

Article

An Integrated CFD–Machine Learning Framework for Flow Assurance Risk Assessment During Hot Oil Commissioning of Subsea Jumpers

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Abstract

To mitigate flow assurance risks during the hot oil commissioning of deepwater jumpers, this study develops a transient displacement risk assessment framework integrating CFD–machine learning surrogate models. A 3D numerical model using VOF and conjugate heat transfer simulated hot crude displacing cold diesel. For three representative jumper configurations (M-shaped, U-shaped, and straight pipes), the effects of spatial geometry on mixing, heat transfer, and gelled oil length were investigated. The results show that jumper geometry significantly affects flow regime and thermal evolution. The M-shaped jumper enhances secondary-flow-induced mixing and heat transfer, yielding the shortest gelled oil length (0.5 m). In contrast, straight pipes show weak mixing and stratified flow, indicating higher local gelation risk. Sensitivity analysis shows that higher flow velocity and water cut reduce gelled oil length by decreasing residence time and increasing fluid thermal inertia. A machine learning surrogate trained on CFD data enables rapid prediction of key flow assurance parameters: maximum temperature drop, pressure drop, and gelled oil length. The multilayer perceptron outperforms the random forest model, with $R^2 > 0.94$ for all three parameters. This study provides a theoretical basis and efficient tool for rapid assessment, parameter optimization, and gelation risk management in deepwater hot oil commissioning.

Keywords: subsea jumper; hot oil commissioning; machine learning; flow assurance



Academic Editor: Hossein Hamidi

Received: 11 June 2026

Revised: 9 July 2026

Accepted: 22 July 2026

Published: 24 July 2026

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1. Introduction

In deepwater oil and gas field development, subsea jumpers are critical transportation components that connect subsea wellhead Christmas trees to production manifolds. They play essential roles in multiphase production-fluid transportation, system interconnection, and local process adaptation [1–3]. Unlike conventional straight pipe sections, subsea jumpers generally feature complex three-dimensional configurations, including M-shaped, U-shaped, and Z-shaped geometries. These geometric characteristics, together with local bends, elevation changes, and free-span sections, can enhance secondary flows, induce phase redistribution, and cause local pressure-drop fluctuations. As a result, flow separation and interfacial disturbances may be intensified, thereby increasing flow assurance risks during both commissioning and long-term operation stages [4–6].

For oilfields producing high-pour-point and waxy crude oils, flow assurance challenges during hot oil commissioning of deepwater subsea jumpers become particularly pronounced. In typical deepwater commissioning procedures, after jumper installation, leak testing, and pressure testing, the jumper is commonly filled with a low-pour-point fluid, such as diesel, which serves as a displacement or pressure-holding medium. This fluid may remain inside the jumper for an extended period under low-temperature seabed conditions. Owing to continuous heat exchange with the surrounding environment, both the jumper wall and the retained diesel gradually approach the ambient seabed temperature, which is typically approximately 4–9 °C in deepwater environments. Consequently, when hot crude oil enters the jumper and displaces the cold diesel, it experiences not only direct-contact heat transfer with the low-temperature diesel but also continuous cooling by the cold pipe wall and the surrounding seawater [7,8]. This cooling effect is especially significant during the initial stage of commissioning, when the leading front of the hot crude oil may undergo rapid temperature decay, giving rise to pronounced axial and local temperature gradients. Once the crude oil temperature decreases below the wax appearance temperature, wax crystals begin to precipitate and may subsequently deposit near the pipe wall, leading to a marked increase in crude oil viscosity and flow resistance [9–11]. If the temperature further approaches or falls below the pour point, crude oil gelation may occur, eventually resulting in pipeline gel blockage or localized plugging [12,13]. Such blockage, once formed, can seriously threaten commissioning safety and cause substantial economic losses due to production interruption, blockage remediation, and repair operations. Therefore, clarifying the dynamic evolution of temperature drop, pressure drop, mixing-zone development, and gelled oil length during hot oil commissioning is of considerable engineering significance. Such understanding is essential for safe commissioning strategy optimization and flow assurance design of deepwater subsea jumpers transporting high-pour-point crude oils.

At present, flow assurance risk assessment and commissioning scheme analysis for subsea pipelines mainly rely on one-dimensional multiphase transient simulation software, such as OLGA [14,15]. These methods have considerable engineering applicability in system-level operating-condition screening, prediction of pipeline pressure and temperature profiles, and preliminary evaluation of commissioning schemes. However, because they are generally based on empirical correlations, simplified geometric representations, and reduced-order descriptions of local flow structures, one-dimensional models are inherently limited in resolving local mixing behavior induced by structural discontinuities in complex three-dimensional subsea jumpers [16]. This limitation becomes particularly critical during hot oil commissioning, where the displacement, mixing, and heat transfer between hot crude oil and cold diesel exhibit strong transient characteristics, spatial non-uniformity, and high sensitivity to jumper configuration. Consequently, relying solely on one-dimensional simulations makes it difficult to comprehensively reveal the mechanisms governing local temperature decay, mixing-zone evolution, and the formation of potential gelled oil regions.

With continuous advances in computational capability and numerical methods, computational fluid dynamics (CFD) has become an important numerical approach for investigating multiphase flow, local heat transfer, and flow assurance mechanisms in complex pipeline systems [17,18]. In recent years, CFD-based studies of complex multiphase flow in subsea jumpers have gradually expanded from straight pipes and simple bends to representative spatial jumper configurations. For example, Zhu et al. [19,20] investigated flow-induced vibration and flow-pattern characteristics of two-phase flow in M-shaped and inverted U-shaped jumpers by introducing slug-flow inlet simulations. Zheng et al. [21] conducted a systematic study on slug formation and pressure fluctuation characteristics in gas–liquid pipelines, demonstrating that local bends can induce significant flow-field

instability and promote slug coalescence. Yurishchev et al. [22] examined an M-shaped jumper in a high-pressure natural gas production system and employed CFD to analyze the effects of liquid-inventory displacement during production start-up on jumper pressure drop, elbow force, and flow-induced vibration. Song et al. [3,5] further focused on M-shaped rigid jumpers and revealed the flow-pattern evolution and flow-induced vibration responses of oil–gas–water three-phase flow under different mixture velocities and phase volume fractions. Collectively, these studies demonstrate the capability of CFD to capture local flow-field evolution, multiphase interaction, and heat transfer mechanisms in complex subsea jumper systems. Nevertheless, despite its high physical fidelity, CFD usually requires substantial computational resources and long simulation times, which limits its direct application in rapid iterative optimization of offshore commissioning schemes and fast decision-making under emergency operating conditions. Therefore, an evident efficiency bottleneck still exists when CFD is applied to engineering-scale flow assurance analysis and commissioning strategy optimization [23].

In recent years, advances in artificial intelligence and machine learning have provided new opportunities to balance the physical fidelity of numerical simulations with the computational efficiency required for engineering prediction. By constructing data-driven surrogate models based on CFD-based numerical simulations or field monitoring data, machine learning methods can capture nonlinear mapping relationships between complex operating parameters and target responses, thereby enabling rapid prediction of key flow assurance indicators [24]. In oil and gas engineering and related flow assurance fields, machine learning has been increasingly applied to structural response prediction, mixing-process modeling, risk identification, and production-parameter prediction. For example, Gulgec et al. [25] developed a long short-term memory network using acceleration data collected from laboratory-scale curved beams to evaluate structural strain responses. Chen et al. [26] combined a conventional mixing model with data-driven methods to predict mixing length in refined-product pipelines, demonstrating the potential of integrating mechanistic knowledge with machine learning. Du et al. [27] proposed a two-stage physics-informed neural network, termed TS-PINN, to predict the concentration distribution of mixed oil during sequential transportation in multi-product pipelines. Zhao et al. [28] reviewed hydrate risk monitoring and prevention technologies and highlighted the engineering potential of data-driven early-warning systems based on pressure, acoustic, and temperature features. Adeyinka et al. [29] introduced a Kolmogorov–Arnold network to predict bottom-hole pressure in offshore oilfields, achieving better predictive performance than traditional regression models, XGBoost, gradient-boosting trees, and reservoir history-matching simulators. Collectively, these studies demonstrate the strong potential of machine learning for flow assurance risk identification, key-parameter prediction, and rapid engineering decision-making in oil and gas systems. However, for hot oil commissioning of deepwater subsea jumpers with complex spatial configurations, further investigation is still required to integrate CFD simulation data with machine learning surrogate models for rapid prediction of key indicators associated with gelled oil risk.

