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Rock physical modeling enhancement in hydrocarbon reservoirs using Choquet fuzzy integral fusion approach

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ABSTRACT

Rock physics models are widely used in hydrocarbon reservoir studies. These models make it possible to simulate a reservoir more accurately and reduce the economic risk of oil and gas exploration. In the current study, two models of Self-Consistent Approximation followed by Gassmann (SCA-G) and Xu-Payne (X-P) were implemented on three wells of a carbonate reservoir in the southwest of Iran. Then, in order to increase the accuracy and improve the efficiency of the models, a fusion model of Choquet Fuzzy Integral (CFI) was applied as a new approach. The compressional wave velocities were estimated using two models, i.e., SCA-G and X-P, and were then integrated using the CFI fusion model. Finally, by comparing the model results and the real well log data, the Choquet model was confirmed as a compatible model with proper results. The correlation coefficient (CC) and Root Mean Squared Error (RMSE) for the estimated velocities versus the actual values showed the reliability of the constructed models. For example, in one of the studied wells, the CC and RMSE values were 99.2 and 44 m/s, respectively, in support of the fusion model. This could be related to the optimization algorithms in the heart of the Choquet model that led to the optimization of the model parameters and also better results in the studied carbonate reservoir.

Keywords : *Carbonate reservoirs, Data fusion, Self-Consistent Approximation model, Rock physics, Xu-Payne model*

1. Introduction

The main objectives of petroleum geophysics are to discover more oil or gas reservoirs, optimize new well locations, and improve oil recovery [1]. In order to achieve these goals, new methods have been introduced for seismic reservoir characterization and monitoring, including the prediction of fluid status, lithology, and pore type [2]. A key question for seismic reservoir characterization is how physical variations of the subsurface geological layers can be related to variations in the seismic properties of the medium. The answer is usually provided by rock physics models, which may offer a new vision to those relationships [3]. In carbonate reservoirs, unlike sandstone reservoirs, rock physics models have been less developed. In fact, due to the nature of carbonate reservoirs, which is complex in terms of porosity and the shape of pores and fractures, it is not recommended to use sandstone rock physics models for carbonate reservoirs [4, 5]. Although recent research studies show the improvement of the appropriate carbonate rock physics models, they are not adequate [6, 7]. However, some rock physics theories are convenient for both carbonate and sandstone reservoirs. One of them is an inclusion-based theory that makes a model between wave velocity and attenuation regard to the scattering theory and estimates the rock as an elastic mass of mineral perturbed by holes (porosity). Among inclusion models, the Kuster-Toksöz model is probably the best classic recognized one [8]. Based on Kuster-Toksöz, the Xu-White model has been suitable for shaley sandstones [9], and it has been extended to the Xu -Payne model which is appropriate for predicting velocities for carbonate rocks [10]. There are two approaches to account interactions for the second- or higher-order scattering effect of each inclusion. Moreover, the interactions between pores are considered in the solutions in the second- or higher-order scattering such as differential effective medium (DEM) [11] and self-consistent approximation (SCA) [12]. Both of these approaches simulate the behavior of high-frequency saturated rocks. Make a low-frequency model requires adding fluid using the Gassmann equation. In these models, the reservoir parameters that affect seismic P- and S-wave velocity and density are water saturation, clay content, and porosity. Also, porosity-velocity relationships are strongly affected by pore types in carbonate rocks. Therefore, the pore systems have the main role in carbonates [13, 14, 15]. In order to improve these models of rock physics in carbonate rocks, data fusion is used as well. Data fusion methods are novel techniques in upgrading and improving different processes and modeling purposes. The application of data fusion methods developed since the establishment of a joint laboratory between military specialists and the development of system researchers. The use of these methods in various scientific fields, including geosciences, has become widespread afterward [16]. Data fusion methods, in particular fuzzy integrals, have been used in different areas of sciences. Examples of such research studies are as follows: the determination of Litho-facies and the estimation of permeability in oil wells by using fuzzy methods [17, 18, 35], seismic image segmentation by fuzzy fusion of the attributes, the discovery of fuzzy rules for assessing the oil content of a formation with soft computing fusion in oil exploration management [19, 20], and a fuzzy combination with geological and geophysical data based on a geographic information system (GIS) to map hydrocarbon resources and to investigate the application of fuzzy logic in geophysics [21, 22]. In this research, the validity of two self-consistent Approximation /Gassmann and Xu-Payne models in a carbonate reservoir in southern Iran was studied and evaluated. Then, these two models were integrated using the Choquet Fuzzy Integral fusion approach, and the new model

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was constructed and evaluated. Therefore, the compressional wave velocities, derived from two different rock physics models and a fusion model, were compared with the measured compressional wave velocity of the three wells. In addition, the model with the best compatibility with the studied carbonate was selected.

2. Materials and Methods

The rock physics models were first named Xu-Payne model using the DEM approach (X-P), and then, Self Consistent model followed by Gassmann equation (SCA-G) used in this study. In the final stage, these two models were fused by Choquet fuzzy Integral fusion model (CFI). This paper briefly implements the needed steps of the procedure and, thereby, proposes the methodology. These steps and the proposed methodology have been found valuable in performing seismic reservoir characterization in carbonate rocks. Below, all the used models and their application in carbonates are discussed.

