

Intelligent deepwater energy development: Flow assurance monitoring and smart decision-making system

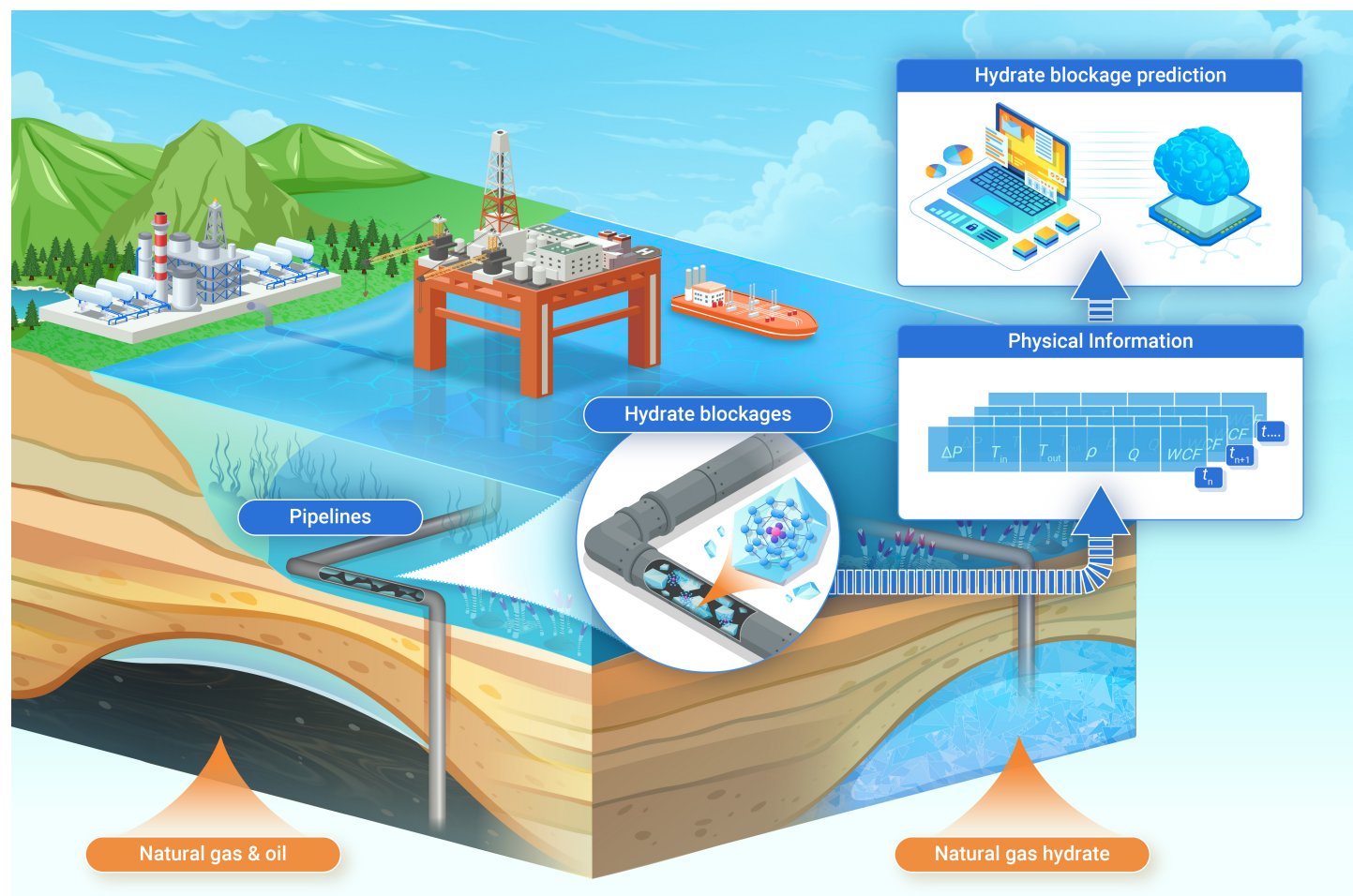
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- A physics-informed deep-learning model for hydrate blockage prediction is developed.
- Two-stage evolution of the fluid differential pressure during hydrate blockage formation is revealed.
- Hydrate blockage prediction is defined as an unsupervised anomaly detection problem.
- The Transformer-LSTM-VAE (TLV) model is developed based on the Variational Auto-Encoder framework.
- The TLV model achieves superior performance in evaluations (F1-score=0.969).