Although previous studies have advanced the understanding of multiphase flow mechanisms, flow-induced vibration responses, and data-driven prediction methods for subsea pipeline and jumper systems, existing research has mainly focused on one-dimensional system-level commissioning simulations, local multiphase flow mechanism analysis, or standalone data-driven prediction models. Systematic studies remain limited regarding the three-dimensional transient flow and heat transfer behavior of hot crude oil displacing cold diesel during hot oil commissioning of deepwater subsea jumpers with complex spatial configurations. In particular, the quantitative characterization of gel blockage risk in complex three-dimensional jumper geometries and the integration of CFD-based analysis with rapid

surrogate prediction for engineering applications have received relatively limited attention. This contradiction between detailed physical mechanism resolution and low-efficiency engineering application highlights the need for an integrated framework that combines CFD-based physical insight with data-driven rapid prediction. To address this need, this study develops an integrated CFD–machine learning framework for flow assurance risk assessment during hot oil commissioning of deepwater subsea jumpers. Figure 1 provides an overview of the proposed framework and illustrates the overall workflow of the study. The central hypothesis of this study is that integrating CFD-based numerical simulations with a machine learning surrogate model can simultaneously preserve the physical fidelity required to characterize complex three-dimensional transient flow and heat transfer while significantly improving computational efficiency for rapid engineering oriented flow assurance risk assessment. First, a three-dimensional transient flow and heat transfer model for hot oil displacement of cold diesel in deepwater subsea jumpers is established based on the VOF multiphase flow model, and the dynamic evolution of the temperature field, pressure field, and gelled oil length is analyzed. Second, the maximum axial temperature drop, pressure drop, and gelled oil length are compared among different jumper configurations, including M-shaped, U-shaped, and straight pipes, to reveal the effects of jumper spatial configuration and key operating parameters on gel blockage risk. An equivalent gelled oil length derived from the three-dimensional temperature field is further introduced to quantitatively evaluate gel blockage risk in complex jumper geometries. Finally, a machine learning surrogate model is developed based on the CFD simulation dataset to enable rapid prediction of key flow assurance indicators within the investigated parameter space. This study provides a theoretical basis and engineering reference for commissioning-parameter optimization, gel blockage risk early warning, and flow assurance scheme design for deepwater subsea jumpers transporting high-pour-point crude oil.

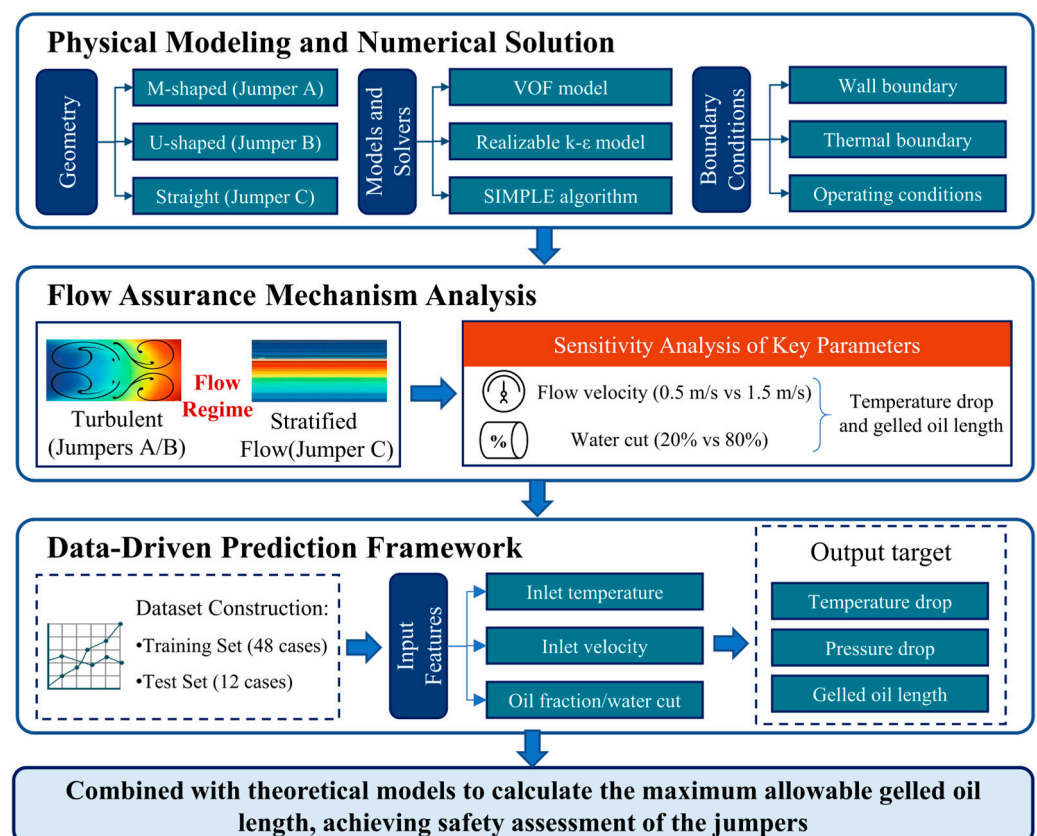


Figure 1. The systematic architectural framework of the data-driven prediction model.

2. Materials and Methods

2.1. Physical Model and Boundary Conditions

2.1.1. Geometric Model

Three typical deepwater jumper structures were selected as physical models: an M-shaped jumper containing multiple elbows and inclined pipe sections (Jumper A), a U-shaped jumper with a long horizontal section (Jumper B), and a horizontal straight pipe as a control baseline (Jumper C), as shown in Figure 2.

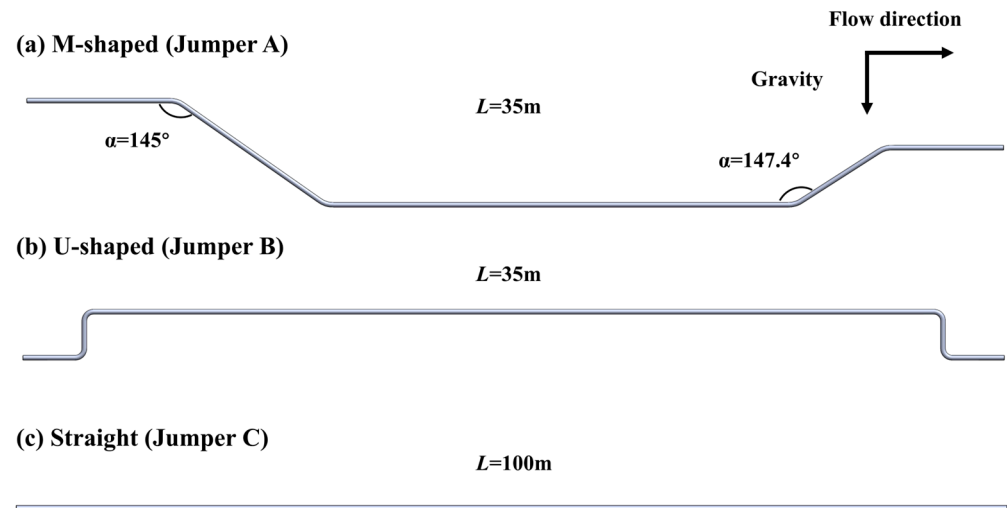


Figure 2. Geometric configurations of the subsea jumpers.

2.1.2. Physical Parameters and Boundary Conditions

Fluid physical properties measured experimentally: The pour point of the high-pour-point crude oil is 41°C , with a density of approximately 841 kg/m^3 (20°C); the density of 0# diesel is approximately 831 kg/m^3 (20°C). The jumper inlet is set as a Velocity Inlet, and the outlet is a Pressure Outlet. The densities of the high-pour-point crude oil and diesel exhibit an approximately linear relationship with temperature; the viscosity of the high-pour-point crude oil is highly sensitive to temperature, and its viscosity-temperature and rheological characteristics are meticulously governed by a temperature-dependent Non-Newtonian constitutive model (e.g., modified Bingham plastic model). Below the wax appearance temperature, the apparent viscosity becomes highly sensitive to both temperature decay and shear rate. These complex rheological coupling relations were fitted through rheometer experimental data and dynamically compiled into the CFD solver via User-Defined Functions (UDFs) to ensure the accurate capture of the phase-transition hydrodynamics (Figure 3). To capture the severe transient thermal lag induced by the thick X65 steel pipe and the 100 mm silicone rubber insulation, whose thermophysical properties are listed in Table 1, a Conjugate Heat Transfer (CHT) strategy was strictly employed. The pipe walls were explicitly meshed as solid domains rather than simplified zero-thickness thermal resistances. This rigorous CHT approach ensures that the massive transient thermal inertia of the cold pipeline materials during the initial hot oil displacement is accurately resolved, before coupling with the constant 9°C external seawater convective boundary.

2.2. Numerical Simulation Method

This study employs the CFD software ANSYS Fluent 2022 R1 (ANSYS Inc., Canonsburg, PA, USA) to conduct transient numerical simulations of the multiphase flow and heat transfer process during the displacement of diesel by hot oil in deepwater jumpers, based on the Finite Volume Method (FVM).