2.1. Xu-Payne model using DEM approach

The concept of the Xu-Payne (X-P) model was supported by the Kuster-Toksöz (K-T) theory using the Differential Effective Medium (DEM) approach. In reality, the X-P workflow improves K-T to be applied in medium- and low-frequency regimes (similar to well logs) for carbonate rocks. Moreover, the DEM approach was used to model two-phase composite by adding the inclusions to the matrix phase. Matrix began as an initial phase when the concentration of inclusions was zero, then changed at every step along with the addition of material inclusions. The process continued until the desired proportion of the material was obtained. The basic foundation of this model is the K-T theory. Regarding the limitation of the K-T model in the low concentration of inclusions, one solution for high inclusion concentration is to first divide the inclusions into numerous parts with a small number of inclusions relative to the medium value of the background and then incrementally add inclusions in the background to simulate the two-phase medium case [23]. This method is the Differential Effective Medium (DEM) model, and it is used to treat rocks with variable lithology and treats the late-added components as isolated inclusions. For the Xu-Payne model, the DEM approach was used; also, this approach categorizes pores in different shape inclusions. Moreover, the Xu-Payne rock physics model [10] is an outstanding choice for sonic log prediction and porosity partitioning in carbonates. This model is an extension of the Xu-White (X-W) model [9] developed to handle stiff and soft pores in clastic reservoirs based on the Kuster-Toksöz theory or the Effective Medium Theory. The X-W model connects these models in order to calculate velocities of the saturated rock. It uses the time average model (Wyllie method) to mix minerals, and then the DEM equation is used to introduce dry pores into the effective minerals. Finally, the Gassmann equation is applied to introduce fluids into the dry pores. Furthermore, the X-W model assumes that there are two minerals (quartz and clay) with defined aspect ratios (clay aspect ratio much lower than quartz). Therefore, the X-W model is more suitable for sandstone reservoirs. The X-P model, on the other hand, is designed for carbonate reservoirs. The X-P model follows almost the same steps as those of the X-W model, but the X-P model assumes that the total porosity consists of four pore types. This assumption makes it more suitable for sediments with various pore structures such as carbonate rocks. Therefore, the Xu-Payne model is a four-part process where the Differential Effective Medium Theory and the Effective Medium Theory are applied. In the X-P model, the total pore volume is separated into four pore types: (1) clay-related pores, (2) inter-particle pores, (3) micro-cracks, and (4) stiff pores, which Equation 1 shows the relation.

$$\phi_T = \phi_{Clay} + \phi_{IP} + \phi_{Crack} + \phi_{Stiff} \quad (1)$$

In addition, the pore space is divided into clay pores (ϕ_{Clay}) and non-clay pores using the method offered by Xu and White as in Equation 2.

$$\phi_{Clay} = V_{sh}\phi_T \quad (2)$$

The stiff pores (ϕ_{Stiff}) generally represent the rounded moldic pores or vugs in carbonate rocks. Finally, the interparticle pores (ϕ_{IP}) make up the dominant pore space in sedimentary rocks. They are, in general, insensitive to stress and have no preferred orientation. As well as ϕ_{Crack} which shows the pores related to fractures. As shown in Figure 1, the X-P model contains four steps [10]:

1) The minerals that are present in the rock are mixed using a mixing law (e.g., the Reuss-Voigt-Hill average (VRH)). Therefore, a solid rock matrix has the properties of this mixture.

2a) Micro-pores with bound water (e.g., clay pores) are added to the matrix using the differential effective medium or DEM [9] process and the Kuster-Toksöz theory to account for the mechanical interaction among the pores (Kuster-Toksöz, 1974). The calculated effective elastic properties (e.g., bulk modulus) will be used later as the "solid" properties for fluid substitution.

2b) Going back to step 2a, all pores, including water-wet micro-pores and empty (or dry) non-bound-water pores, are added into the system using the effective medium theory to provide the effective elastic properties (e.g., bulk modulus) of the "dry" rock frame.

3) The remaining water (which is not bound to micro-pores) is mixed with the hydrocarbons (oil and/or gas) using a fluid mixing law such as the Wood Suspension Model.

4) Gassmann's equations are used to add the fluid mixture into the pore system in order to obtain the final effective elastic properties of the saturated rock [10].

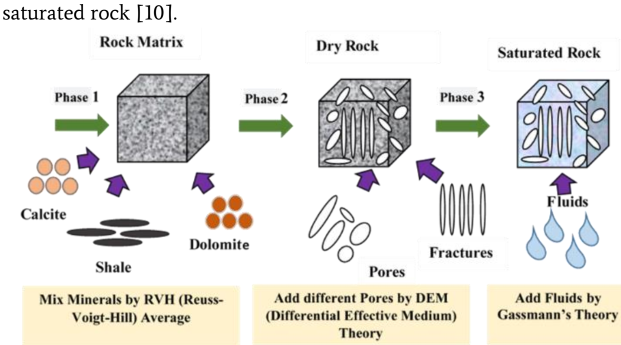

Fig. 1. Diagram of Xu-Payne rock physics model [after 10].