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Deepwater hydrocarbon resources (oil, gas, and hydrate) constitute an important part of the world's existing and emerging energy landscape. The high hydrostatic pressure, low temperature, and complex geological structures of deepwater environments present significant challenges for energy development. The development of flow assurance monitoring and intelligent decision-making systems to quantify the risk of hydrate blockage is a prerequisite for safe and efficient development. In this work, the hydrate growth and blockage under varying liquid loading, pump speed, pipe inclination, subcooling, and oil-water ratio were investigated using a high-pressure visual flow loop. A database containing 27 sets of tests with about 510,000 pieces of data was created. The evolution of differential pressure in oil-gas-water-hydrate multiphase flow was found to have two stages. Stage I, differential pressure remains stable or rises slightly with increasing hydrate concentration. Stage II, differential pressure changes abruptly after the hydrate reaches the critical concentration. Therefore, the prediction of hydrate blockage was defined as an unsupervised anomaly detection problem. The Transformer-LSTM-VAE (TLV) blockage prediction model was developed based on the Variational Auto-Encoder framework. The Transformer and LSTM models were utilized as encoder and decoder, respectively. Two uneven weight adjustment methods were proposed to achieve earlier warnings of blockage. In systematic comparisons with three classic and two state-of-the-art machine learning models, the TLV model consistently performed the best with an F1-score of 0.969. The TLV model demonstrated the potential of deep learning methods in deepwater energy development.

INTRODUCTION

According to a study by the International Energy Agency (IEA), total natural gas consumption is expected to increase by 40% by 2024.¹ Natural gas, as a stable and clean energy source, produces only a small amount of carbon dioxide when burned. Global demand for natural gas is rising to support the Paris Agreement and the Sustainable Development Goals.² Marine hydrocarbon resources (natural gas, gas hydrate, oil) with significant reserves, particularly in deepwater, are becoming major contributors to global energy. Deepwater oil and gas reserves discovered in the last decade account for 60% of the world's total reserves,^{3,4} while the organic carbon in gas hydrates exceeds twice that of all known conventional fossil fuel sources.⁵ The South China Sea, as one of the world's four major marine hydrocarbon resource aggregation centers, is referred to as the Second Persian Gulf.

The high hydrostatic pressure, low temperature, and complex geological structures of deepwater environments present challenges for the transportation of hydrocarbon resources from the reservoir to the wellhead equipment and from the subsea pipeline to the downstream facilities.⁶ The multiphase transportation of gas, oil, and water encounters several threats, including hydrate blockage, wax deposition, dangerous flow patterns, and multiphase flow corrosion.⁷⁻⁹ The occurrence of these issues can cause production cuts or shutdowns, equipment damage, crude oil spills, and even marine ecological disasters.¹⁰ However, research on solid-phase blockage monitoring and detection technologies, wall corrosion detection technologies, and flow assurance management technologies needs to be further refined. Deepwater

energy development is currently one of the world's relatively less digitized industries, well below the global industry average¹¹. The recent boom in artificial intelligence technologies has rendered them powerful tools for addressing the high-dimensional nonlinear problems prevalent in deepwater energy development.^{12,13} The massive amounts of production data generated in deepwater energy development created a fertile ground for the application of advanced information technologies. The integration of big data analytics, artificial intelligence algorithms, and advanced measurement technologies for yield optimization, real-time monitoring, and intelligent decision-making has become an inevitable trend (Figure 1).¹⁴⁻¹⁶

