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Research Progress on the Prediction Model of Wellbore Temperature and Pressure Fields

Zexin Chen, Tengyu Kong, Zhisheng Tan
(School of Petroleum Engineering, Yangtze University, WuHan 40100, China)

***Abstract*：** *In the exploration of deep oil and gas reservoirs, significant engineering challenges are frequently encountered, including abnormal formation temperatures, high pore pressures, and narrow safe mud density windows. The temperature and pressure fields within the wellbore are critical parameters for both wellbore stability analysis and drilling design, and they also exert a substantial influence on critical operations such as well control, drilling fluid performance, and cementing integrity. The mechanism of wellbore temperature and pressure fields, along with the accurate prediction of their distribution, has been widely applied in deepwater drilling operations. Given the complexity of the temperature-pressure field coupling interaction within the wellbore and the challenges in predictive modeling, extensive applications of temperature and pressure prediction models have been conducted. This paper reviews the research progress on the mechanisms of wellbore temperature models and wellbore pressure models.*

Keywords: *deepwater high temperature and high pressure; wellbore temperature; wellbore pressure; prediction model*

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I. Introduction

With exploration and development continually advancing into new frontiers, the South China Sea has entered the realm of ultra-deepwater, deep strata, high-temperature, and high-pressure environments. Alongside the Gulf of Mexico (USA) and the North Sea (UK), the South China Sea is recognized as one of the world's three major offshore high-temperature, high-pressure regions. During deepwater drilling, the complex coupling mechanisms of wellbore temperature and pressure fields are influenced by factors such as seawater temperature gradients, drillstring rotation, and mud thermal expansion, making accurate prediction extremely challenging (Galvao et al., 2019). Particularly under HTHP conditions, temperature variations can induce changes in drilling fluid properties, thereby disrupting the pressure balance and stability within the wellbore (Zheng et al., 2020). Therefore, understanding the coupling mechanisms of temperature and pressure fields and achieving precise predictions of their distribution within the wellbore are imperative for ensuring the safety and efficiency of deepwater drilling operations.

II. Current Research Progress of Wellbore Temperature Models

Accurate prediction of wellbore temperature distribution during drilling operations is of critical significance for ensuring safe and efficient drilling processes. Current research on wellbore temperature fields predominantly employs analytical and numerical methods. Ramey (Ramey, 1962) established a wellbore-formation heat transfer model under steady-state conditions based on the principle of energy conservation. Holmes (Holmes et al., 1970) developed an analytical model for calculating steady-state heat transfer between drilling fluid in the drill string and annular fluid. Hasan (Hasan et al., 1996) proposed a one-dimensional transient heat transfer model under dimensionless time conditions by assuming steady-state heat transfer between drill string fluid and annular fluid.

The numerical method is founded on the one-dimensional numerical model developed by Raymond (Raymond, 1969) for calculating the temperature distribution of annular fluid in vertical wells under steady-state and pseudo-steady-state conditions. Wang (Wang et al., 2017)established a coupled heat transfer model for wellbore-permafrost, conducted an in-depth analysis of the temperature field and water content, and proposed special designs to ensure wellhead stability. Mao (Mao et al., 2018) established a prediction model for the wellbore temperature distribution applicable to shale gas in horizontal wells and geothermal energy development. YANG H (Yang et al., 2019) established a transient heat transfer model for wellbores applicable to deepwater multi-gradient drilling based on mass, momentum, and energy conservation equations. Zhang (Zhang et al., 2021) established a coupled temperature-pressure field model applicable to deepwater multi-gradient drilling, and concluded that the mass fraction of hollow glass spheres. Zhang (Zhang et al., 2022) established a wellbore temperature field model applicable to such conditions and studied the wellbore temperature distribution patterns under these conditions. The physical model of eccentric annulus fluid flow and heat exchange is demonstrated in Fig.1 (Chen et al., 2024).

