The 4th International Conference on Environmental Geoscience and Earth Ecology
DOI: 10.54254/2753-8818/2026.33375

Multi-source Data Integrated Prediction Method and Application for Fractured-Vuggy Carbonate Oil and Gas Reservoirs

Jingjing Wang

School of Geosciences, Yangtze University, Wuhan, China
2583410631@qq.com

Abstract. Fracture-cavity carbonate oil and gas reservoirs are characterized by complex pore structures, strong heterogeneity, and significant uncertainties in seismic response. Traditional seismic prediction methods struggle to accurately characterize the distribution of fractures and cavities, hindering the exploration and development of deep carbonate oil and gas reservoirs. This paper proposes a comprehensive characterization and prediction method suitable for fracture-cavity carbonate reservoirs, integrating rock physics analysis, seismic attribute sensitivity assessment, post-stack seismic fracture-cavity characterization, and pre-stack fracture prediction techniques. In rock physics modeling, based on core and well logging data, the control laws of different diagenetic processes on elastic parameters are systematically analyzed, clarifying the correlation mechanism between fracture-cavity development and elastic parameters. For the comprehensive prediction method, seismic attribute sensitivity analysis is performed using drilling lithology combinations and well logging responses to select the most sensitive attributes. The characterization results of large faults and karst caves identified by seismic inversion are jointly analyzed with pre-stack fracture prediction results to establish a multi-scale phasic modeling workflow, constructing matrix and fracture models separately. This method is applied to the prediction of deep fracture-cavity carbonate reservoirs. The results show that this method can characterize the contact relationship between fractures and caverns, and the prediction results are consistent with the drilling results. This effectively improves the modeling accuracy and numerical simulation accuracy of complex carbonate reservoirs prediction, which provides the reliable support for the exploration and deployment of fracture-vuggy carbonate reservoirs.

Keywords: Fractured-vuggy carbonate reservoirs, multi-source integrated prediction, rock physics, seismic inversion

1. Introduction

Fracture-vuggy carbonate reservoirs have an important role in global oil and gas resources and have enormous exploration potential in marine carbonate distribution areas [1-3]. These reservoirs are mainly composed of dissolution pores, fractures, and caverns, with complex pore structures and strong heterogeneity, which makes them key areas for current deep and ultra-deep oil and gas exploration. However, the strong heterogeneity and complex pore structure of fracture-dissolution-cavern carbonate reservoirs lead to significant uncertainty in their seismic response [4]. Traditional single seismic data or conventional stacked seismic prediction methods are difficult to accurately characterize the distribution of fractures and caverns, which severely restricts the exploration and development of deep carbonate oil and gas reservoirs [5].

In recent years, scholars have conducted extensive research on carbonate reservoir prediction, mainly covering rock physics analysis, well-logging interpretation, seismic inversion, and integrated prediction [6,7]. In terms of rock physics, studies have shown that the pore structure of carbonate rocks has a profound impact on their acoustic properties; fractures and mineral composition jointly control rock physics properties. An improved rock skeleton model is established based on the Xu-Payne model, which can effectively characterize the pore space of carbonate reservoirs [8]. In seismic inversion and prediction, pure P-wave reservoir inversion technology can be used to analyze favorable locations in karst reservoirs, and frequency-dependent AVO inversion methods can effectively predict hydrocarbon potential. Multi-attribute prediction methods based on pre-stack and post-stack seismic data can identify large faults and karst caves through frequency-guided coherence attributes, and characterize fracture distribution through wide-aperture-guided anisotropic intensity of phase attributes, clearly showing the contact relationship between fractures and caves [9]. In terms of comprehensive prediction, the seismic multi-attribute fusion method that combines well logging and seismic analysis determines the effective threshold by intersecting imaging well logging fracture porosity with seismic attributes, and then fuses multiple attributes, which can effectively eliminate ambiguity and improve the prediction accuracy of fracture-vuggy systems.