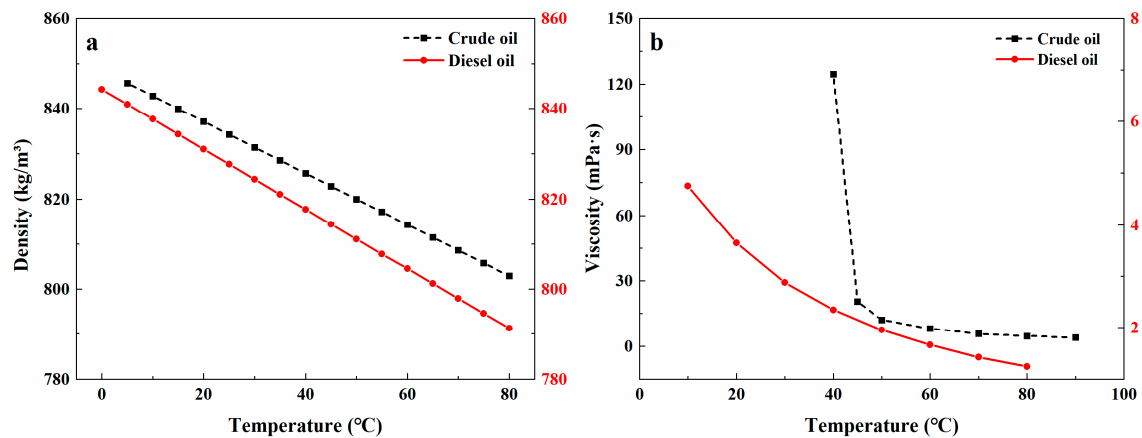


Figure 3. Temperature-dependent density and viscosity curves for high-pour-point crude oil and diesel: (a) density vs. temperature, (b) viscosity vs. temperature.

Table 1. Basic parameters of the subsea jumpers.

Material Properties		
X65 Steel	Density [kg/m³]	7850
	Specific Heat Capacity [J/(kg·°C)]	470
	Thermal Conductivity [W/(m·°C)]	49.5
Silicone Rubber	Density [kg/m³]	1100
	Specific Heat Capacity [J/(kg·°C)]	1450
	Thermal Conductivity [W/(m·°C)]	0.17
Inner Diameter [mm]		126.3
Outer Diameter [mm]		152.4
Insulation Thickness [mm]		100

2.2.1. Multiphase Flow Model

Considering the actual commissioning process, while crude oil and diesel are partially miscible, the rapid macroscopic displacement mechanism physically dominates over the microscopic molecular diffusion owing to the high initial injection velocity. Therefore, as a widely adopted conservative engineering assumption to decouple complex mass transfer, the fluids are treated as immiscible phases.

To describe the transient evolution of the gas–liquid interface, the Volume of Fluid (VOF) multiphase model is adopted [30]. In this framework, a single set of Reynolds-Averaged Navier–Stokes (RANS) equations is solved for the mixture, while the phase distribution is tracked through the volume fraction function α_q .

The transport equation for each phase is written as:

$$\frac{\partial \alpha_q}{\partial t} + \nabla \cdot (\alpha_q \mathbf{u}) = 0 \quad (1)$$

where α_q denotes the volume fraction of phase q , and $\mathbf{u}$ is the shared velocity field of the mixture.

The physical constraint of the multiphase system is:

$$\sum_{q=1}^n \alpha_q = 1 \quad (2)$$

The mixture density and viscosity are defined using volume-weighted averaging:

$$\rho = \sum_q \alpha_q \rho_q, \quad \mu = \sum_q \alpha_q \mu_q \quad (3)$$

To ensure consistency with the momentum and energy equations, the mixture properties are coupled with turbulence-enhanced transport through the effective viscosity formulation introduced in the turbulence model section. This VOF formulation enables accurate prediction of interface deformation, phase displacement, and transient mixing behavior in complex subsea jumper geometries.

2.2.2. Turbulence Model

Common turbulence models for multiphase flow simulations include the standard k- ϵ model, RNG k- ϵ model, and Realizable k- ϵ model. Compared with the standard and RNG k- ϵ models, the Realizable k- ϵ model incorporates an improved transport equation for the turbulent kinetic energy dissipation rate and delivers superior predictive performance in flow fields featuring complex shear flows [31,32].

The turbulent flow field is described using the Reynolds decomposition:

$$u_i = \bar{u}_i + u'_i \quad (4)$$

Substituting Equation (4) into the instantaneous Navier–Stokes equations and applying Reynolds averaging yields the Reynolds-Averaged Navier–Stokes (RANS) equations. The momentum conservation equation is:

$$\rho \left(\frac{\partial \bar{u}_i}{\partial t} + \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} \right) = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j} \left[\mu \left(\frac{\partial \bar{u}_i}{\partial x_j} + \frac{\partial \bar{u}_j}{\partial x_i} \right) \right] - \frac{\partial}{\partial x_j} (-\rho \overline{u'_i u'_j}) \quad (5)$$

where the last term represents the Reynolds stresses, which are closed using the Boussinesq eddy-viscosity hypothesis.

The turbulent kinetic energy equation is:

$$\frac{\partial(\rho k)}{\partial t} + \nabla \cdot (\rho k \mathbf{u}) = \nabla \cdot \left[\left(\mu + \frac{\mu_t}{\sigma_k} \right) \nabla k \right] + G_k - \rho \epsilon \quad (6)$$

The dissipation rate equation for the Realizable k- ϵ model is:

$$\frac{\partial(\rho \epsilon)}{\partial t} + \nabla \cdot (\rho \epsilon \mathbf{u}) = \nabla \cdot \left[\left(\mu + \frac{\mu_t}{\sigma_\epsilon} \right) \nabla \epsilon \right] + \rho C_1 S \epsilon - \rho C_2 \frac{\epsilon^2}{k + \sqrt{\nu \epsilon}} \quad (7)$$

where S is a function of the mean strain rate tensor, and C_1 , C_2 are model coefficients.

The turbulent viscosity is defined as:

$$\mu_t = \rho C_\mu \frac{k^2}{\epsilon} \quad (8)$$

where C_μ is calculated according to the Realizable k- ϵ formulation.

To account for turbulence-enhanced transport effects in the energy equation, the effective viscosity and thermal conductivity are defined as:

$$\begin{aligned} \mu_{eff} &= \mu + \mu_t \\ k_{eff} &= k + \frac{\mu_t c_p}{Pr_t} \end{aligned} \quad (9)$$

where c_p is the specific heat capacity and Pr_t is the turbulent Prandtl number (typically 0.85 for engineering flows).

Consequently, the momentum and energy transport equations incorporate both molecular and turbulence-induced diffusion effects, ensuring consistency between the VOF multiphase framework and the RANS turbulence closure. Considering that the crude oil undergoes severe viscosity escalation near the pour point, leading to local relaminarization

near the cold pipe wall, the Enhanced Wall Treatment (EWT) strategy was strictly coupled with the turbulence model. This combined approach ensures accurate resolution of both the highly turbulent secondary flows in the core region and the viscous-dominated thermal boundary layer at the solid boundaries.

2.2.3. Solution Control and Setup

In the transient displacement simulation, the pipe is completely filled with subsea ambient diesel at a temperature of 9 °C at the initial moment (i.e., the volume fraction of diesel is 1). A velocity inlet boundary condition was prescribed at the inlet, where the hot crude oil–water mixture entered the jumper with the specified flow velocity and inlet temperature. A pressure outlet boundary condition with atmospheric gauge pressure was imposed at the outlet. No-slip boundary conditions were applied to all pipe walls. Heat transfer through the pipe wall was considered using the specified thermal properties of the pipe and insulation layers, while the external boundary was subjected to the constant ambient seawater temperature. The hot crude oil–water mixture was injected through the velocity inlet to displace the initially filled diesel. The SIMPLE algorithm is adopted for pressure-velocity coupling [33]. To balance computational accuracy and convergence, the Second-order Upwind scheme is utilized for the discretization of both momentum and energy equations, while the Geo-Reconstruct scheme is applied for volume fractions to ensure interface sharpness.

Considering the sensitivity of interface tracking in the VOF multiphase model, a rigorous Courant number control criterion was implemented. During the transient solution process, the global Courant number was strictly limited to below 0.25 to ensure the accuracy of geometric interface reconstruction and prevent divergence of the energy equation during the initial displacement stages. An adaptive time-stepping strategy (ranging from 10^{-4} to 10^{-2}) was employed, ensuring that the residual convergence criteria for all governing equations reached below 10^{-6} , thereby guaranteeing the reliability of capturing the three-dimensional transient flow fields within the complex jumpers. These numerical settings were selected to ensure stable interface reconstruction and accurate prediction of transient multiphase flow and heat transfer throughout the commissioning process.

2.2.4. Grid Independence Verification

To eliminate the influence of grid resolution on numerical accuracy, a systematic grid independence study was conducted using a straight pipe model with the highest blockage risk, corresponding to a flow velocity of 1.5 m/s and a water cut of 20%. Five sets of structured hexahedral meshes were generated, with cell numbers ranging from 0.35 million to 1.5 million. The maximum pressure drop and maximum temperature drop during the hot oil displacement process were selected as key monitoring parameters, and the relative variation between successive mesh refinements was used as the grid convergence criterion. When the mesh size increased from 0.92 million to 1.25 million cells, the relative changes in maximum pressure drop and maximum temperature drop were 1.2% and 0.8%, respectively, both below the predefined engineering tolerance of 1.5%. Further mesh refinement resulted in only marginal improvements in accuracy but a significant increase in computational cost. Considering both computational efficiency and numerical accuracy, the mesh with approximately 0.92 million cells was selected as the optimal grid for all subsequent simulations. The grid independence results are presented in Figure 4.