Hydrate blockage is a critical concern in deepwater energy development due to its rapid formation (several hours) and enormous hazards (shutdowns, equipment damage, casualties, oil spills).¹⁷⁻¹⁹ In the absence of flow assurance monitoring and intelligent decision-making systems, most areas of the energy development system are in a black box. The amount and location of hydrate formation cannot be determined. Therefore, in shallow water development, the thermodynamic hydrate inhibitors (THI) are injected at any cost to alter hydrate phase equilibrium conditions, achieving complete avoidance.²⁰ In deepwater development, the THI-based complete avoidance strategy is not practical. The significant demand for THI (60 vol%) in deepwater development exacerbates the economic costs and ecological threats.²¹ In recent years, the control strategy for hydrate blockage has shifted from complete avoidance to risk management, allowing the presence of hydrate without causing blockage¹. Accurately quantifying the risk of operating within the hydrate formation region is the key to a successful risk management strategy.^{22,23} Therefore, there is an urgent demand for flow assurance monitoring and intelligent decision-making systems to realize information-based deepwater energy development.

The physical regularities embedded in the challenges of deepwater energy development guarantee the research of a physics-informed neural network. Hydrate blockage is a non-equilibrium phase transition process that occurs in multiphase flow, involving multiphase hydrate growth kinetics (microscopic),^{24,25} particle motion kinetics (mesoscopic),²⁶ and flow pattern evolution (macroscopic).²⁷ The blockage characteristics vary with transport systems (oil/water/gas-dominated, partially dispersed),²⁸ pipe configurations (horizontal, vertical, inclined, dead leg),²⁹ thermodynamic conditions (pressure, temperature)³⁰ and hydrodynamic conditions (unsteady pressure). Karpenko et al.³¹ analyzed the influence of hydrodynamic processes on the fluid flow characteristics using CFD methods, considering the shapes, connections, and positions (vertical, horizontal, diagonal) of the pipelines. Sloan et al.³² proposed the four-step conceptual model for hydrate blockage in oil-dominated systems, along with the CSMHyK model, which is the first transient risk assessment model developed specifically for the oil-dominated system. However, related research on other transport systems is still at the exploratory stage. Furthermore, the inevitable simplifications and assumptions made during mathematical modeling limit the applicability of these models in the field. The hydrate phase transition that occurs in a multiphase flow environment is essentially a multivariate high-dimensional nonlinear problem,¹⁶ making the establishment of accurate mathematical equations challenging. Some researchers have made initial attempts to predict hydrate blockage using data-driving machine learning methods,^{33,34} where hydrate