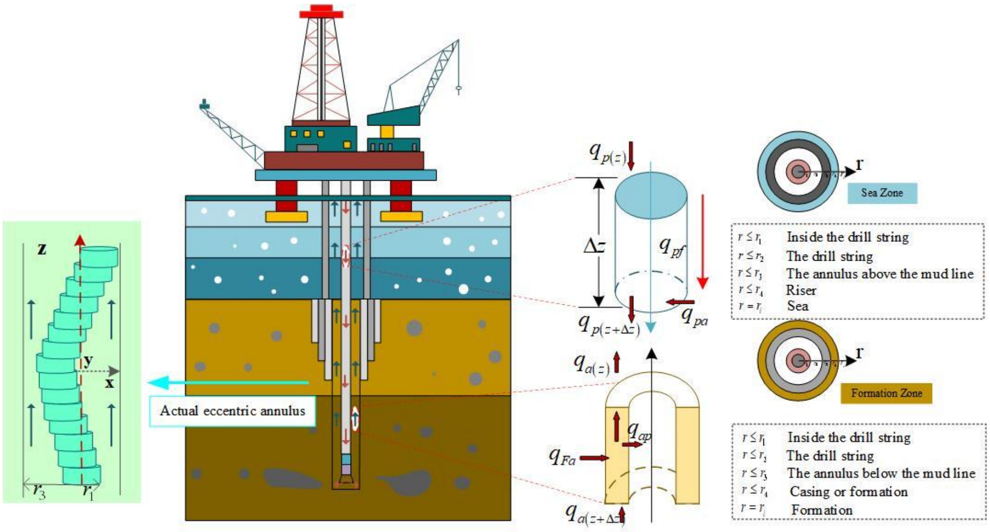

Fig. 1 Schematic diagram of fluid flow and heat transfer in eccentric annulus wellbore

Compared to numerical methods, analytical methods offer high computational efficiency and unconditional stability. However, the nonlinear partial differential equations representing the wellbore temperature field lack analytical solutions, and it is challenging to adequately incorporate the influence of fluid thermal properties, heat sources, and wellbore structure on the wellbore temperature distribution. This makes it difficult for analytical models to effectively study the temperature distribution patterns of wellbores during deepwater and ultra-deep drilling operations. Consequently, an increasing number of scholars prefer to use numerical methods to investigate the transient heat transfer process between the wellbore and formation.

III.Current Research Progress of Wellbore Pressure Models

Matter typically exists in three phases: solid, liquid, and gas. When only one phase flows within a pipeline, it is classified as single-phase flow. Conversely, the simultaneous flow of two or more distinct phases constitutes multiphase flow. Wellbore pressure models can be categorized into models for single-phase flow and multiphase flow systems. In engineering applications, multiphase flow predominantly manifests as various forms of two-phase flow, which currently represents the primary focus of pressure model research.

3.1 Research progress of Wellbore Pressure Models for Single-Phase Flow

Moody(Moody, 1944) conducted experiments on pipes with varying roughness levels and subsequently plotted curves illustrating the corresponding Dancy friction factors. Chang Zhiqiang et al (Chang et al., 2012) proposed a thermodynamic coupling model that integrates fluid property parameters while optimizing the calculation methods for natural gas thermodynamic properties.

3.2 Research progress of Wellbore Pressure Models for Two-Phase Flow

Accurate identification and calculation of flow patterns are crucial when determining multiphase flow pressure drop. Hasan and Kabir (Hasan at al., 2010) classified flow patterns in two-phase pipe flow based on the drift model, improved the method for distinguishing slug flow to churn flow. Bao Zhijing (Bao, 2016) established a pressure calculation model for injection and production wells based on percolation theory, using formulas to calculate formation pressure during well shut-in. Chen Dechun and colleagues (Chen et al., 2017) compared and validated commonly used gas-liquid two-phase flow pressure drop calculation models. Liu (Liu et al., 2023) established a wellbore pressure field model under vertical, transverse and torsional vibration modes of drilling string in deep-water riserless drilling. Fig. 2 shows dominant flow pattern that exist for upward flow in the annuuls(Aladwani and Gray, 2012).

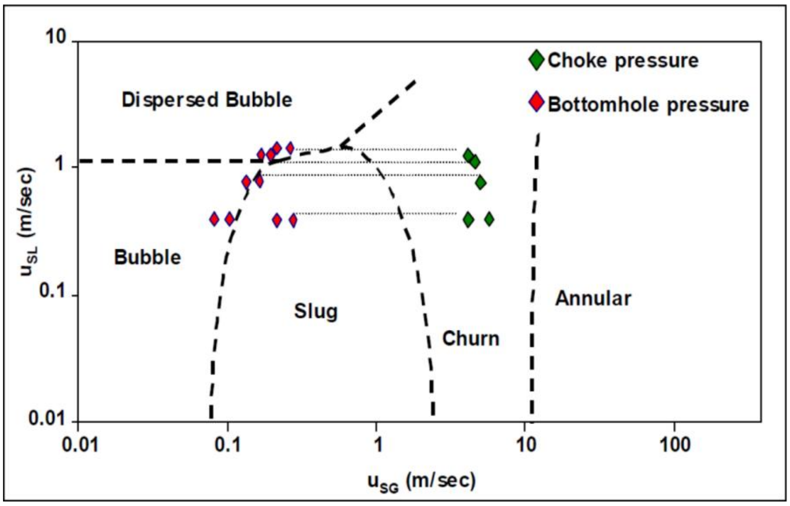

Fig.2. The flow pattern in the annulus during UBD operations (Perez-Tellez)