Although independent field measurements and full-scale experimental data for deep-water jumper commissioning are currently unavailable, the present CFD model was established using the widely adopted VOF multiphase model and Realizable k - ϵ turbulence model, together with rigorous grid independence verification and strict convergence crite-

ria. Therefore, the numerical framework provides physically reasonable predictions under the investigated operating conditions.

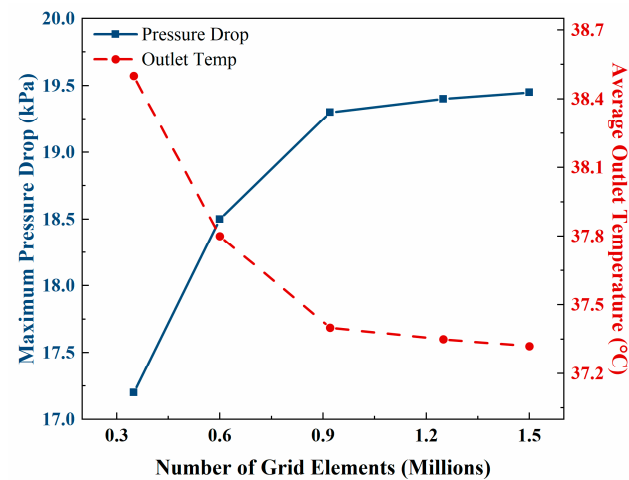


Figure 4. Variations of maximum pressure drop and average outlet temperature with grid number.

2.3. Machine Learning Prediction Model

To break through the bottleneck of time-consuming CFD calculations, a machine learning prediction model driven by CFD simulation data was constructed, as shown in Figure 5.

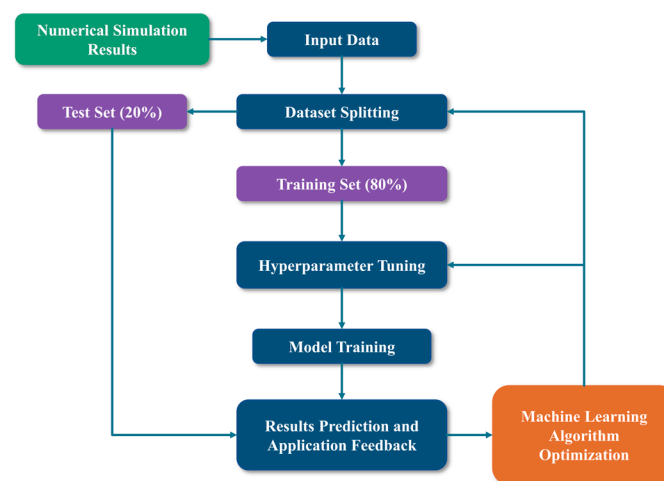


Figure 5. The machine learning prediction framework.

2.3.1. Dataset Construction

Through batch CFD calculations under different operating conditions, a dataset containing 69 samples was constructed and randomly divided into a training set (55 samples) and an independent testing set (14 samples) with a ratio of 8:2. A fixed random seed of 0 was adopted to ensure reproducibility of the data partition. The testing set was excluded from both model training and hyperparameter optimization and was used only for the final evaluation of the model generalization performance.

Assuming a constant environmental boundary with a fixed Overall Heat Transfer Coefficient (OHTC) strictly governed by the 100 mm silicone rubber insulation, three dynamic operational parameters with a decisive impact on transient flow assurance were selected as input feature variables (X): inlet temperature, inlet velocity and water cut.

To align with the most conservative flow assurance safety criteria, the output target variables (Y) were defined as the asymptotic maximum temperature drop, peak pressure drop, and ultimate gelled oil length under sustained displacement. Before model training,

all input variables were normalized to eliminate the influence of differences in variable magnitude. By targeting the ultimate steady-state limits of these transient parameters rather than their intermediate dynamic trajectories, the surrogate model provides a conservative safety envelope (conservative engineering prediction), ensuring that the millisecond-level early warnings inherently encompass the absolute upper bounds of potential operational risks. Therefore, the predictive capability of the surrogate model is intended for interpolation within the CFD-generated parameter space rather than extrapolation beyond the investigated operating conditions.

2.3.2. Model Construction and Evaluation

Considering the limited size of the CFD dataset, both a Random Forest (RF) model and a Multilayer Perceptron (MLP) model were developed to reduce the risk of overfitting. A fixed random seed (seed = 0) was consistently adopted throughout the training procedure to improve reproducibility.

The MLP consisted of three hidden layers with 64, 32 and 16 neurons, respectively. The ReLU activation function was adopted for all hidden layers, while a linear activation function was used in the output layer for continuous regression. Model parameters were optimized using the Adam optimizer with an initial learning rate of 0.001 ($\beta_1 = 0.9$ and $\beta_2 = 0.999$). The Mean Squared Error (MSE) was adopted as the loss function. L2 regularization with a coefficient of 0.001 was introduced to constrain model complexity. The model was trained using a batch size of 32 for a maximum of 500 epochs. Early stopping with a patience of 30 epochs was employed to prevent overfitting, and the model parameters corresponding to the minimum validation loss were retained.

For the RF model, hyperparameter optimization was performed using Randomized-SearchCV with 5-fold cross-validation. The optimal hyperparameter combination was determined as follows: $n_estimators = 200$, $max_depth = 10$, $min_samples_split = 2$, $min_samples_leaf = 1$, and $max_features = "sqrt"$.

Model performance was quantitatively evaluated using the Root Mean Square Error (RMSE) and the coefficient of determination (R^2) [34]. In addition, 5-fold cross-validation was conducted to evaluate the robustness and generalization stability of both surrogate models. The prediction performance reported in this study is based on the independent testing set, while the cross-validation results are provided to quantify the stability of the surrogate models under different training subsets.

(1) RMSE

RMSE is the square root of the average of the squared differences between the predicted values and the actual values (Equation (1)), representing the average error magnitude between the predicted and actual values. A smaller RMSE value indicates a more accurate model prediction.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (10)$$

(2) R^2

R^2 quantifies the proportion of variance in the dependent variable explainable by the model, indicating the square of the correlation between the model's predicted values and the actual values (Equation (2)). The value of R^2 ranges from 0 to 1; the closer the value is to 1, the more accurate the model's prediction.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (11)$$

2.4. Theoretical Model

To evaluate whether the gelled oil length predicted by CFD and machine learning remains within the operational safety limit, a force-balance-based restart model is employed as a physics-based verification criterion. The physical assumptions underlying this model include static force equilibrium during restart initiation and an approximately uniform gel strength along the gelled pipeline section. Under the assumption of static equilibrium, flow restart is assumed to occur when the pressure-driven wall shear stress exceeds the yield stress of the gelled crude oil formed below its pour point, while also overcoming the hydrostatic head associated with elevation changes in subsea configurations [35,36]. Based on this balance, the critical restart pressure difference can be expressed as:

$$\Delta P = \frac{4L\tau_y}{D} + \rho_{mix}g\Delta H \quad (12)$$

where ΔP is the minimum pressure required to initiate flow, Pa; L is the length of the gelled pipeline segment, m; τ_y is the static yield stress of the crude oil in the gelled state, Pa; D is the inner diameter of the pipeline, m; ρ_{mix} is the average density of the multiphase mixture, kg/m³; and ΔH represents the elevation difference in the gelled segment, m. Rearranging the equation enables estimation of the maximum allowable gelled oil length under a given pumping capacity, thereby defining a clear operational threshold for restart feasibility.

This model provides a physics-based constraint that links fundamental force balance with operational limits, and is further used as a benchmark to assess the consistency of CFD simulations and machine learning predictions under different operating conditions.

3. Results

3.1. Impact of Spatial Geometric Configuration on Flow Assurance

Numerical simulation results indicate that the three-dimensional geometric configuration of the jumper has a decisive impact on the evolution of multiphase interfaces and the efficiency of heat and mass transfer, which directly determines the distribution of gelation risk. To exclude the interference caused by different total pipe lengths, the comparison in this section was conducted over the same displacement distance. Specifically, the flow and thermal fields of the three jumper configurations were analyzed when the hot oil front had propagated approximately 35 m from the inlet. Therefore, the different time instants shown in Figure 6 correspond to the same axial displacement distance rather than the same elapsed commissioning time, allowing the influence of spatial geometry on local mixing, heat transfer, and gelled oil formation to be evaluated more consistently. For consistency across the full manuscript, the gelled oil length is uniformly defined as the volumetric equivalent centerline length derived from the 3D temperature field: the total volume of fluid with temperature below the crude oil pour point (41 °C) is integrated over the computational domain and divided by the pipe cross-sectional area. It should be noted that the gelled oil length values reported in this section are instantaneous values captured at the 35 m displacement distance, and are intended exclusively for cross-geometry comparative analysis.