2.2. Self-Consistent Approximation model / Gassmann theory

Various attempts have been made to investigate the scattering effect of each inclusion. The first order scattering solutions, such as Kuster-Toksöz (K-T), do not account for the pore to pore interactions. These interactions among pores are considered in solutions in the second- or higher-order scattering such as Differential Equation Medium (DEM) and Self-Consistent Approximation (SCA). The DEM approach utilizes the principle of porosity growth to extend the results of the first-order scattering K-T solution to be valid at high porosities, while SCA considers a uniform host material embedded with ellipsoidal inclusions [12]. Moreover, both of these approaches simulate high-frequency saturated rock behavior and, therefore, are appropriate to apply to ultrasonic laboratory conditions.

The concept of the SCA model originates from K-T. Note that the K-T model is limited by the low concentration of inclusions in the background medium, owing to the difficulty of modeling the elastic interaction between nearby inclusions. However, in most cases, the inclusions exceed the dilute concentration limit. If some effective medium replaces the background medium with unknown elastic moduli, the interaction of inclusions can be approximately solved in the case of a slightly higher concentration of inclusions. The above description is related to the SCA model [24, 12, 25]. Constituents are continuously distributed and equally treated in the SCA model; therefore, it is more suitable for the rock matrix to consist of many different minerals.

The SCA model is a part of the Effective Medium Theory, the same as the DEM model. The Effective Medium Theory undertakes that separated pores and cracks may or may not be connected [26, 27].

Unlike the DEM theory, the SCA theory does not possess any limitation regarding the porosity and the aspect ratio. However, SCA is computationally much more expensive than DEM. Different pore systems and mineral constituents are added to the system to form a "dry" rock frame, and the effective elastic moduli are calculated through numerically solving differential equations (Equations 3 and 4 for N phases) of the SCA theory. Furthermore, the SCA equations are simultaneous. This is solved by taking the initial guess of elastic moduli as the VRH average value and iterating until suitable convergence is acquired. Hill introduced the SCA model, and then Budiansky computed the elastic properties of a two-phase medium [24, 28]. This method is based upon the following idea: a single inclusion, representing one of the components, is embedded within a large surrounding matrix whose elastic properties are those of the effective medium. Berryman gave a more general form of the SCA for N-phase composites:

$$\sum_{i=1}^{N} x_i \,(K_i - K_{SC}^{*}) P^{*i} = 0 \tag{3}$$

$$\sum_{i=1}^{N} x_i \,(\mu_i - \mu_{SC}^{*}) Q^{*i} = 0 \tag{4}$$

where i refers to the i^{th} material, x_i is its volume fraction, P and Q are geometric factors, and the superscript $*i$ on P and Q indicates that the factors are an inclusion of material i in a background medium with self-consistent effective moduli K_{SC}^{*} and μ_{SC}^{*}. Besides, K and μ are the bulk and shear moduli of an un-cracked medium, respectively. The summation is over all of the parts containing minerals and pores. These equations are coupled and must be solved by simultaneous iterations. In this research, the SCA model is used, following the Gassmann equation, in order to be applicable for carbonate rocks in a well-log-scale. In other words, since the pores are isolated to the flow, the SCA model simulates very high-frequency saturated rock behavior appropriate to ultrasonic laboratory conditions. At low frequencies, when there is time for wave-induced pore-pressure increments to flow and equilibrate, the best way is to find the effective moduli for dry pores and then saturate them with the Gassmann low-frequency equation [8]. Therefore,the Gassmann theory is described in the following paragraph in summary. One of the most significant problems in the rock physics analysis of logs, cores, and seismic data is using seismic velocities in rocks saturated with a fluid to predict those of rocks saturated with another fluid, or equivalently, predicting saturated-rock velocities from dry-rock velocities, and vice versa. This is the fluid substitution problem [8]. The most common rock physics method for fluid substitution problem is to use the Gassmann theory [29], which the relationship can be written as Equation 5:

$$\frac{K_{sat}}{K_0 - K_{sat}} = \frac{K_{dry}}{K_0 - K_{dry}} + \frac{K_{fl}}{\phi\,(K_0 - K_{fl})}, \; \mu_{sat} = \mu_{dry} \tag{5}$$

Here, $K_{sat}, K_{dry}, \mu_{sat}, \mu_{dry}, K_0, K_{fl}, \emptyset$ are saturated bulk modulus, dry bulk modulus, saturated shear modulus, dry shear modulus, mineral bulk modulus, effective fluid bulk modulus, and porosity, respectively. In Fig. 2, some of the characteristics of rocks are shown in Gassmann's theory as a cube of rock is characterized by four components: the rock matrix, pore/fluid system, dry rock frame, and saturated rock [30].

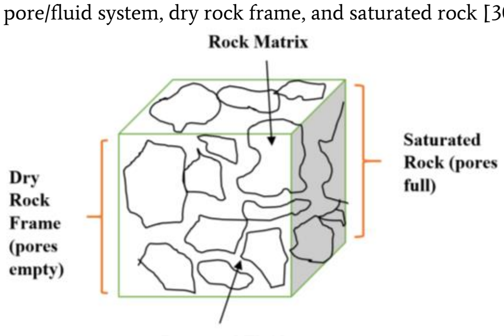

Fig. 2. Different parts of rock for rock physics model [after 30].