Despite the significant progress made in the above studies, the prediction of fractured-vuggy carbonate reservoirs still faces a series of challenges: First, the relationship between the quantitative characterization of pore structure parameters in rock physics modeling and seismic response remains unclear, especially since samples with both fractures and dissolution cavities exhibit high P-wave velocity dispersion characteristics, the physical mechanism of which needs further investigation [10,11]; second, post-stack seismic data is insufficient to characterize small-scale fractures, and the relationship between pre-stack anisotropic fracture prediction results and imaging logging calibration needs to be strengthened; third, prediction results for different seismic attributes exhibit multiple solutions, and there is a lack of an effective well-seismic combined constraint mechanism; fourth, the accuracy of fluid identification methods in fractured-vuggy reservoirs needs further improvement, especially the oil-water differentiation, which remains a challenge.

This paper systematically studies the multi-source data integrated prediction method and its application for fractured-vuggy carbonate oil and gas reservoirs. First, based on core and well logging data, rock physical characteristics are analyzed to systematically investigate the control laws of different sedimentary facies zones and different diagenetic processes (dolomitization, dissolution, tectonic fracturing) on elastic parameters (P-wave impedance, Poisson's ratio, velocity dispersion), establishing a rock physical quantifier for fractured-vuggy reservoirs to provide a theoretical basis for subsequent predictions. Second, well logging interpretation and seismic inversion studies are conducted, including shear wave velocity estimation based on the improved Xu-Payne model, high-precision pre-stack inversion based on L_{1-2} norm sparsity constraints, and fracture anisotropy characterization based on wide-azimuth data, constructing a technical prediction foundation for fractured-vuggy reservoirs. Finally, based on the fusion of multi-source data from well logging, seismic, and geological data, a comprehensive prediction process for fracture-vuggy systems is proposed: the results of post-stack large fault and cave characterization, pre-stack fracture prediction, and sedimentary facies and paleogeomorphological analysis are jointly analyzed to establish a dual-medium modeling method that integrates well-seismic-attribute fusion, thereby achieving high-precision comprehensive prediction of fracture-vuggy carbonate reservoirs and providing technical support for the exploration and deployment of deep carbonate oil and gas reservoirs.

2. Petrological characteristics of complex carbonate oil and gas reservios

The physical basis for predicting fractured-vuggy carbonate reservoirs lies in the controlling effect of pore structure on rock elastic response. Unlike clastic rocks, the pore type, pore morphology, and connectivity of carbonate rocks are the key factors determining the changes in their elastic parameters, rather than simply relying on porosity or mineral composition [11]. For this reason, traditional prediction methods based on the empirical relationship between porosity and velocity often perform poorly in carbonate rocks, and it is essential to return to the fundamental issue of pore structure.

2.1. Basic theories

1) Pore structure dominates elastic response. Numerous rock physics experiments have shown that fractures and mineral composition jointly influence the elastic properties of rocks, and both are significantly controlled by sedimentary environment and diagenesis. Taking the Dengying Formation in the Sichuan Basin as an example, fractures and dissolution pores coexist in the hilly facies microbial dolomite, exhibiting obvious high-frequency dispersion characteristics; while the crystalline dolomite developed in the hilly facies depression is dominated by fractures and intercrystalline pores, with pressure effects and water saturation effects being more prominent [12].

2) Simplified characterization of pore aspect ratio. Due to the complex and diverse pore morphology of carbonate rocks, direct description is extremely difficult. Currently, the ellipsoidal equivalence theory is generally adopted, which simplifies pores into two categories based on the pore aspect ratio: stiff pores (aspect ratio 0.3~1.0) and compliant pores (aspect ratio 0.01~0.1) [13]. Although this classification method simplifies the actual pore morphology, it still provides an effective physical basis for rock physics modeling.

3) Diagenesis affects the pore structure. The diagenetic evolution of carbonate rocks determines their final pore morphology [14]. Reservoirs in different depositional facies zones undergo completely different diagenetic pathways. For example, microbial dolomites in shoal facies develop fractures and dissolution pores after experiencing multi-stage dolomitization, quasi-syngenetic dissolution, and structural fracturing, forming high-quality fracture–pore type reservoirs; whereas crystalline dolomites in intershoal depressions or dolomite lagoons are mainly controlled by mechanical compaction and burial dolomitization, forming reservoir spaces dominated by fractures and intercrystalline pores, with relatively poor properties. Different diagenetic pathways directly lead to significant differences in rock properties, which is the fundamental reason for the heterogeneity of fracture–pore type reservoirs.