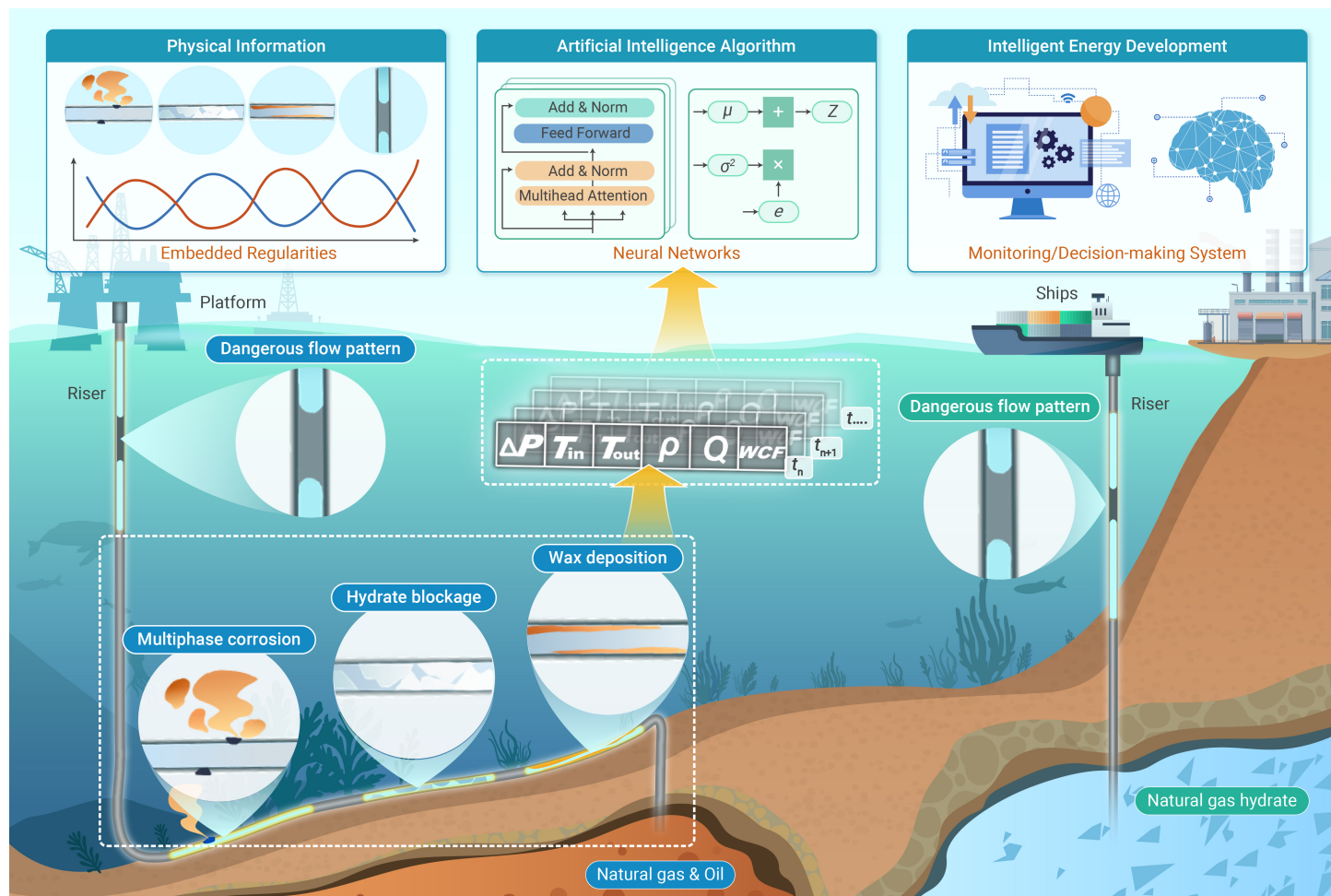


Figure 1. Challenges in deepwater hydrocarbon energy development and informatization development approaches

blockage prediction was formulated as a classification problem and addressed through supervised learning methods. Indeed, the performance of supervised learning methods heavily relies on the quality of data labeling.³⁵ However, accurate and timely labeling of production data is challenging for engineers in the fields. In contrast, unsupervised learning relies on the inherent regularities rather than labels of data.³⁶ In general, the flow parameters are relatively stable during normal transportation. Hydrate blockage is a cumulative process involving the formation, agglomeration, and deposition of particles, developing in a time series manner.³⁷

Therefore, hydrate blockage prediction was formulated as an unsupervised time-series anomaly detection problem in this work. The physical regularities of hydrate blockage were investigated under various liquid loadings (LL), oil-water ratio (OWR), pump speeds, pipe inclination, and subcooling conditions using a pilot-scale high-pressure visual flow loop. A deep-learning hydrate blockage prediction model, Transformer-LSTM-VAE (TLV), was proposed. The TLV model was developed based on the Variational Auto-Encoder (VAE) framework utilizing Transformer and long-short-term memory (LSTM) as the encoder and decoder models, respectively. Two uneven weight adjustment (UWA) methods were further proposed to enable the TLV model to provide earlier warnings of hydrate blockage.

METHODOLOGY

Hydrate blockage experiment

The dataset significantly impacts the performance of artificial intelligence algorithms. With the support of high-quality and large-scale training data, deep learning techniques demonstrate stronger predictive capabilities than traditional machine learning methods.³⁸ Furthermore, the smaller the discrepancy between the training and practical production data, the higher the generalizability of the model. Based on the two guidelines, we have estab-

lished a large dataset for training and evaluation, which contains 509,494 laboratory data entries. To obtain a substantial amount of high-quality data, a pilot-scale, high-pressure visual flow loop was constructed to minimize the discrepancy between experiments and actual production.^{27,39} The loop contained vertical, horizontal, and inclined piping configurations, as shown in Figure S1.