Briefly, the SCA-Gassmann method represents the low-frequency model, which describes well-connected pore spaces where the high-frequency SCA method treats inclusions as isolated to the fluid flow, preventing hydraulic communication and pore-pressure equilibrium. In the current study, the SCA-Gassmann method is used for creating one of the rock physics models. First, the SCA method is applied for dry ellipsoidal pores to obtain the elastic modulus of a dry frame, and then Gassmann's theory is applied to obtain the elastic properties of a fluid-saturated rock [8].

2.3. Choquet Fusion Model:

Choquet Fuzzy Integral (CFI) is one of the data fusion methods which is applicable for industrial uses. Based on fuzzy integral operators, a method has been developed to integrate various evidence linearly or nonlinearly. The practice of fusion on the membership functions and taking into account the relative importance of information resources in decision making is applied. When using the fuzzy theory for data fusion, two main goals are to maximize accuracy and minimize complexity. Fuzzy generators are suitable combiners to integrate the output of other classifiers. The philosophy of fuzzy combiners is that they not only examine the power of each classifier individually but also examine the effective power of each subset of classifiers separately. This most influential power is called the fuzzy number (measure). The algorithm used for the most effective fuzzy integral is the Choquet integral, which is a linear compound [21, 31, 22]. Inside aggregation operators, fuzzy integrals are recognized to be one of the most powerful and flexible functions as they allow the aggregation of the information under different assumptions on the independence of the information sources. Besides, fuzzy integrals, in general, and Choquet integrals, in particular, are well-known aggregation operators. The flexibility of such operators is tightly related to the difficulties of using them in practical applications. Fuzzy integrals combine the data supplied by several information sources, according to a fuzzy measure [32, 33]. Choquet-fuzzy integral is an effective fusion method based on fuzzy integral introduced by Choquet, whose definition is:

Choquet integral of a function: $d\,\mathrm{X} \rightarrow [0, 1]$ with regard to fuzzy measure g is defined, and suppose that g is a fuzzy measure on X. For each input vector *x,* whose components are the output of other classifiers, a new vector is created, whose components are arranged from small to large, respectively. The new vector follows Equation 6 in which d is a function of x:

$$\left[d_{i_1,k}(x), d_{i_2,k}(x), d_{i_3,k}(x), \ldots, d_{i_l,k}(x)\right]^{T} \tag{6}$$

where, the following relation is established (Equation 7):

$$d_{i_1,k}(x) < d_{i_2,k}(x) < d_{i_3,k}(x) < \ldots < d_{i_l,k}(x) \tag{7}$$

The alternatives of the initial values of the fuzzy size corresponding to the high-order vector are selected as g, which is a fuzzy measure in the following equation:

$$g^{i_1}, g^{i_2}, g^{i_3}, \ldots, g^{i_L} \tag{8}$$

Recursively, the final values of the fuzzy size are calculated according to the following equation.

$$g(t) = g^{i_t} + g(t-1) + \lambda g^{i_t} g\,(t-1) \tag{9}$$

where, according to the fundamental theorem regarding the fuzzy measure, λ -value has three cases, and t is the component. The following procedure is performed to calculate the integral operator value for each input vector: the function of the Choquet integral ($\mu_j(x)$) is as follows (Equation10):

$$\mu_j(x) = d_{i_1,k}(x) + \sum_{k=2}^{L}\left[d_{i_{k-1},j}(x) - d_{i_k,j}(x)\right] g\;(k\text{-}1) \tag{10}$$

Where, i, j, k are the components in set X [34].

In the Choquet fuzzy integral method, first, shear wave velocities are calculated from two rock physics models, and each of these velocities is considered as an independent source of information. Then, to calculate the fuzzy number or worth values (weight), such as each one, the values of the rock physics model velocities are compared with the actual values of the measured velocity at each depth of the well, and the worth values with the minimum error are selected and used for the calculation of the next value. Then, using weight values and the Choquet Fuzzy Integral algorithm, the velocity estimation of each rock physics model is fused with their fuzzy numbers with the velocity estimation values of another rock physics model.

3. Results and Discussions

The main objective of this study is to improve the predictions of elastic properties of carbonate rock type through the SCA/Gassmann and X-P rock physics models using the Choquet fusion method. In the current research, first, the X-P (Xu-Payne) model is used. This model conceptually originates from the Kuster-Toksöz theory. Also, the X-P model is supported by the Differential Effective Medium (DEM) approach. Consequently, the X-P model is applicable for carbonate rocks. Second, the SCA-Gassmann model is used. This model is a Self-Consistent Approximation followed by the Gassmann equation. Furthermore, the SCA-Gassmann model is applicable for carbonates, even on a well-log scale. These two models have two major advantages for carbonates: ease of calculation and flexibility of application. Finally, the Choquet fusion model is used to improve the two previous major models. The target of the studied wells is carbonate reservoirs which consist of limestone, dolomite, shale, and some streaks of anhydrite. The rock properties mostly depend on the inclusion shape. For carbonate rocks, the inclusion shape and generalized formula affect the moduli and velocities of inclusion models [12].