2.2. S-wave prediction application

Shear wave velocity is a key parameter for seismic inversion and fluid identification of fractured-vuggy reservoirs. In actual production, due to the scarcity of shear wave logging data, shear wave prediction based on rock physics models has become a necessary method. Depending on the reservoir type and data conditions, the following methods are currently the main approaches:

1) Xu-Payne Model simplifies the traditional method by integrating the three types of pores (cavities, intergranular pores, and fractures) into two categories: hard and soft. A dual-pore porosity estimation algorithm is designed, and the computationally intensive DEM iteration process is replaced with the dry rock approximation equation [10]. This improvement not only retains the original model's ability to characterize pore structure but also significantly improves computational efficiency. In its application in the Gaoshiti area of the Sichuan Basin, the correlation coefficient between the predicted shear wave velocity and the measured value is very high, and the computational efficiency was significantly improved. This method has good applicability to reef-shoal carbonate reservoirs.

2) A particle swarm optimization (PSO) inversion method is developed. For cases where mineral content is unknown, this method can construct a fitness function by the difference between two types of fluid factors (Gassmann fluid term and Russell fluid factor), and then uses the particle swarm optimization algorithm to invert the equivalent matrix modulus and equivalent porosity [15]. Compared with the traditional human-machine search method, the PSO algorithm not only converges faster, but also avoids getting trapped in local optima. When applied to the tight carbonate strata, the inverted P-wave velocity is highly consistent with the measured results, and the maximum relative error is very low, indicating that even in areas lacking mineral content information, this method has high prediction accuracy.

3) The Hudson anisotropic model uses the VRH average model to estimate the modulus of the background matrix. It constructs a dry rock skeleton by combining it with the Hudson fracture model and then uses the Brown-Karringa equation to complete the fluid replacement. For fractured reservoirs, this method can effectively reflect the development direction and intensity of fractures and shows strong anisotropic characterization ability [16].

3. Seismic inversion prediction combined well-logging data

The combination of well logging data and seismic inversion is a key technical means to achieve high-precision prediction of fracture-vuggy carbonate reservoirs. Well logging data has high vertical resolution and rich information, which can provide accurate information on lithology, physical properties, and fluidity; while seismic data has good lateral continuity and wide coverage. The effective combination of the two can fully leverage their respective advantages, significantly improving the accuracy and reliability of reservoir prediction. Therefore, constructing a seismic inversion technology system constrained by well logging data is the core element for multi-source data integrated prediction of fracture-vuggy reservoirs [17].

3.1. Basic theories

Well-seismic calibration is a basic step connecting well-logging and seismic data. By comparing synthetic seismic records with real seismic profiles, accurate time-depth relationships are determined, and seismic wavelets are extracted. Based on this, statistical analysis of rock physics parameters for different lithologies is performed using well-logging interpretation results to establish a quantitative petrophysical model, providing a basis for understanding the seismic wavefield characteristics of the target reservoir.

The basic principle of well-logging constrained seismic inversion is to combine the high-frequency information from well-logging data with the low- and mid-frequency information from seismic data. Combining forward modeling and iterative inversion, the distribution of elastic parameters in the subsurface strata can be obtained. To address the problem of the insensitivity to weak reflection coefficients, sparse-constrained inversion theory is introduced. This theory utilizes the sparsity of the reflection sequence and employs the regularization constraint [18], which can recover weak reflection coefficients and thereby improve inversion accuracy.