IV. Application of PINN in wellbore temperature and pressure fields

The rapid prediction of wellbore temperature fields is crucial for optimizing wellhole pressure calculations and identifying hydrate-related risks. However, traditional numerical methods are constrained by the CFL stability condition, resulting in low computational efficiency, particularly time-consuming in simulations of kilometer-scale wellbore depths. Pure data-driven deep learning methodologies heavily rely on extensive high-quality datasets and exhibit limitations in generalization capabilities. In contrast, deep learning approaches that integrate physical prior knowledge have emerged as a novel research direction by reducing data dependency and enhancing model robustness. This methodology, integrated with heat transfer equation constraints, effectively overcomes the efficiency limitations inherent in traditional numerical solutions, thereby enabling real-time transient temperature calculations.

Physics-Informed Neural Network (PINN) represents a synergistic integration of deep learning and mechanistic modeling, which not only adhere to the physical laws governed by nonlinear partial differential equations but also demonstrate the capability to learn highly generalizable models with minimal data, including scenarios involving unlabeled datasets. Fig. 3 illustrates the architecture of the PINN. Jagtap (Jagtap et al., 2020) introduced the conservative Physics-Informed Neural Network (cPINN) and extended PINN (XPINN) in discrete domains, which significantly reduced training costs through parallel computing. Franklin (Franklin et al., 2022) integrated the PINN and LSTM methodologies to enable the early prediction of the average flow velocity within production tubing, thereby reducing the uncertainties associated with physical models. Xu Baochang (Xu et al., 2023) employed the adaptive Physics-Informed Neural Network (PINN) method to predict the annular pressure of two-phase flow within the wellbore.Yuan (Yuan et al., 2023) employed the PINN methodology to forecast medium- and long-term seawater temperature variations, thereby demonstrating the applicability of this approach in the field of climate prediction.

Research findings indicate that, in comparison to conventional numerical solution methods such as finite difference and finite volume, the black-box model based on the PINN approach circumvents truncation errors during equation discretization, thereby accelerating computational speed by several orders of magnitude while maintaining computational accuracy. This dual advantage of ensuring precision and significantly enhancing computational efficiency is particularly critical for the real-time calculation of temperature fields in oil and gas wellbores.

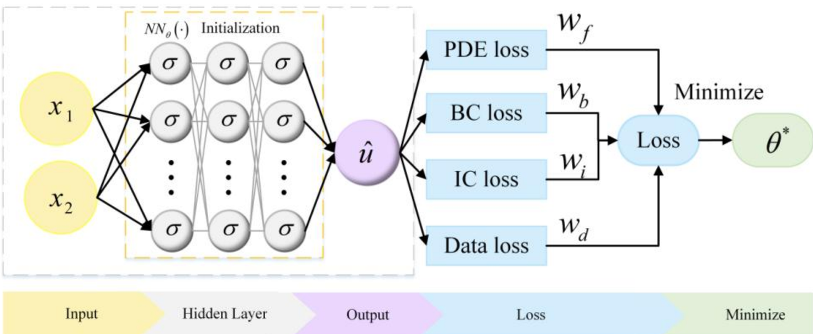

Fig.3. Physical information neural network structure

V. Conclusion

As deepwater oil and gas exploration extends into high-temperature and high-pressure complex formations, the coupling mechanism of wellbore temperature and pressure fields, along with their precise prediction, has become a core challenge in ensuring safe drilling operations. Although current research has established a foundational understanding, significant gaps remain in the construction and dynamic analysis of multi-physical field coupling models under extreme deepwater conditions, necessitating systematic breakthroughs.

(1) Traditional wellbore temperature and pressure prediction models predominantly rely on steady-state assumptions or single physical field analyses, which inadequately represent the coupling mechanisms of multiple factors in deepwater drilling, such as the interaction between low-temperature seawater and high-temperature formations, transient pressure fluctuations within narrow density windows, and cement hydration heat effects. Furthermore, existing two-phase flow models exhibit insufficient accuracy in simulating phase transition and mass transfer processes of high-temperature and high-pressure gas-liquid mixtures, and the coupling effects of frictional heating and the Joule-Thomson effect have yet to be fully quantified.

(2) Addressing the unique challenges of deepwater high-temperature and high-pressure drilling, the following areas require focused breakthroughs: integrating the thermodynamic responses of the formation-wellbore-riser system, quantifying the disturbance mechanisms of shallow gas/fluid influx and hollow sphere injection on temperature and pressure distributions. By combining machine learning with real-time downhole monitoring data, developing adaptive temperature and pressure prediction-control integrated models to enhance dynamic adaptability within narrow density windows. Validating the engineering applicability of theoretical models for high-temperature and high-pressure gas-liquid two-phase flow and transient non-equilibrium heat transfer through full-scale simulation tests and field data inversion.

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