In order to implement the rock physics model, in the current examination, the clay-related pore space is represented utilizing the shale volume curve. Pores in clay are relied upon to be water-saturated, bound, and of low aspect ratio (0.02-0.05). The rest of porosity has been partitioned into contributions from commonly three representative pore space segments, each with a characteristic pore aspect ratio, see Table 1. This step is performed by inverting the measured log data on a sample by sample basis. The generated multi-porosity results are used in the X-P and SCA/G models. The main pore types considered in the establishment of rock physic models in this study are intra-particle pores, Micro-cracks, and Stiff pores, as observed in the examined rock thin section. These pores have been used for rock physics modeling.

Table 1. The aspect ratio for the range of pore types used to construct the multi-porosity model [after 10].

Pore component	Range of pore aspect ratio
Intra-particle pores	0.15-0.20
Microcracks	0.01-0.02
Stiff pores	0.80-0.90

Fig. 3.a shows a section related to pore type of fracture. The dominance of fine-grained or muddy matrix indicates a deep sedimentary environment in which the high frequency of fossil particles reflects sedimentation in a shallow environment. Fig. 3.b illustrates a thin section related to inter-particle pores or inter-granular porosity. In addition, Fig. 3.c shows a section a fracture pore type, part of which is filled and some unfilled. There is a fracture in the middle of the section with a right-left direction where the fracture porosity remained unfilled whereas the fracture on the top looks different. Also, the fracture on the top is filled with some secondary crystals. Fig. 3.d shows a section related to pore type of moldic beside fracture.

Moreover, in a rough estimation, it can be argued that about one-fifth of porosity can be subsumed under the fracture pore category, three-fifth of the moldic pore type, and the rest can be inter-particle. Fig.s 3.e and 3.f both are typical moldic pore types. It can be seen from Fig. 3.f that some diagenetic events such as dissolution and replacement affect the particles which embody porosity.

The reservoir rocks are significantly heterogeneous. To validate the studies, the CT-Imaging also was used. According to the CT scan of the pore structure, the pores are mostly spherical, or nearly spherical or ellipsoidal with large pore aspect ratios. It shows that the aspect ratio of these pores may vary between 0.1 and 0.8, and they constitute the more significant fraction of the pores. Fractures are primarily credited to tectonic activities during late diagenesis, and the majority of them are half or completely filled with calcite; nevertheless, a few numbers of unfilled fractures are detected. The presence of fractures contributes little to the total porosity of the reservoir rocks, but significantly affects the physical and elastic properties (e.g., velocity). The pore types of the collected samples fall into two groups: The first group comprises vuggy and Inter-particle pores, and the second group includes fractures. Fig. 4 shows the epoxy resin thin sections beside the X-ray CT (computed tomography) scan of core plugs from the carbonate reservoir in a well, which the blue parts in thin sections represent pore space. These blue parts indicate that they are unsaturated in terms of fluid content. These thin sections are representatives of the carbonate reservoir, which show a mud-supported texture with variable porosity ranging from fracture-like pores to micro-porosity and vuggy pores, which indicate that these rocks are modified and imprinted by complicated diagenetic history. As mentioned above, Fig. 4 indicates the matrix porosity and vuggy/moldic pores.

Also, for validation of microstructure, the SEM (Scanning Electron Microscope) images were used for the determination of aspect ratio for various types of pores available in samples. Fig. 5 exposes that main porosity is a vuggy porosity which results from the dissolution of benthic foraminifera and in some case from the dissolution of matrix framework (Fig. 5).

Compressional wave velocity logs were calculated from sonic logs to evaluate the performance of X-P, SCA-G, and Choquet model, and these logs were compared with estimated compressional wave velocity logs from models. Also, to compare the mentioned models in the studied carbonate reservoir, three wells were used for making the models. The estimation was performed by two main rock physics models (X-P, SCA-G), and was fused by the fusion model (Choquet). The estimations of P-wave velocities from these models for one well (Well A) are shown in Fig. 6. It displays the estimated and measured velocities for the studied carbonates described as typical carbonate sediments. In fact, on the right side of the figures, the cross plot has been drawn better to understand the correlation between real and modeled velocity. To define the axes of the cross plot, the measured P-wave velocities (real) are on the Y-axis, and the estimated P-wave velocities from models are on the X-axis.

On the left side of Fig. 6, the composite log with real and estimated velocities is shown. In the velocity graphs, the red graph is the real Vp log, which is measured (from the sonic log), and the blue graph is the estimated Vp using different models. Moreover, cross plots and graphs have been analyzed for the evaluation of these models.

The acceptable and fairly good compliance of the measured and estimated Vp-logs in well A using the SCA-G model is visible (Fig. 6.a). In this graph, the composite log verified that this correlation was significant from the depth of 1175m to 1190m. There is a good correlation between the SCA-G model and real data, for which the correlation coefficient is 97.8 percent (Fig. 6.b).

Fig. 6.c presents the results of the X-P model, in which the trend and value are good for all interval depths of 1155m-1190m except the interval depths of 1165m-1175m. In the remaining intervals that the difference between these two logs is increased, major differences are not observed. The same fluctuation trend, however, is visible, although the values may be slightly different. It seems that the mineralogy and fluid contents have leading roles, which causes these results. As shown in Fig. 6.d, the correlation coefficient is 98.4 percent, which shows the high correlation between real and X-P model velocities. There is a highly significant correlation between the Choquet model and the real data for which the correlation coefficient is 99.2 percent. Also, the composite log demonstrates that this correlation is significant in all depths of investigation (Fig. 6.e and Fig. 6.f). Furthermore, the velocity cross-plots of well A show a root mean square error (RMSE) of 83 m/s, 80 m/s, and 44 m/s for SCA-G, X-P, and Choquet models, respectively. The estimation of compressional wave velocities using all these models has error values of less than 100 m/s. The analysis of these graphs also shows the good ability of these models to estimate the P-wave velocity in a carbonate reservoir, especially in the range of 3500 to 5500 m/s.

