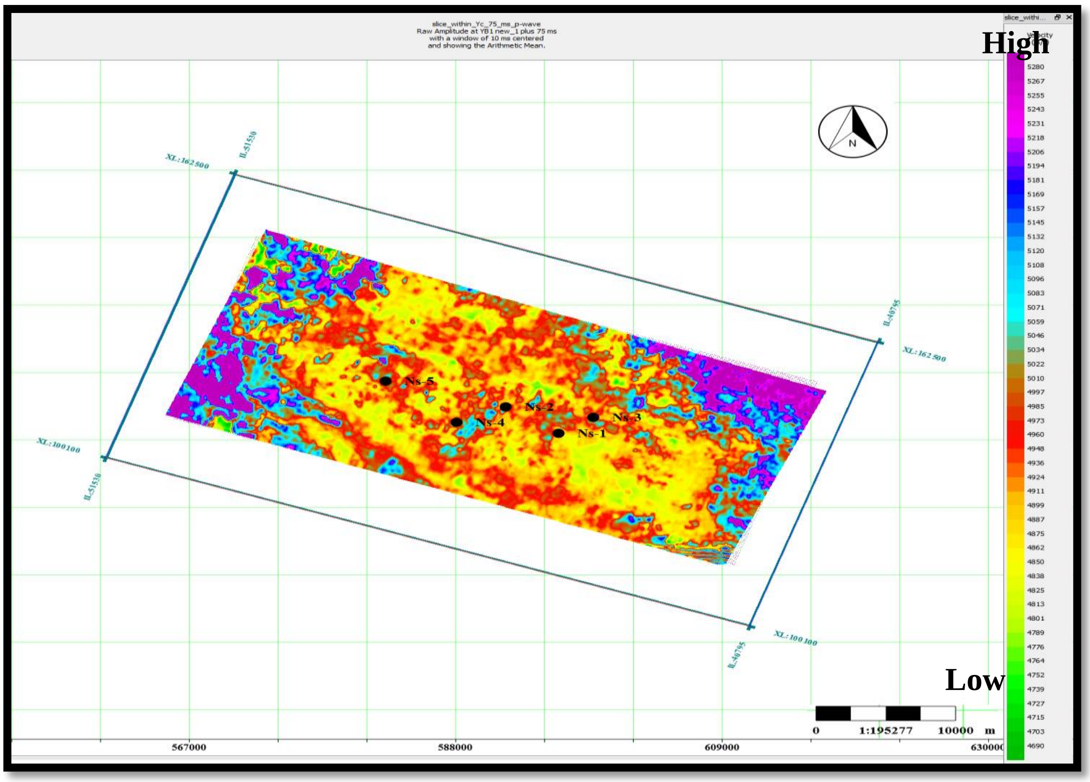

Figure 14- The P- wave horizon slice for unit Yc from the velocity of P-wave centered window below Yc horizon.

7. Conclusions

EMERGE analysis (training and application) was used to estimate reservoir properties (P-wave velocity) with neural network analysis and the relations between them were derived at well locations.

The results of P-wave velocity horizon slices of units Yb1, Yb3, and Yc suggest a number of conclusions. First, the P-wave velocity horizon slice of unit Yb1 is a centered window below Yb1 horizon. This unit shows low velocity at the center of the anticline, which is a promising area for hydrocarbon in the eastern limb. Second, the P-wave velocity horizon slice of unit Yb3 is a centered window below Yb3 horizon. This unit also shows low velocity at the top of anticline that trends north-west to south-east, which is a promising area for hydrocarbon. Third, the P-wave velocity horizon slice of unit Yc is a centered window below Yc horizon. It is the third part of the decreasing velocity at the axes of anticline, which shows the same trend to the north-west to south-east. This is also an indication of a promising area for hydrocarbon.

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