3.2. Research approach and technical workflow

Seismic inversion prediction research based on well-logging data follows a technical route:

The first step is rock physics modeling and well-logging calibration. The improved Xu-Payne model and Hudson model are calibrated and validated using well-logging data. The improved Xu-Payne model classifies porosity into stiff and compliant porosity and employs a dual porosity estimation algorithm, which achieves a high correlation coefficient in P-wave velocity fitting and exhibiting better detail compared to traditional models. The Hudson model performs better in highly anisotropic formations, which reflects fracture development direction and intensity.

The second step is elastic parameters prediction based on well-logging constraints. In cases where the mineral content is unknown, a particle swarm optimization algorithm is used to invert the equivalent matrix modulus and equivalent pore aspect ratio, thereby predicting shear wave velocity [19].

The third step involves multi-attribute fusion and inversion combining well-logging and seismic data. To address the issue of multiple solutions in the prediction results for different seismic attributes, the average porosity of reservoir fractures obtained from imaging well log is cross-analyzed with the predicted results of post-stack seismic attributes to determine the effective threshold for each attribute. Then, the attribute values within the effective range are combined to obtain the final prediction result for large-scale fractures. For small-scale fractures, the azimuth frequency gradient attribute is used for pre-stack prediction. Similarly, the anisotropy intensity value is determined through cross-analysis of imaging well log to obtain the prediction result for small-scale fractures.

The fourth step is fluid substitution forward modeling and AVO analysis. Based on well logging data, reservoir mineral composition is determined. The V-R-H hybrid model is applied to determine the matrix bulk modulus. The reflection coefficient at different incident angles is simulated using the Zoeppritz equation, and fluid substitution forward modeling is performed [20]. By comparing the differences in AVO response of reservoirs with oil and water content, an intercept-gradient cross-analysis template is established to achieve hydrocarbon identification.

3.3. Field application

In the application to the Yijianfang Formation of the Hudson Block in the Tarim Basin, the pure P-wave reservoir inversion technique obtained pure P-wave data with significantly higher resolution than traditional full-stack data. The inverted P-wave impedance showed good agreement with actual drilling results [21]. The P-wave dispersion gradient inverted by the frequency-dependent AVO inversion method was sensitive to fluid response, achieving good agreement rate with actual drilling. The P-wave dispersion gradient for oil and gas reservoirs and water reservoirs are different.

In the application to the H Block of the Western T Oilfield, the multi-attribute fusion inversion method combining well and seismic data determined effective threshold values for variance, dip, and maximum positive curvature attributes through cross-plotting of imaging logging fracture porosity and seismic attributes. The fused large fracture prediction results removed redundant information and showed significantly improved agreement with faults. For the prediction of small fractures, cross plot analysis determined the anisotropic strength threshold. Drilling verification showed that the prediction results were consistent with the actual drilling conditions, which effectively avoids interpretation errors.

3.4. Technical system summary

The seismic inversion prediction method based on well logging data can be summarized as a complete technical system. This system uses well logging data as the core constraint, selects appropriate methods for different prediction targets, and forms the corresponding technology for fracture and fluid identification [18].

In terms of reservoir structure characterization, pure P-wave inversion is the fundamental method. This method obtains pure P-wave information after removing the AVO effect based on the pre-stack reflection coefficient formula, and extracts the well-side channel wavelet for post-stack inversion. Pure P-wave data has significantly higher resolution than traditional stacked data, and the inverted wave impedance matches well results well, making it suitable for karst reservoir prediction.

In characterizing fracture systems, different methods are employed for fractures of different scales. Large-scale fractures are characterized using multi-attribute fusion inversion combining well and seismic data. This involves determining effective thresholds using the intersection of fracture porosity and attributes such as dip angle, curvature, and variance from imaging well logging data, and then fusing them to obtain the fracture distribution. Small-scale fractures are predicted using broad-azimuth steering facies attributes. Singular value decomposition quantifies the anisotropy intensity of different azimuth attributes. This method is highly sensitive to weak structures and can detect small-scale fractures. In fluid property identification, frequency-dependent AVO inversion uses the dispersion differences caused by fluids to invert the P-wave dispersion gradient; the dispersion gradient of oil and gas reservoirs is significantly higher than that of water reservoirs. Forward modeling of fluid substitution based on logging mineral composition uses the Zoeppritz equations to simulate the AVO response of different fluids, establishing an intercept-gradient crosspoint template [9].