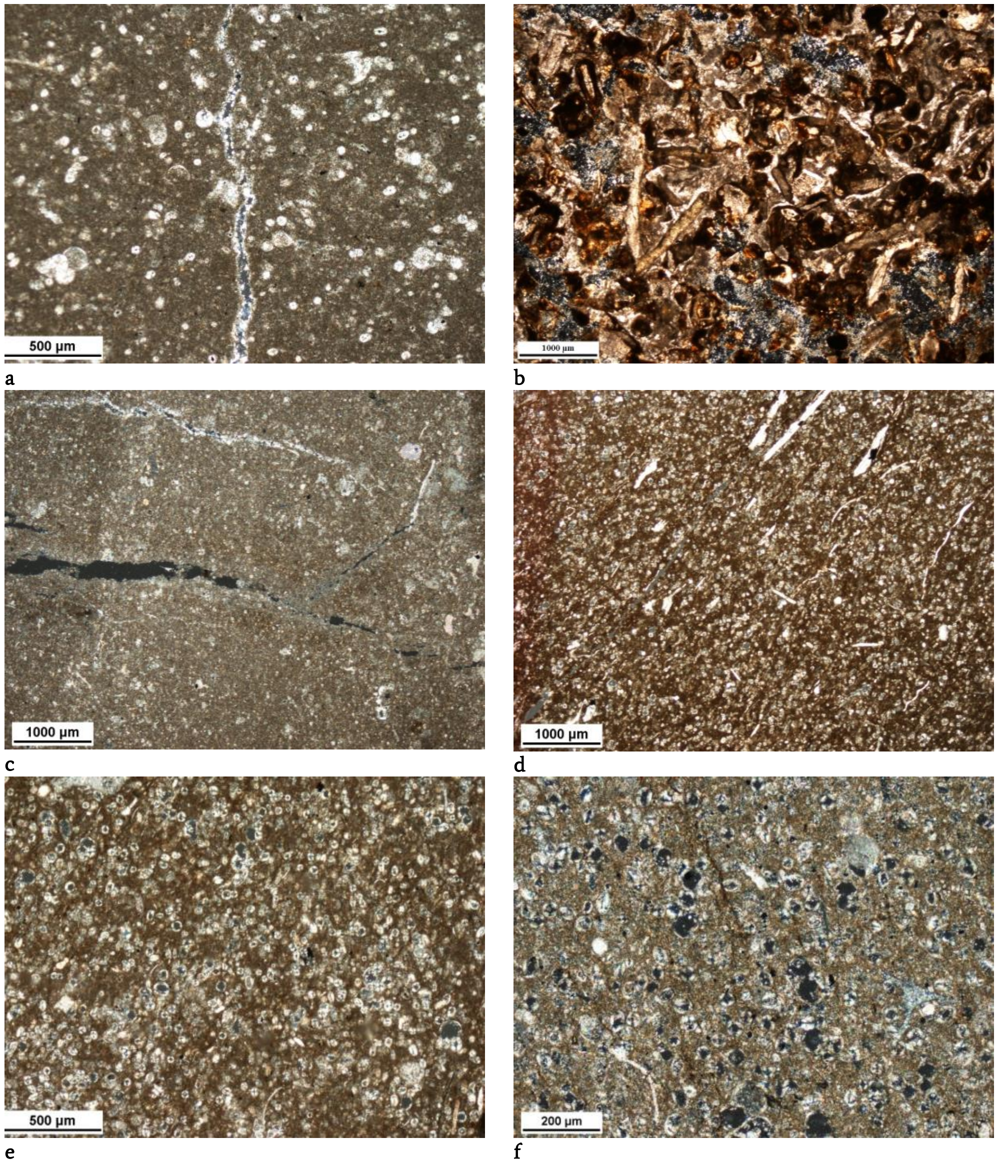

Fig. 3. Pore types in carbonate formation, (a) shows a photomicrograph related to pore type of fracture, (b) related to inter-particle pores or inter-granular porosity, (c) fracture pore type, (d) pore type of moldic beside fracture, and (e and f) both are typical moldic pore type.