Five basic variables were rotated as independent variables: LL (40–80%), OWR (0–3), pump speed (62.3–124.6 Revolutions Per Minute (RPM)), pipe inclination (0°–90°), and subcooling (3–12 °C). The selection of basic variables is based on their influence on hydrate formation and blockage as well as the feasibility of altering these parameters. Orthogonal experiments were designed to cover as many working conditions as possible. In each hydrate blockage test, the directly measured dependent variables included temperature (T), pressure, differential pressure of pump (ΔP), mixed mass flow rate, and fluid density (ρ). The dependent variables obtained by calculation included volume flow rate (Q_m) and water conversion fraction (WCF). A Sankey diagram was used to illustrate the structure of laboratory data, which contained the variable values, combination methods, and data proportions (Figure 2). Although the hydrate blockage process varies across different tests, the early warning method based on differential pressure is applicable, which will be discussed in detail in Section 3.1. A detailed description of the flow loop and experimental procedures are presented in supplemental information.

Model design

Model Architecture. The architecture of the hydrate blockage prediction model (TLV) developed in this study is shown in Figure 3. The model is built based on the VAE framework. Transformer and LSTM layers are used as encoder and decoder, respectively. Two layers of Transformer block are

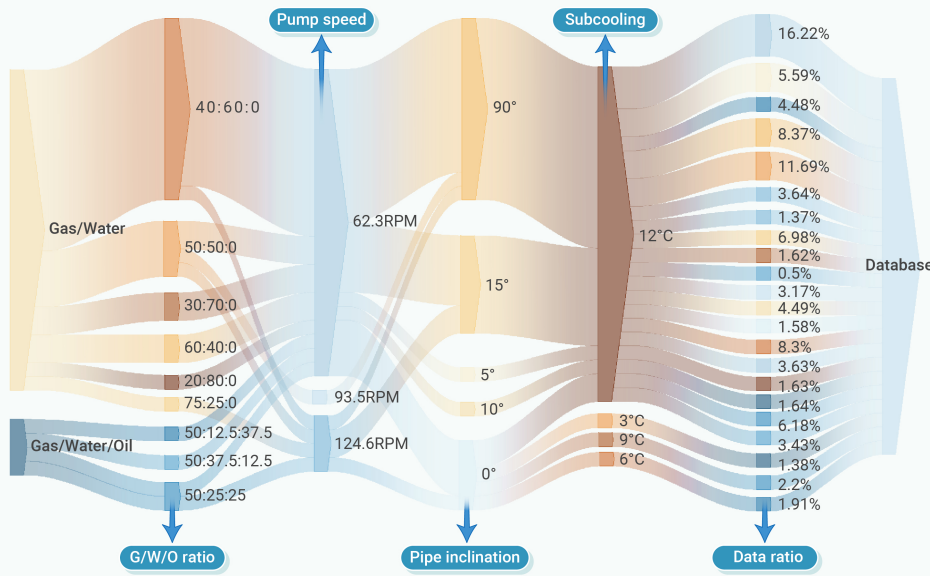


Figure 2. Sankey diagrams of data structure. G/W/O ratio refers to the volume ratio of gas, water, and oil in the flow loop, encompassing two basic variables: liquid loading and oil-water ratio. Pump speed is measured in revolutions per minute (RPM). Pipe inclination 0-15° refers to the slope of the middle section, and 90° indicates the opening of the riser. Data ratio refers to the proportion of data in the database for this test condition.

dependence on previous time steps during the decoding process, which is important for reconstructing sequence data. The cell state and gating mechanism of LSTM enable the network to retain useful information from the previous time step while reconstructing data at each time step. In summary, the VAE framework-based TLV model with Transformer encoder and LSTM decoder is proposed for hydrate blockage prediction.