Regarding the improvement of inversion accuracy, the sparse constraint stacking pre-inversion addresses the insensitivity of carbonate rocks to weak reflection. An adaptive regularization strategy is employed, which can effectively recover the weak reflection coefficient and is applicable to tight reservoirs.

Each of the above six techniques has its applicable conditions: pure P-wave inversion is suitable for karst reservoirs; frequency-dependent AVO inversion is suitable for hydrocarbon detection; sparse-constrained inversion is suitable for tight reservoirs; multi-attribute fusion inversion is suitable for fractured-vuggy systems; wide-azimuth attribute anisotropy is suitable for fractured reservoirs; and fluid substitution forward modeling is suitable for fluid identification. By combining multiple methods, it is possible to achieve a comprehensive characterization of fractured-vuggy reservoirs, from structure to fluid dynamics and from macroscopic to microscopic dimensions.

4. Integrated prediction based on multi-scale data including well logging, seismic, and geological data

4.1. Basic theories

The basic idea of multi-scale data-driven integrated prediction is to make full use of the advantages of different data sources and to constrain fracture–porous reservoirs from multiple perspectives and scales.

Geological data provide a macroscopic background. Sedimentary facies zones determine the material basis for reservoir development, paleogeography controls the extent of karst development, diagenesis shapes the final form of pore structures, and fracture systems provide channels for fluid migration. These geological elements together constitute the macroscopic framework of reservoir development and guide subsequent geophysical predictions [12].

Well logging data provide high-precision vertical constraints. Through well-to-seismic calibration, well logging information can be transformed into seismic-identifiable features; through statistical analysis of rock physical parameters, a conversion relationship between elastic parameters and reservoir properties can be established [1]; through the intersection of imaging logs and seismic attributes, effective thresholds for fracture prediction can be determined. Seismic data provides lateral continuity. Seismic data has good lateral continuity and wide coverage, reflecting the distribution patterns of reservoirs in a plane. Post-stack data is suitable for characterizing large-scale structures, while pre-stack wide-azimuth data is suitable for detecting small-scale fractures. By extracting and fusing multiple seismic attributes, reservoir characteristics can be characterized from different perspectives.

The most important basis of multi-scale fusion is reducing uncertainty. Predictions based on single data or a single attribute often have uncertainty. Integrating geological, well logging, and seismic data at three different scales allows for mutual constraints and verification, which helps make the predictions closer to the real subsurface conditions.

4.2. Research approach and technical workflow

The comprehensive prediction research method based on multi-scale data includes geological guidance, well logging constraints, seismic inversion, attribute integration, and geological validation. First, through geological analysis, the main controlling factors such as depositional facies, paleogeography, diagenesis, and fault systems are clarified, and a geological model is established. Then, using well logging data, well-seismic calibration, rock physics analysis, and attribute cross-checking are performed to establish a quantitative relationship between well logging data and seismic data. Next, with seismic data as the main body, pure P-wave inversion, frequency-related AVO inversion, and sparse-constrained inversion are carried out to extract reservoir structure, fractures, and fluid information [9]. Then, different attributes such as post-stack and pre-stack, amplitude and phase, frequency and attenuation are integrated to comprehensively characterize the fracture-porosity system. Finally, the prediction results are interpreted within the geological framework and validated through actual drilling, forming a closed loop.

4.3. Field application

4.3.1. Hudson block, tarim basin

The main characteristics of the study area are deep reservoir burial and strong heterogeneity. First, predictions were made through paleogeomorphology reconstruction, identifying karst highlands and slopes as favorable areas for reservoir development. Then, well-seismic calibration was conducted to obtain subwave data at three angles. Next, pure P-wave inversion was performed to obtain impedance data with higher resolution than traditional stacked data; at the same time, frequency-related AVO inversion was used to obtain the P-wave dispersion gradient. Finally, combined with geological understanding, it was clarified that reservoir development is controlled by paleogeomorphology, unconformities, faults, and structural dip positions. Actual drilling verification showed that the P-wave dispersion gradient is consistent with drilling results [22].