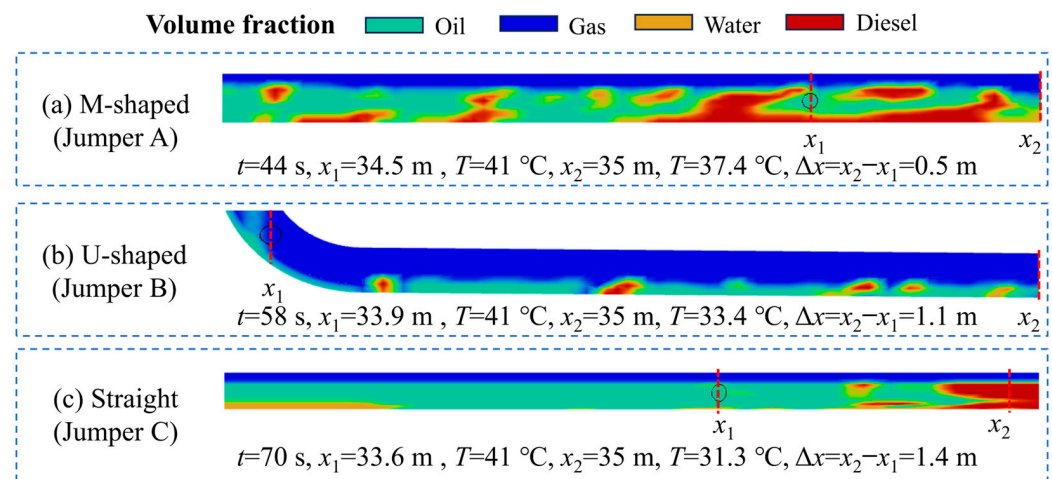


Figure 6. Contours of phase volume fraction and temperature distribution for different jumper configurations at the same displacement distance of approximately 35 m.

As shown in Figure 6, for Jumper A, when the multiphase fluid flows through continuous elbows and inclined sections, significant secondary flows and interface instabilities are induced inside the pipe under the coupled effects of gravity and strong centrifugal forces. This intense turbulent mixing greatly promotes heat exchange and physical dilution between the high-pour-point crude oil and the diesel phase. Simulations show that in the initial stage of commissioning displacement ($t = 44$ s), due to the most adequate mixing, its maximum gelled oil length is only 0.5 m, presenting the lowest system blockage risk. For the U-shaped jumper (Jumper B), the fluid maintains strong mixing kinetic energy when passing through the vertical descending section, but upon entering the long middle horizontal section, affected by gravity stratification, the flow regime gradually degenerates into stable stratified flow, leading to weakened convective heat transfer across the two-phase interface. At $t = 58$ s, the maximum gelled oil length evolves to 1.1 m. For the horizontal straight pipe (Jumper C), acting as the baseline control group, the fluid consistently maintains a clear stratified flow regime with weak shear mixing at the interface, resulting in the maximum suppression of the pour point-depressing effects caused by diesel dilution and heat conduction. At $t = 70$ s, the maximum instantaneous gelled oil length reaches 1.4 m, exhibiting the highest pipeline blockage risk. The gelled oil length here is strictly defined based on a macroscopic equivalent transformation of the 3D temperature field. Specifically, it is calculated as the equivalent centerline length, which is derived by integrating the volume of all computational cells where the local fluid temperature drops below the pour point (41 °C), divided by the pipeline's cross-sectional area. This volumetric-to-linear conversion rigorously mitigates the measurement ambiguity caused by highly asymmetric, 3D eccentric thermal boundary layers induced by secondary flows.

3.2. Sensitivity Analysis

This section focuses on the full 100 m horizontal straight pipe (Jumper C), which presents the highest gelation risk, to further quantify the impacts of inlet velocity and water cut on the fluid dynamics and heat transfer behaviors within the pipe. Unlike the instantaneous local values at 35 m displacement in Section 3.1, the gelled oil length discussed in this section represents the ultimate maximum equivalent gelled oil length of the entire pipeline after complete steady-state displacement, which characterizes the maximum gelation risk of the full pipe under different operating conditions.

3.2.1. Effect of Flow Velocity

As shown in Figure 7, during single-phase displacement of high-pour-point crude oil by diesel, increasing the commissioning flow velocity simultaneously modifies the system's hydraulic and thermodynamic characteristics. Concerning the temperature distribution, after entering the pipeline, the crude oil exhibits an overall decrease in central temperature along the flow direction, forming a downstream-propagating thermal transition zone as commissioning progresses. Under low-velocity conditions, the extended fluid residence time allows more complete radial heat dissipation; consequently, the temperature along the pipeline declines more rapidly, and the location of sharp temperature drop occurs upstream, indicating a slower propagation of the low-temperature front but a stronger cooling effect. As the flow velocity increases from 0.5 m/s to 1.5 m/s, the displacement timescale is significantly shortened, external heat dissipation is reduced, the decay of the oil-head temperature slows, and the maximum temperature drop along the pipeline decreases from 63.8 °C to 55.2 °C. The reduced temperature drop directly mitigates the wax-gelation tendency of the crude oil, shortening the maximum gelled oil length from 8.8 m to 6.6 m, as illustrated in Figure 8. Here, the gelled oil length is strictly defined based on the temperature field, i.e., the region where the crude oil temperature falls below its pour point. Regarding pressure, the pipeline exhibits an approximately linear pressure decline, indicating that frictional resistance primarily governs the pressure drop during commissioning. As crude oil gradually displaces diesel, the increasing proportion of high-viscosity crude oil locally enhances flow resistance, rendering upstream pressure more sensitive. With higher flow velocity, the overall pipeline pressure rises significantly, reflecting that maintaining greater throughput requires a larger driving pressure difference. In summary, increasing the commissioning flow velocity shortens the displacement duration, mitigates along-pipeline cooling, and compresses the gelled oil segment, but simultaneously increases the pressure drop and pumping load. Therefore, selecting an optimal commissioning flow velocity for the jumper pipeline requires balancing anti-gelation safety and pressure-bearing capacity to achieve a trade-off between thermal safety and hydraulic feasibility.

3.2.2. Effect of Water Cut

Under oil–water two-phase transport conditions, the introduction of water simultaneously modifies the fluid's heat transfer characteristics and flow resistance. At a flow velocity of 1.5 m/s, increasing the water cut from 20% to 80% reduces the maximum gelled oil segment length from 17.1 m to 13 m, as shown in Figures 9 and 10. The increase in water cut introduces two competing physical mechanisms to the evolution of the temperature field. On the one hand, changes in the flow regime enhance disturbances and convective heat transfer within the pipeline, potentially accelerating local cooling. On the other hand, water's higher specific heat increases the thermal inertia of the mixture, delaying temperature decay along the pipeline. The pressure distribution further indicates that higher water cut reduces hydraulic resistance during commissioning. Pressure profiles at each time step decrease approximately linearly along the pipeline, demonstrating that frictional losses still dominate the overall pressure drop. Under low water-cut conditions, the profiles at different times are nearly coincident, suggesting minimal variation in flow resistance during displacement. In contrast, at high water cuts, pressure profiles shift downward, and upstream pressure decreases more noticeably over time, implying that a smaller driving pressure difference is required at the same commissioning flow velocity. This effect primarily results from the reduced apparent viscosity of the mixture due to the increased water fraction, while the high specific heat mitigates viscosity increases induced by low temperatures. Consequently, the evolution of the gelled oil segment is determined by the balance between enhanced convective heat transfer and increased thermal inertia. Under

water-containing conditions, the temperature-retarding effect of water's high specific heat predominates, outweighing the accelerated cooling associated with enhanced turbulent mixing. As a result, the region of fluid below the pour point is reduced, leading to a shorter maximum gelled oil segment.