Threshold Value Setting and Uneven Weight Adjustment. Different from traditional classification models, the TLV model outputs

stacked inside the encoder and each Transformer block embedding dimension is 6. The number of heads in the multihead attention mechanism is 4 and the number of neurons in the feedforward neural network is 16. The decoder contains an LSTM Layer with 16 neurons. The latent space dimension is set to 16. The multivariate time series data is serialized via the sliding window algorithm and positional embedding module before being fed into the TLV model. The value of d_{model} of positional embedding module is equal to the number of input features, which is equal to 6. The input features include ΔP , inlet temperature (T_{in}), outlet temperature (T_{out}), ρ , Q_{in} , and WCF. The VAE encodes and decodes the input parameters to obtain the reconstructed input. The anomaly detector determines the reconstruction error by comparing the difference between the reconstructed input and original input. By comparing the reconstruction error value with the threshold, the TLV model determines whether the transportation is in a safe region. In the training phase, the Kullback-Leibler (KL) and mean squared error (MSE) loss functions were used to optimize the model parameters. In the testing phase, thresholds were calculated based on the reconstruction error. Furthermore, two Uneven Weight Adjustment (UWA) methods are developed to adjust the threshold to achieve early warning.

The VAE framework has significant advantages in addressing anomaly detection problems. VAE combines variational inference and auto-encoder, aiming to control the distribution of latent space while reconstructing the original data. The distribution of the original data is approximated as closely as possible by maximizing the marginal log likelihood probability of input data. In this work, we use VAE to build a continuous and structured latent space via the normal flow parameters of transportation lines and, in turn, reconstruct the normal data by transversing the latent space. In the latent space, the distribution of normal (safe) data is more concentrated and ordered than that of abnormal (risk) data. The difference in data characteristics leads to large errors when reconstructing abnormal data. Then, the TLV model differentiates the normal and abnormal data based on reconstruction errors.

The encoder is used to project the multivariate high-dimensional input into the latent space by converting time series into probability distribution parameters (e.g., mean and variance in multivariate Gaussian distribution). During hydrocarbon transportation, flow parameters usually change slowly with time. Owing to the self-attention mechanism, the Transformer model is good at capturing these long-term dependencies. Furthermore, the multi-head attention mechanism enables the Transformer to learn relationships between flow parameters and extract effective latent space. The decoder maps the points in the latent space back to the data space based on the mean and variance from the encoder. The reconstructed data must be close to the original input. LSTM can generate coherent and logically consistent sequences based on the recursive structure. Furthermore, LSTM can maintain long-term

the reconstructed data. The reconstruction error between the original and reconstructed data is used to determine if it is safe at that moment, which is calculated as:

$$\text{error} = \frac{1}{dT} \sum_{i=1}^T \sum_{j=1}^d (y_{ij} - \hat{y}_{ij}) \quad (1)$$

where T is the time point, d is the feature dimension, y_{ij} and $\hat{y}_{ij}$ are the original and reconstructed data, respectively. If the reconstruction error is greater than the threshold, the input is abnormal (risk), and vice versa.

Owing to the proportion of risk data being higher than that of safe data, the typical “3 σ ” threshold-determining method is inapplicable. Therefore, an individual sub-dataset is separated from the database for threshold calculation. Specifically, an error series is obtained by feeding the sub-dataset into the trained TLV model. The value at a specific percentile in the error series is the threshold (Equation 2).

$$\text{Threshold} = \text{percentile}(\text{list}_{\text{error}}, \text{percent}) \quad (2)$$

where the *percentile* is a function that calculates the percentile. The *percent* is designed as a hyperparameter in the model. The percentile range was usually between 80% to 95%.