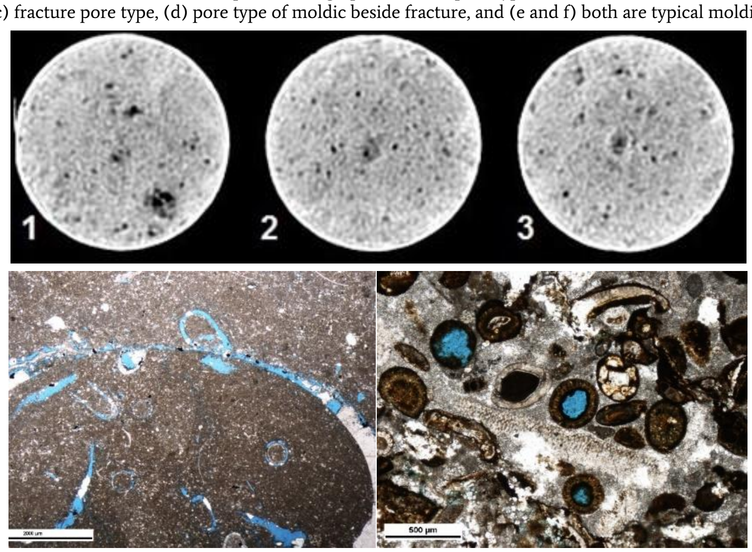

Fig. 4. The epoxy resin thin sections beside the X-ray CT scan of core plugs from the carbonate reservoir in well A indicating matrix porosity and vuggy pores.

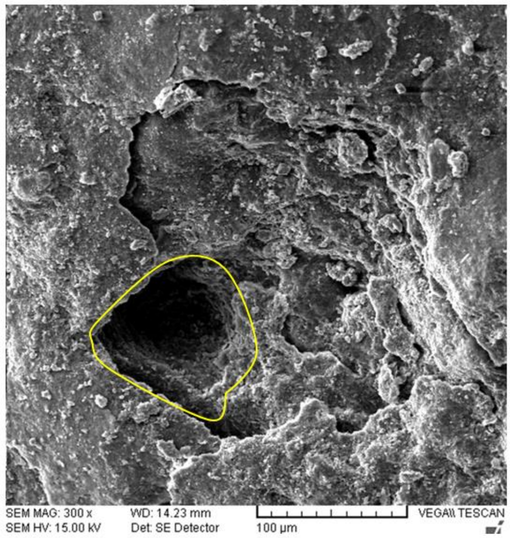

Fig. 5. The SEM (Scanning Electron Microscope) photomicrograph of the sample from the carbonate reservoir in well A.

Compared with the estimated results, the compression wave velocity obtained from the Choquet fusion model has a higher correlation coefficient than the two self-consistent Approximation/Gassmann and Xu-Payne rock physics models in the studied wells. In addition, the estimated error of the Choquet fusion model is the lowest.

After comparing the different models and also comparing them with real log data (measured log) from the same well, the following results are concluded. The blue and red graphs corresponding to sonic logs and models, respectively, show the appropriate correlation. Above, log-measured P-wave velocities are on the Y-axes, while the estimated P-wave velocities from various models are on the X-axes. The RMSE error is low for all the estimations. Even, the correlation coefficient is relatively high for the models. The results of models indicate that SCA-G slightly underestimates the P-wave velocities. The discrepancy between the estimated and measured P-wave velocities increases as the aspect ratio of pore decreases in the sedimentation environment.

Generally, the Choquet model gives the best estimation, while the X-P and SCA-G models underestimate the values. The accuracy of Choquet estimations varies across the log. There is a good correlation between modeled data and the sonic data in some parts, while other parts show reduced correlation. Moreover, the investigation of these differences is important and provides useful information. For instance, an evaluation of the composite logs with the estimated velocity logs exposes that the accuracy of the models decreases as the shale content increases.