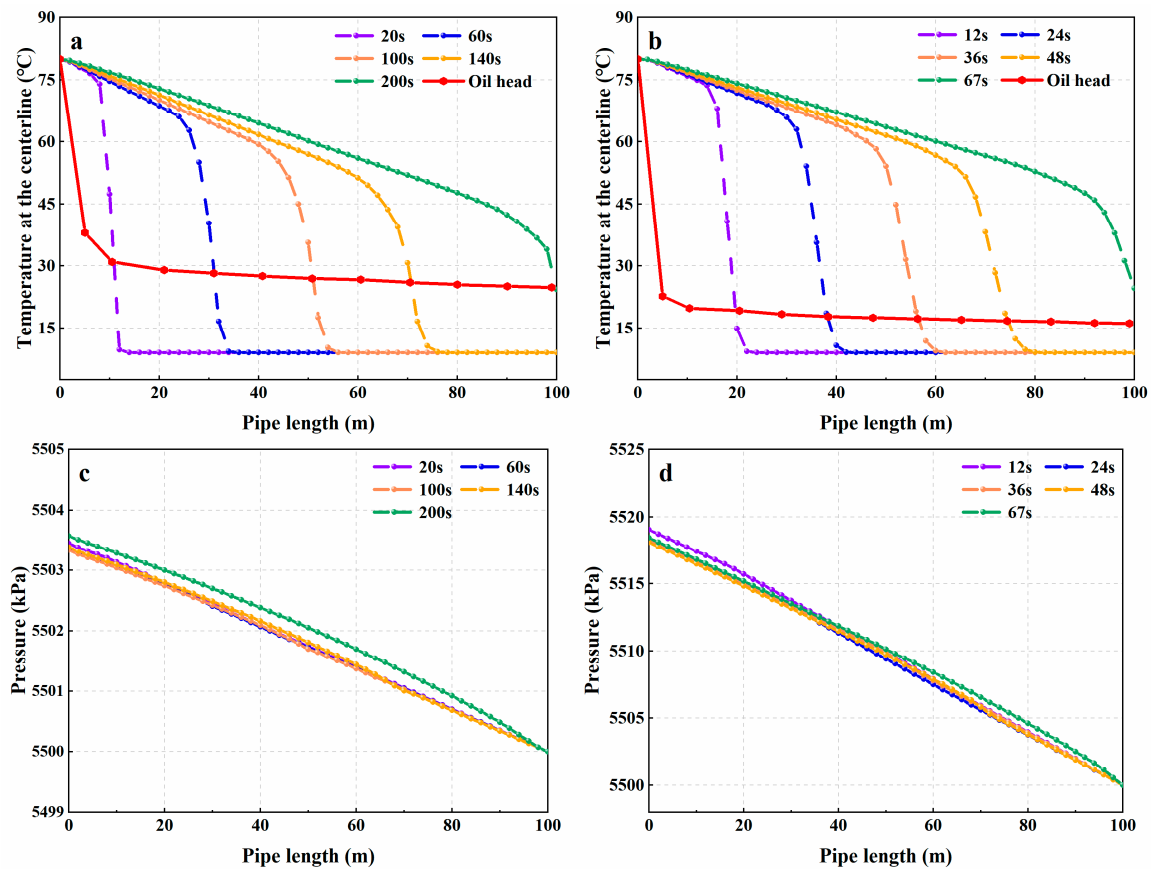


Figure 7. Temperature and pressure variations at monitoring points over time under different flow velocities: (a,c) Velocity = 0.5 m/s. (b,d) Velocity = 1.5 m/s.

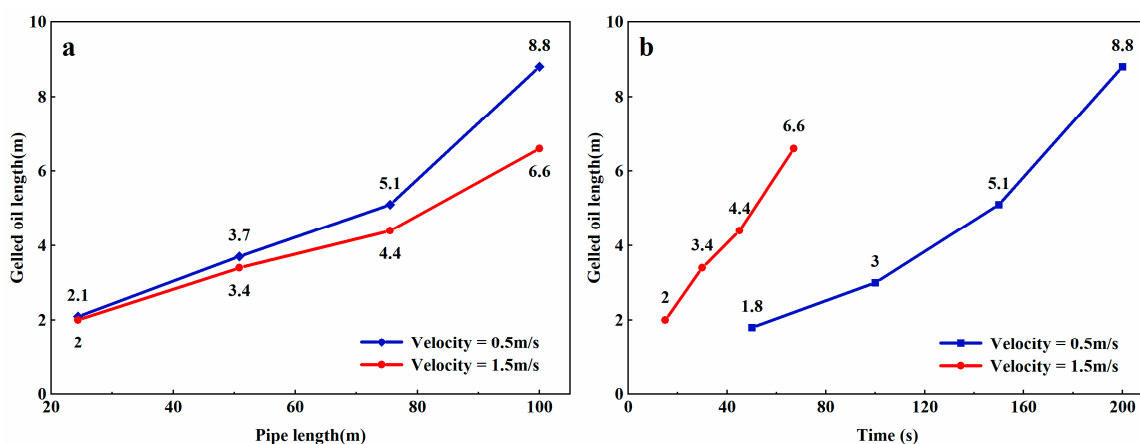


Figure 8. Effect of flow velocity on the maximum gelled oil length: (a) Variation in gelled oil length along the pipeline. (b) Variation in gelled oil length with displacement time.

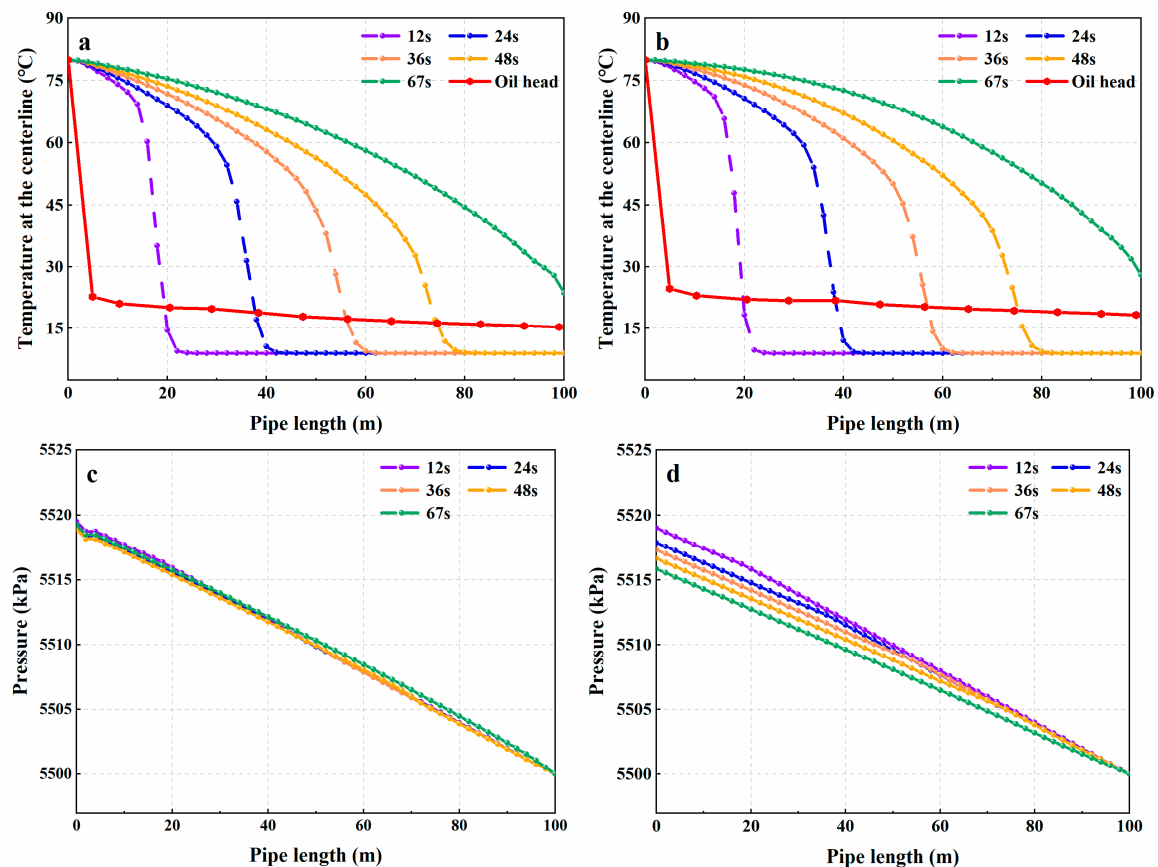


Figure 9. Temperature and pressure variations at monitoring points over time under different water cuts: (a,c) Water Cut = 20%. (b,d) Water Cut = 80%.

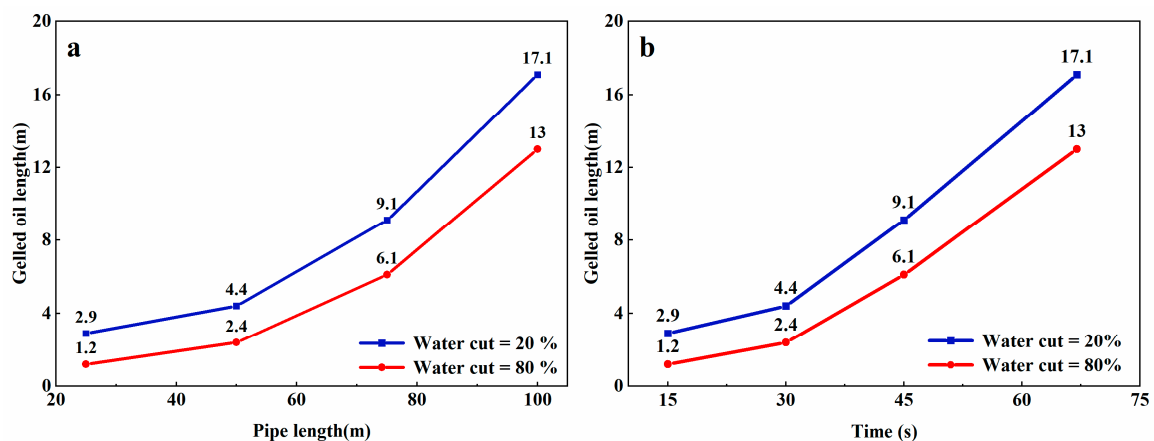


Figure 10. Effect of water cut on the maximum gelled oil length: (a) Variation in gelled oil length along the pipeline. (b) Variation in gelled oil length with displacement time.