Furthermore, two UWA methods for reconstruction error series calculation are proposed to improve the model's ability to find the imminent hydrate blockage. In normal reconstruction error calculations, each time point in a subsequence has the same weight (Equation 2). The UWA methods assign higher weights for the later points in a time subsequence. By amplifying errors, the TLV model can capture anomalies at an early stage, which is crucial for actual production. Specifically, UWA includes linear and quadratic methods. The t points are sampled uniformly between 0 and 1 (Equation 3).

$$W = \{s_1^n, s_2^n, s_3^n \dots s_t^n\} = \{w_1, w_2, w_3 \dots w_t\} \quad (3)$$

where $S_i = 0$, $S_t = 1$, $S_{k+1} - S_k = S_k - S_{k-1}$. W is the weight before normalization. For the linear method, $n = 1$. For the quadratic method, $n = 2$. To maintain consistency in magnitude, W is normalized as:

$$w'_i = \frac{w_i}{\sum_{i=1}^t w_i} \quad (4)$$

$$\sum_{i=1}^t w'_i = 1 \quad (5)$$

The reconstruction error is calculated as

$$\text{error}' = \frac{1}{d} \sum_{i=1}^T w'_i \sum_{j=1}^d (y_{ij} - \hat{y}_{ij}) \quad (6)$$