4.3.2. S gas field cluster on the right bank of the amu darya river in turkmenistan

The study play has extremely high reservoir heterogeneity and complex fractures. The prediction process first conducts multi-level facies-controlled inversion to establish a low-frequency model using sedimentary facies-controlled information. Subsequently, combining deterministic inversion and secondary facies-controlled inversion, the internal reservoir characteristics of reef-flat structures are finely characterized. At the same time, multi-attribute integration technology is used to predict fractures, and linear coherence enhancement combined with curvature volume analysis is applied to eliminate fracture artifacts. This establishes a dual-porosity model: a structural model based on seismic interpretation of faults and structures; a matrix model constrained by multi-level facies-controlled inversion results; and a fracture model constrained by multi-attribute integration prediction results. Finally, a factor is used to connect the matrix and fractures. This method can finely characterize reservoir heterogeneity and fracture distribution, improve modeling accuracy, enhance numerical simulation results, effectively evaluate reservoir connectivity, and accurately determine the direction of water sources.

4.3.3. Gaoshiti area of Sichuan basin

This study play mainly consists of reef-shoal type reservoirs. First, a modified Xu-Paine model was used for rock physics modeling, classifying pores into hard and soft types, achieving a high correlation coefficient for P-wave velocity fitting. Then, a theoretical model was established, designing three reservoir development modes (one for the top, one for the top, and one for the bottom), and forward modeling was used to analyze the seismic response characteristics of different modes. Next, the navigation pyramid technique was used to process the seismic data, improving resolution and extracting sensitive attributes. Finally, the correlation between attributes and well production capacity was analyzed. The results show that reservoir thickness, physical properties, and location have a significant impact on seismic response.

5. Conclusion

1) Pore structure is the key factor controlling the elastic response of fracture-cave carbonates. The dual-porosity classification based on pore aspect ratio provides an effective physical basis for rock physics modeling. The improved Xu-Payne model significantly enhances computational efficiency and shows a high correlation coefficient in fitting P-wave velocity.

2) Logging constraints are crucial for eliminating ambiguity in seismic attributes. By determining effective thresholds through the intersection of imaging logging attributes and seismic attributes, and performing integration, the reliability of fracture prediction can be effectively improved. Joint analysis of pre-stack and post-stack data allows the characterization of large faults and karst cavities using post-stack data, while small fractures can be detected using pre-stack wide-azimuth data, clearly representing the distribution of fractures and caves.

3) AVO templates have high accuracy in fluid identification. When hydrocarbons are present, the intercept and gradient have opposite signs; when water is present, they have the same sign. This makes it an effective method for predicting fluid components in fracture-porosity reservoirs. The workflow for multi-source data integration prediction mainly includes geological guidance, logging

constraints, seismic inversion, attribute fusion, and geological validation, enabling comprehensive characterization of fracture-porosity reservoirs.