3.3. Prediction Performance of the Machine Learning Model

The training loss curve is used to evaluate the convergence and stability of the neural network model. By monitoring the changes in the Mean Squared Error (MSE) of the training and validation sets over the training epochs, whether the model overfits or underfits is analyzed. The optimized model utilizes the Adam optimizer and MSE loss function. During training, the validation loss continuously decreases and closely aligns with the training loss, indicating that the model has good generalization ability. The curve shows convergence after approximately 50–100 epochs, with the validation loss stabilizing at a low level (e.g., $MSE < 0.01$) (Figure 11). In terms of computational efficiency, all CFD simulations were

conducted on the high-performance computing platform equipped with Intel Xeon 6248R processors, with 32 cores allocated for parallel computation for each working condition. The average computational time for a single transient hot-oil displacement working condition is approximately 12 to 15 h. In comparison, the well-trained MLP surrogate model only takes 2 to 3 s to predict the three flow assurance indicators for a single working condition, achieving a computational speedup ratio of approximately 10^4 times. This provides an efficient numerical tool for the rapid parameter optimization and real-time flow assurance risk assessment of deepwater jumper system.

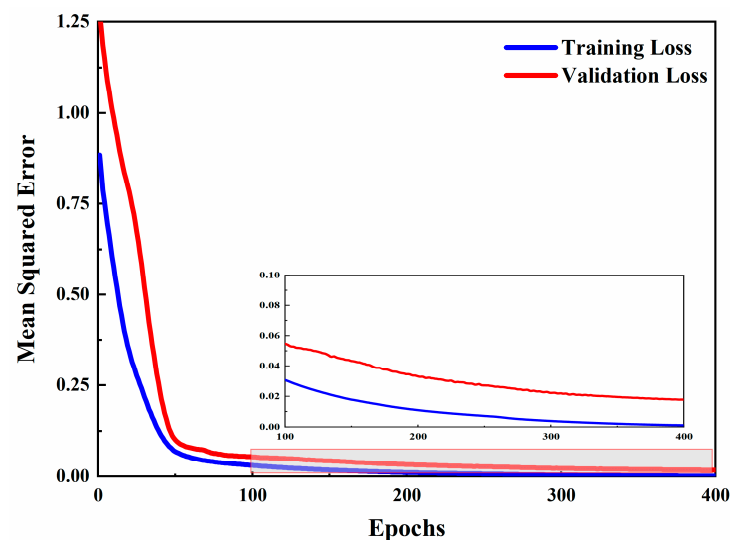


Figure 11. Training and validation loss curves of the optimized MLP neural network over epochs.

Apart from favorable prediction accuracy and generalization, the MLP surrogate model also exhibits extraordinary computational efficiency compared with CFD simulations. All CFD simulations were conducted on the high-performance computing platform equipped with Intel Xeon Gold 6248R processors (Intel Corporation, Santa Clara, CA, USA), with 32 cores allocated for parallel computation for each working condition. The average computational time for a single transient hot-oil displacement working condition is approximately 12 to 15 h. In comparison, the well-trained MLP surrogate model only takes 2 to 3 s to predict the three flow assurance indicators for a single working condition, achieving a computational speedup ratio of approximately 18,000 times. This provides an efficient numerical tool for the rapid parameter optimization and real-time flow assurance risk assessment of deepwater jumper system.

To improve the comprehensiveness and reliability of model evaluation, 5-fold cross-validation results (R^2_{CV}) are introduced in addition to the original test set metrics (RMSE and R^2_{test}). The results are reported as mean $\pm$ standard deviation to quantify performance variability across different training splits, thereby assessing the generalization stability of the model. Table 2 compares the performance of the Random Forest and MLP models on both the independent test set and 5-fold cross-validation. It should be noted that the independent test set is used solely for final model evaluation, while the 5-fold cross-validation is conducted only within the training set. These two evaluation schemes are independent and together provide a comprehensive assessment of predictive accuracy and model robustness.

The results demonstrate that the optimized neural network model outperforms the random forest algorithm across all prediction tasks. The underlying reason for this performance disparity lies in the mathematical characteristics of how these algorithms process physical field data. As a tree-based ensemble method, random forest constructs its prediction space using a series of discrete step functions. When dealing with smooth, continuous non-linear problems governed by partial differential equations (such as the Navier–Stokes and Energy equations) inherent in fluid flow and heat conduction, random forest is prone to truncation errors at the boundaries. Conversely, the MLP model, utilizing continuous ReLU activation functions, shows greater flexibility in capturing nonlinear relationships within the CFD-derived dataset. It can more naturally fit the continuous and smooth temperature and pressure gradients within the multiphase flow system, thereby achieving better predictive performance and generalization on the present dataset, particularly in predicting pressure drop and gelled oil length.

Table 2. Performance comparison of Random Forest and MLP neural network on the test set.

Prediction Target	Model	RMSE	R ²	R ² _{CV} (Mean ± Std)
Max Temperature Drop	Random Forest	4.21	0.87	0.89 ± 0.027
	Neural Network	2.00	0.96	0.95 ± 0.018
Max Pressure Drop	Random Forest	3.13	0.92	0.91 ± 0.021
	Neural Network	0.78	0.99	0.98 ± 0.007
Max Gelled Oil Length	Random Forest	2.67	0.88	0.86 ± 0.025
	Neural Network	1.63	0.94	0.95 ± 0.022

In addition to the statistical metrics, both surrogate models reproduced the same physical variation trends observed in the CFD simulations. Specifically, increasing inlet temperature and inlet velocity reduced the gelled oil length, while increasing water cut generally improved heat retention and further suppressed gel formation. These results indicate that the machine learning models preserve the underlying physical relationships represented by the CFD dataset.

To visually assess the fitting accuracy and generalization capability of the optimized MLP surrogate model, Figure 12 presents scatter plots comparing the CFD-derived actual values with the corresponding model predictions. Three target variables are considered, including maximum temperature drop, maximum pressure drop, and maximum gelled oil length.

As shown in Figure 12, the predicted values for both the training and testing datasets are closely distributed around the ideal parity line ($y = x$), indicating strong agreement between the surrogate model outputs and CFD reference results. This near-linear alignment demonstrates that the model has successfully learned the nonlinear mapping relationship between operating parameters and flow assurance responses generated from the CFD dataset. In particular, the testing dataset, which consists of unseen samples, exhibits a similarly tight error distribution without noticeable outliers or systematic deviation. This indicates that the surrogate model maintains stable predictive performance under new input conditions, confirming its strong generalization capability. The consistency between training and testing performance further suggests that the model is not affected by overfitting, as the learned relationships are not restricted to the training domain but are transferable across the entire dataset space. This behavior is consistent with the high coefficient of determination values reported in Table 2, further supporting the predictive reliability of the proposed surrogate model for rapid prediction of key flow assurance parameters.