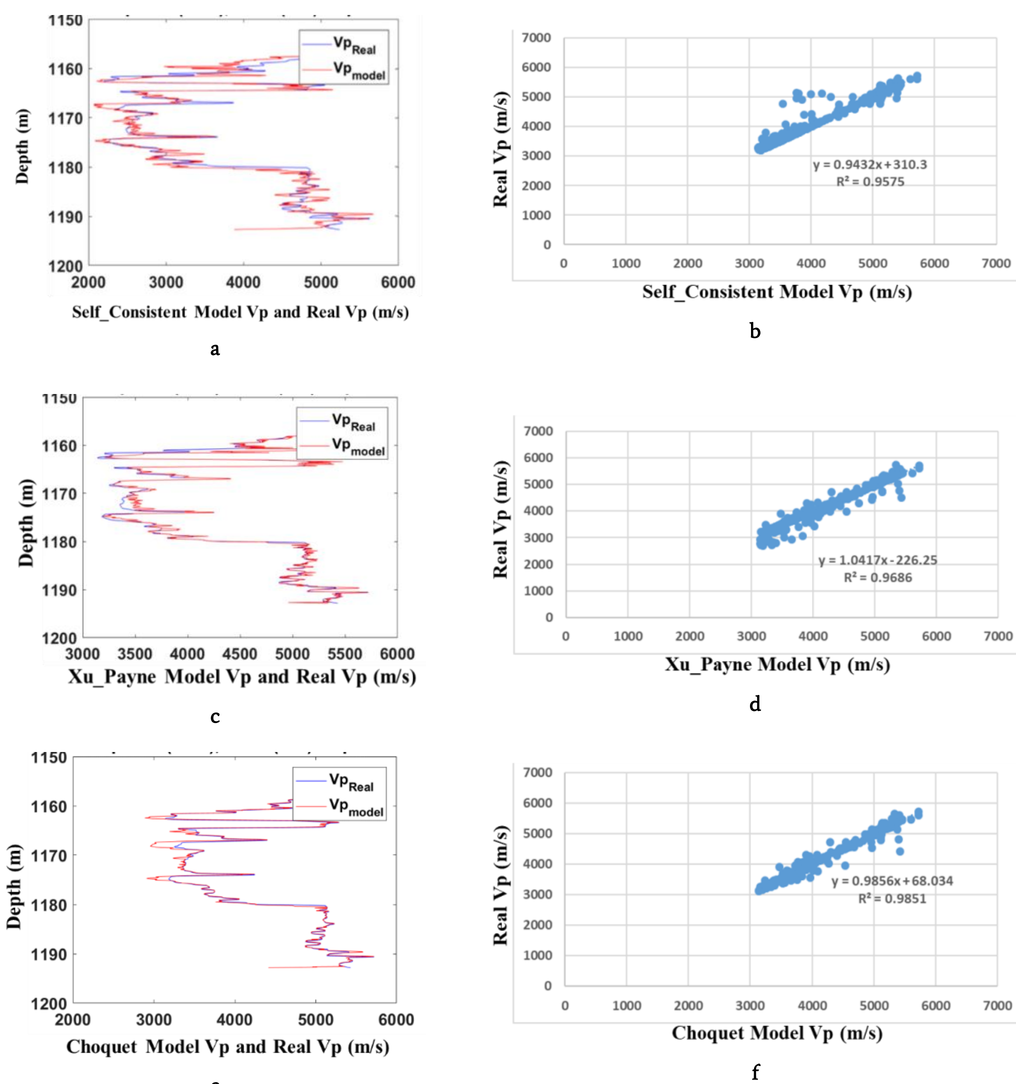

Fig. 6. Comparing P-wave velocities in well A: (a,c,e) Graphs related to composite log with real P-wave velocities and estimated P-wave velocities using three models, (b,d,f) Cross-plots of real P-wave velocities (Y-axis) versus the estimated P-wave velocities using the three models (X-axis).

Shales change the matrix of the rocks, and thus, the physical properties of shales extensively change shear and bulk moduli, which may explain the observed discrepancies. In order to assemble an exact model, the volume of shale, related shear, and bulk moduli must be assessed definitely. Therefore, the logs have to be accurately adjusted for shale content and correct relative saturation logs. Consequently, these adjusted logs must be used in the calculations. Despite the mentioned pitfalls, the Choquet model provides the best estimates for carbonate rocks in comparison with the other models considered in this paper. Table 2 is used for analyzing data and model results in all three wells. The RMSE error is used between the real and model data in each plot. Also, the correlation coefficient is used to show how close the estimate is to the measured velocities (see details in Table 2).

Table 2. The RMSE and Correlation Coefficient of Results.

VP	RMSE(m/s)			Correlation Coefficient (%)		
Well	Xu_Payne	SCA/Gassmann	Choquet	Xu_Payne	SCA/Gassmann	Choquet
A	80.4	83.6	44.5	98.4	97.8	99.2
B	66.6	87.2	35.2	96.2	94.8	98.3
C	115.3	205.4	79.3	97.8	93.6	98.5

4. Conclusions

Having a single model for estimating wave velocities is highly crucial but often unachievable. In this study, the accuracy of different rock physics models was investigated in three wells of an Iranian oil field in which the carbonate rock is the main reservoir. Two models of Self-Consistent-Gassmann and Xu-Payne rock physics were evaluated and compared using petrophysical and geological data. Moreover, observations showed that although Self-Consistent-Gassmann and Xu-Payne models were considered for sedimentary carbonate rocks, the fused model improved the accuracy and efficiency of these models by using the Choquet fuzzy integral fusion method. According to the consequences, it can be concluded that choosing one universal rock physics model for carbonate rocks requires precise considerations. However, regarding the results, it is evident that with a roughly similar correlation coefficient, one model can provide better results in terms of Root Mean Squared Error (RMSE). In this regard, the Choquet model shows the best performance in the estimation of compressional wave velocity with the minimum error and highest correlation coefficient among all models for three wells (wells A, B, and C). Furthermore, microstructure and pore type are of the main factors that control the elastic properties of the rocks; therefore, before choosing any model, the rock microstructure and pore type must be studied in detail. As for the complexity and the abundance of microstructures and pore types of the studied carbonate rock, the best results from the Choquet model were acquired. Also, it can be concluded that this model was successful in providing robust outcomes. The study of these two different rock physics models (SCA/Gassmann and Xu-Payne) in carbonate rocks provides rock elastic parameters (velocities) that have been obtained from the modeling of inputs, i.e., properties of lithology, fluid content, and pore type. The lateral discontinuity of geological facies such as inter-well variation of shale content might affect the amount of applicability of these models in the studied area. In conclusion, evaluating the velocity values obtained from the models with actual velocities shows enhancement in the results in the fused method compared to those of the two rock-physics models. The reason for this could be related to the use of optimization algorithms in the Choquet. The results of this study can be used in feasibility studies for time-lapse seismic projects and also in forward-modeling workflows when the studies deal with fluid substitution and saturation changes. The rock physics models should experience an upscale approach to be bridged to the bigger scale properties log and seismic responses. This approach is practical and easily repeatable in each reservoir. It can be claimed that the effect of involving complementary data such as adequate thin sections, sidewall core plugs, digital rock images, and accurate laboratory measurements is undisputable on acquiring more reliable results.

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