References

[1] Li Z, Li H, Liu J, et al. 3D seismic intelligent prediction of fault-controlled fractured-vuggy reservoirs in carbonate reservoirs based on a deep learning method [J]. Journal of Geophysics and Engineering, 2024, 21(2): 345-358.
[2] Fabricius I L, Bachle G T, Eberli G P. Elastic moduli of dry and water-saturated carbonates — Effect of depositional texture, porosity, and permeability [J]. GEOPHYSICS, 2010, 75(3): N65-N78.
[3] Chapman S, Lissa S, Fortin J, et al. Poroelastic Response of a Fractured Rock to Hydrostatic Pressure Oscillations [J]. Geophysical Research Letters, 2024, 51(20): e2024GL109992.
[4] Chen F, Zong Z, Yin X. A squirt-flow model in isotropic porous rocks containing wedge-shaped cracks and its interpretation for laboratory measurements [J]. Geophysics, 2025, 90(2): MR141-MR153.
[5] Chen F, Sun L, Jiang B, et al. A review of AI applications in unconventional oil and gas exploration and development [J]. Energies, 2025, 18(2): 391.
[6] Chen F, Zong Z, Lang K, et al. Geofluid Discrimination in Stress-Induced Anisotropic Porous Reservoirs Using Seismic AVAZ Inversion [J]. IEEE Transactions on Geoscience and Remote Sensing, 2024, 62: 1-14.
[7] Zong Z, Sun Q. Density stability estimation method from pre-stack seismic data [J]. Journal of Petroleum Science and Engineering, 2022, 208: 109373.
[8] Xu M, Yin X, Zong Z. Wave dispersion and attenuation due to multi-scale wave-induced fluid flow in layered partially saturated pore-crack media [J]. Journal of Petroleum Science and Engineering, 2022, 208: 109447.
[9] Zuo Y, Zong Z, Li K, et al. Bayesian AVOAz Inversion of Fluid and Anisotropy Parameters Using Gibbs Sampling With AISM Algorithm [J]. IEEE Transactions on Geoscience and Remote Sensing, 2024, 62: 1-15.
[10] Li J, Zong Z, Chen F. A dual-porosity model incorporating uniaxial stress effect and its application in wave velocity estimation with well-logging data [J]. Geophysical Prospecting, 2025, 73(2): 712-731.
[11] Chen F, Zong Z, Yin X, et al. Pressure and frequency dependence of elastic moduli of fluid-saturated dual-porosity rocks [J]. Geophysical Prospecting, 2023, 71(8): 1599-1615.
[12] Ng K, Santamarina J C. Mechanical and hydraulic properties of carbonate rock: The critical role of porosity [J]. Journal of Rock Mechanics and Geotechnical Engineering, 2023, 15(4): 814-825.
[13] Glubokovskikh S, Gurevich B, Saxena N. A dual-porosity scheme for fluid/solid substitution: A dual-porosity scheme for fluid/solid substitution [J]. Geophysical Prospecting, 2016, 64(4): 1112-1121.
[14] Zong Z, Zhang J, Chen F. Seismic Prediction for Formation Pressure Considering Diagenesis Effect [J]. IEEE Transactions on Geoscience and Remote Sensing, 2024, 62: 1-13.
[15] Alkhimenkov Y, Quintal B. A simple and accurate model for attenuation and dispersion caused by squirt flow in isotropic porous rocks [J]. GEOPHYSICS, 2024, 89(1): MR1-MR10.
[16] Bakulin A, Grechka V, Tsvankin I. Estimation of fracture parameters from reflection seismic data—Part I: HTI model due to a single fracture set [J]. GEOPHYSICS, 2000, 65(6): 1788-1802.
[17] Cao N, Lei G, Su Y, et al. A New Model for Predicting Flow in Fractured-Vuggy Carbonate Reservoirs under Pseudosteady State Condition [J]. Geofluids, 2021, 2021: 1-13.
[18] Yang Y, Yin X, Li K, et al. A Linearized Alternating Direction Method of Multipliers Algorithm for Prestack Seismic Inversion in VTI Media Using the Quadratic PP-Reflectivity Approximation [J]. IEEE Transactions on Geoscience and Remote Sensing, 2023, 61: 1-18.
[19] Wang D X, Wang H F, Ma J F, et al. Fluids discrimination by ray-path elastic impedance inversion: A successful case from Sulige tight gas field [J]. Applied Geophysics, 2019, 16(2): 218-232.
[20] Zong Z, Yin X, Wu G. Geofluid Discrimination Incorporating Poroelasticity and Seismic Reflection Inversion [J]. Surveys in Geophysics, 2015, 36(5): 659-681.
[21] Wei Y, Ba J, Carcione J M, et al. Temperature, differential pressure, and porosity inversion for ultradeep carbonate reservoirs based on 3D rock-physics templates [J]. GEOPHYSICS, 2021, 86(3): M77-M89.
[22] Qi H, Ba J, Muller T M. Temperature Effect on the Velocity-Porosity Relationship in Rocks [J]. Journal of Geophysical Research: Solid Earth, 2021, 126(1): e2019JB019317.