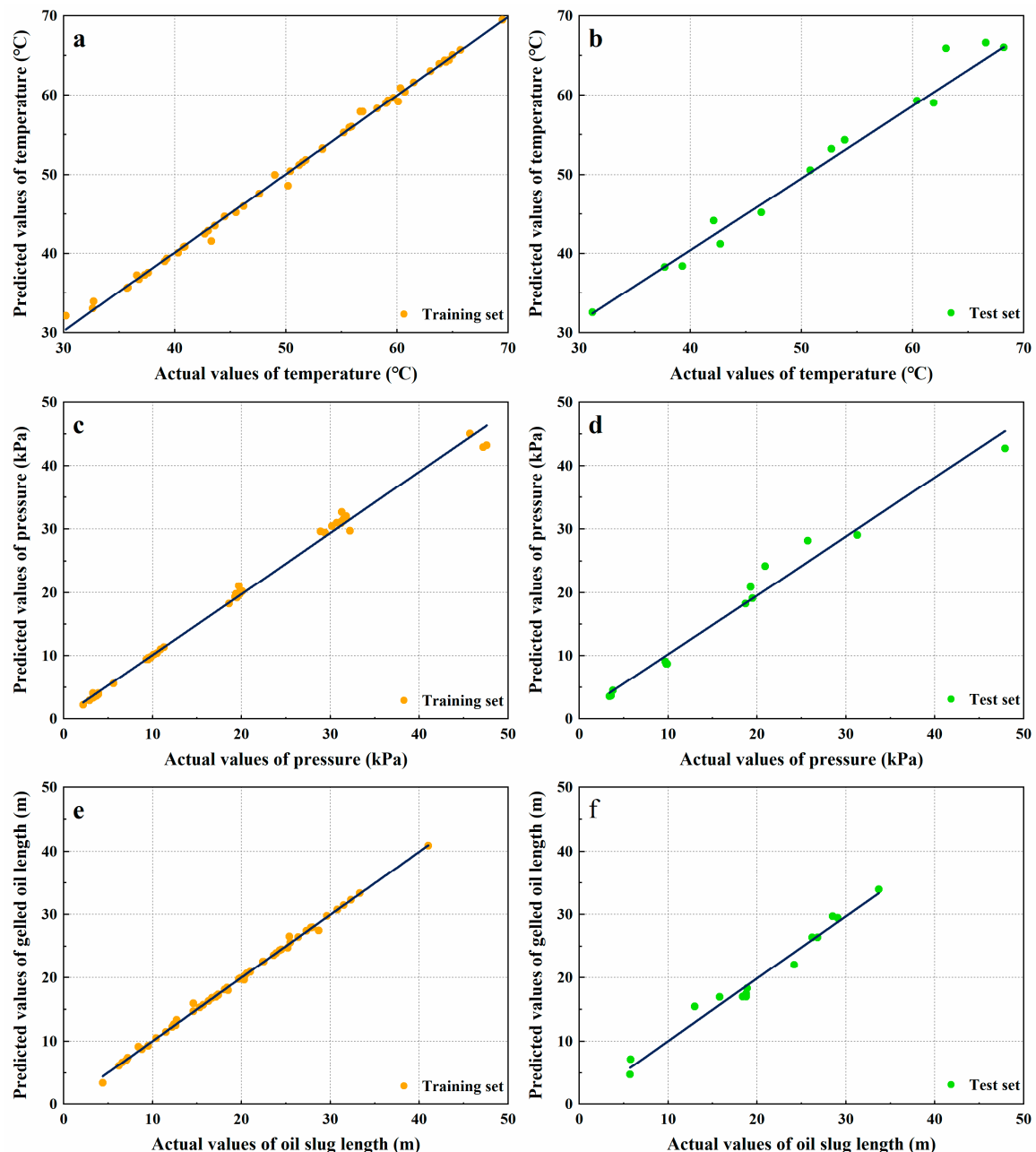


Figure 12. Scatter plots of actual versus predicted values for the training and testing sets. (a) Temperature prediction results of the training set; (b) Temperature prediction results of the test set; (c) Pressure prediction results of the training set; (d) Pressure prediction results of the test set; (e) Gelled oil slug length prediction results of the training set; (f) Gelled oil slug length prediction results of the test set.

4. Discussion

4.1. Comparison with Baseline Methods

To further evaluate the advantages of the proposed method, a comparison with existing flow assurance analysis approaches is necessary. CFD-based methods can provide accurate physical descriptions of multiphase flow and heat transfer; however, they are computationally expensive and therefore not suitable for rapid engineering prediction. In contrast, one-dimensional or empirical models offer high computational efficiency but are limited in their ability to capture three-dimensional transient flow and heat transfer phenomena in complex subsea jumper configurations. Purely data-driven machine learn-

ing surrogate models, while computationally efficient, are generally dependent on the distribution of training data and may exhibit limitations in physical consistency and generalization capability under unseen operating conditions. Compared with these baseline approaches, the proposed CFD–machine learning coupled framework achieves a balanced improvement. It retains the physical fidelity of CFD simulations while significantly reducing computational cost through the surrogate model. As a result, it provides an effective trade-off between accuracy and efficiency, making it more suitable for engineering scale rapid flow assurance assessment.

4.2. Model Applicability and Methodological Assumptions

This study proposes a CFD–machine learning integrated framework for analyzing deepwater jumper hot-oil commissioning processes under conditions where field measurements and full-scale experimental data are not yet available. The surrogate model is developed exclusively on CFD simulations and rigorously validated through grid independence tests, physics-consistency checks, independent test set evaluation, and 5-fold cross-validation. These results demonstrate that the proposed framework provides a computationally efficient and physically consistent tool for rapid evaluation and comparative screening of operational scenarios. However, its predictive capability is strictly confined to the parameter space represented by the CFD dataset, and should therefore be interpreted as a physics-informed interpolation tool rather than a general-purpose predictor.

From a methodological perspective, the CFD model is constructed based on several physically motivated assumptions to ensure a tractable representation of the real system. The VOF method is adopted to capture the oil–diesel interface, while interphase diffusion and mutual solubility are neglected due to convection-dominated transport. A constant seabed temperature is assumed to represent relatively stable deep-sea thermal conditions. In addition, experimentally measured crude oil rheological properties are used, and second-order spatial discretization together with strict time-step control and mesh independence verification are employed to minimize numerical errors. These assumptions collectively define a controlled physical abstraction that enables efficient surrogate modeling while preserving the dominant transport physics.

4.3. Limitations and Future Perspectives

Despite the satisfactory predictive performance of the proposed framework within the CFD-defined domain, its applicability is fundamentally constrained by the nature of its underlying data source. Both the CFD and surrogate models are exclusively trained on numerical simulation data, while field measurements and full-scale experimental observations for deepwater jumper hot-oil commissioning processes remain unavailable. Consequently, the model exhibits reliable interpolation performance within the training distribution but lacks validated extrapolation capability beyond the sampled parameter space. This reflects the inherent epistemic uncertainty of data-driven surrogate modeling in complex multiphase thermal systems without real-world calibration.

To overcome these limitations, future work will focus on integrating laboratory-scale loop experiments and field monitoring data to improve model calibration and physical fidelity. Furthermore, uncertainty quantification methods will be incorporated into the prediction framework to explicitly characterize confidence bounds and enhance robustness under operational variability. These developments are expected to further improve the engineering reliability of the proposed framework and support risk-informed decision-making in offshore thermal transport applications.

5. Conclusions

This study developed an integrated framework combining CFD-based mechanistic analysis and machine learning prediction to evaluate flow assurance risks during hot oil commissioning of deepwater high-pour-point crude oil. A three-dimensional transient VOF-CHT numerical model was established to simulate the multiphase flow and heat transfer behavior during the displacement of cold diesel by hot crude oil. Based on the CFD simulation database, machine learning surrogate models were further developed to enable rapid prediction of key flow assurance parameters. The main conclusions are as follows:

1. The spatial configuration of subsea jumpers has a significant influence on interfacial mixing, heat transfer enhancement, and local gelation risk. Under the same displacement distance, the M-shaped and U-shaped jumpers induce stronger secondary flow effects due to the presence of continuous bends and inclined pipe sections. These secondary flows enhance interfacial mixing and heat exchange between the hot oil front and the cold diesel phase, thereby reducing the risk of crude oil gelation. In contrast, the straight pipe exhibits weaker interfacial mixing and a more pronounced stratified-flow pattern, resulting in the largest equivalent gelled oil length of 1.4 m. Overall, the equivalent gelled oil length follows the order of M-shaped jumper < U-shaped jumper < straight pipe.
2. Increasing the commissioning velocity effectively reduces the equivalent gelled oil length by shortening the residence time of the hot fluid in the cold deepwater environment and suppressing heat dissipation. When the inlet velocity increases from 0.5 m/s to 1.5 m/s, the equivalent gelled oil length decreases by approximately 25%. Under oil–water two-phase flow conditions, increasing the water cut further mitigates gelation risk. As the water cut increases from 20% to 80%, the equivalent gelled oil length decreases from 17.1 m to 13.0 m. This reduction is mainly attributed to the enhanced overall heat capacity and thermal inertia of the mixed fluid, as well as the decrease in apparent flow resistance caused by the introduction of the water phase. Therefore, higher water cut can improve both anti-gelation performance and hydraulic characteristics during hot oil commissioning.
3. Based on the CFD simulation database, machine learning surrogate models were constructed using random forest and multilayer perceptron neural network algorithms to rapidly predict the maximum temperature drop, maximum pressure drop, and equivalent gelled oil length. Compared with the random forest model, the multilayer perceptron neural network exhibited stronger nonlinear mapping capability for complex multiphase flow and heat transfer data. The coefficients of determination, R^2 , for all three target parameters exceeded 0.94. These results indicate that the proposed machine learning prediction model can provide effective support for rapid screening, parameter optimization, and preliminary risk assessment of hot oil commissioning schemes for deepwater subsea jumpers.

It should be noted that the machine learning surrogate model developed in this study remains a CFD-based numerical proof of concept. Although the CFD data can capture the coupled characteristics of multiphase flow and heat transfer during hot oil commissioning, the results still depend on certain engineering assumptions and idealized boundary conditions. Future work should incorporate uncertainty quantification and further calibrate and validate the model using offshore field commissioning data or large-scale flow-loop experimental data, in order to improve its robustness and engineering applicability.

Author Contributions: Conceptualization, P.L. and S.D.; methodology, P.L.; software, S.D.; validation, P.L., Q.X. and W.W.; formal analysis, Q.X. and W.L.; resources, P.L. and X.L.; data curation, S.D.; writing—original draft preparation, S.D. and Q.X.; writing—review and editing, P.L. and Q.X.; visualization, W.L. and W.W.; supervision, J.C.; project administration, J.C.; funding acquisition, X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Research Project of CNOOC Research Institute Co., Ltd., grant number CCL2024RCPS0376PSN.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to commercial confidentiality agreements with the cooperating enterprise.

Conflicts of Interest: Authors Pengcheng Li, Qi Xiang, Weican Wang and Jinghua Chen were employed by the company CNOOC Research Institute Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that this study received funding from CNOOC Research Institute Co., Ltd. The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article or the decision to submit it for publication.

Abbreviations

The following abbreviations are used in this manuscript:

CFD	Computational fluid dynamics
CHT	Conjugate heat transfer
MLP	Multilayer perceptron
RMSE	Root mean square error
R ²	Coefficient of determination
TS-PINN	Two-stage physics-informed neural network
UDFs	User-defined functions
VOF	Volume of fluid
XGBoost	Extreme gradient boosting

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