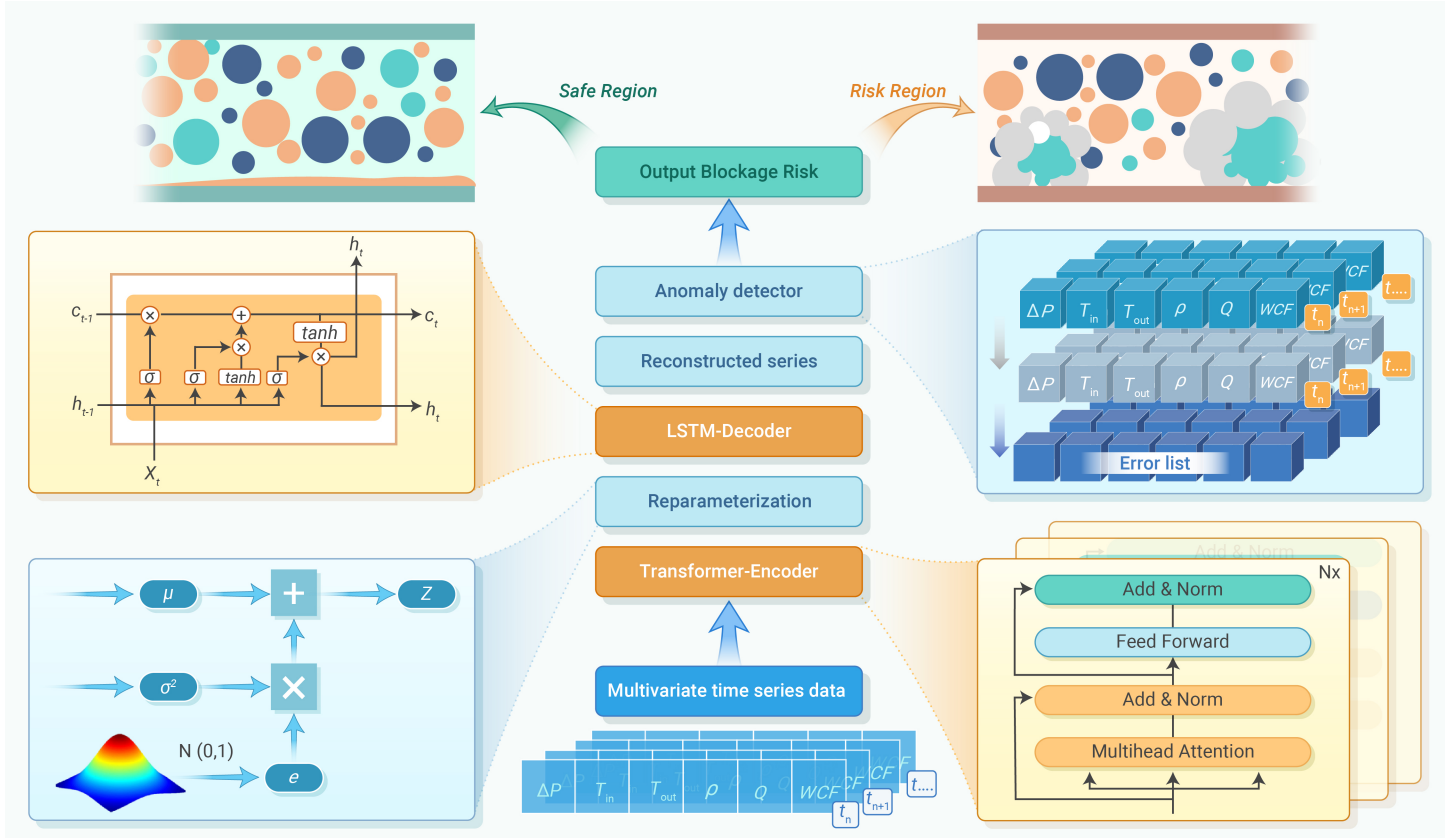


Figure 3. Schematic of TLV model architecture The arrows indicate the order of the model's operations. The panels on both sides illustrate the schematic of the vital modules.

Model evaluation

Experiment Environment. We built the TLV model with the TensorFlow deep-learning framework configured with Adam optimizer (Table S2). The learning rate was 0.001, and the epoch was 15. The threshold value was set to 90%. The 1650 Ti GPU was used for model training and inference.

Experiment Procedure. The database was divided into the training set, threshold calculation set, and testing set. All data were split into fixed-size overlapping time subsequences via the sliding window method. A fixed-size window was moved along the time series, and the data within the window was extracted as a time subsequence at each step of the move. The window contained 64 points of data. The sliding step of the window was 1. In production, operating conditions will evolve with time. For instance, the water cut during the development continues to increase as the field matures. Therefore, two sets of data with extreme operating conditions (No. 16-17) were used entirely as testing sets to evaluate the model's generalizability (15,146 normal and 35,400 abnormal time subsequences). The normal data in the remaining dataset was divided into training (136,292 time subsequences) and threshold calculation (34,074 time subsequences) sets in an 8:2 ratio with a five-fold cross-validation. The abnormal data (286,662 time subsequences) in the remaining dataset was also used as the test set. The training set was normalized to follow a normal distribution. Then, the testing and threshold calculation sets were normalized using the mean and standard deviation of the training set. We further shuffled the order of the time subsequences to improve the generalization and robustness of the model.

The objective of the model training was to make the reconstructed sequence as similar as possible to the original sequence. We froze the model parameters after the specified training epochs, input the threshold calculation set, and determined the threshold based on Equation 2. Finally, the risk of blockage of the input parameters was determined based on the threshold and reconstruction errors. We calculated the performance metrics, including Accuracy, Recall, Precision, and F1-score, as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (7)$$

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

$$Recall = \frac{TP}{TP + FN} \quad (9)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (10)$$

where TP, TN, FP, and FN refer to the number of true positives, true negatives, false positives, and false negatives, respectively. We compared the performance metrics of the TLV model with that of the baseline models. Then, we conducted ablation experiments by fixing the model architecture and replacing various encoders and decoders.

RESULTS AND DISCUSSION

Physical basis of hydrate blockage prediction

As pressure drop and flow rate reflect the flow conditions in the pipeline, the three-dimensional scatter plots illustrate the evolution of Q_m and ΔP with WCF (Figures 4-5) in five independent variable systems. The hydrate blockage processes at different LL (40-80 % LL (Figure 4A-E), OWR = 0) are present in Figure 4. The Q_m of the mixed fluids fluctuated with hydrate formation, decreasing, increasing, and finally decaying. The increase in LL weakened the fluctuation in the Q_m . Furthermore, the evolution of ΔP in various LL showed the same pattern. Stage I: ΔP jumped rapidly in small increments followed by stabilization or slow increase. Stage II: ΔP increased dramatically after the WCF reached the critical point, which was denoted as φ (gray planes). The evolution of ΔP with WCF in all tests was compared in Figure 6A. The ΔP increased with increasing LL at the same hydrate concentration, and the φ was approximately linearly related to the LL.

The concentration and movement of hydrate particles determined the evolution of ΔP and Q_m . In stage I, the small increase in ΔP was caused by the transition from gas-liquid two-phase flow to gas-liquid-solid three-phase flow, corresponding to the appearance of hydrate particles. Then, ΔP remained stable until the critical point owing to the carrying capacity of the

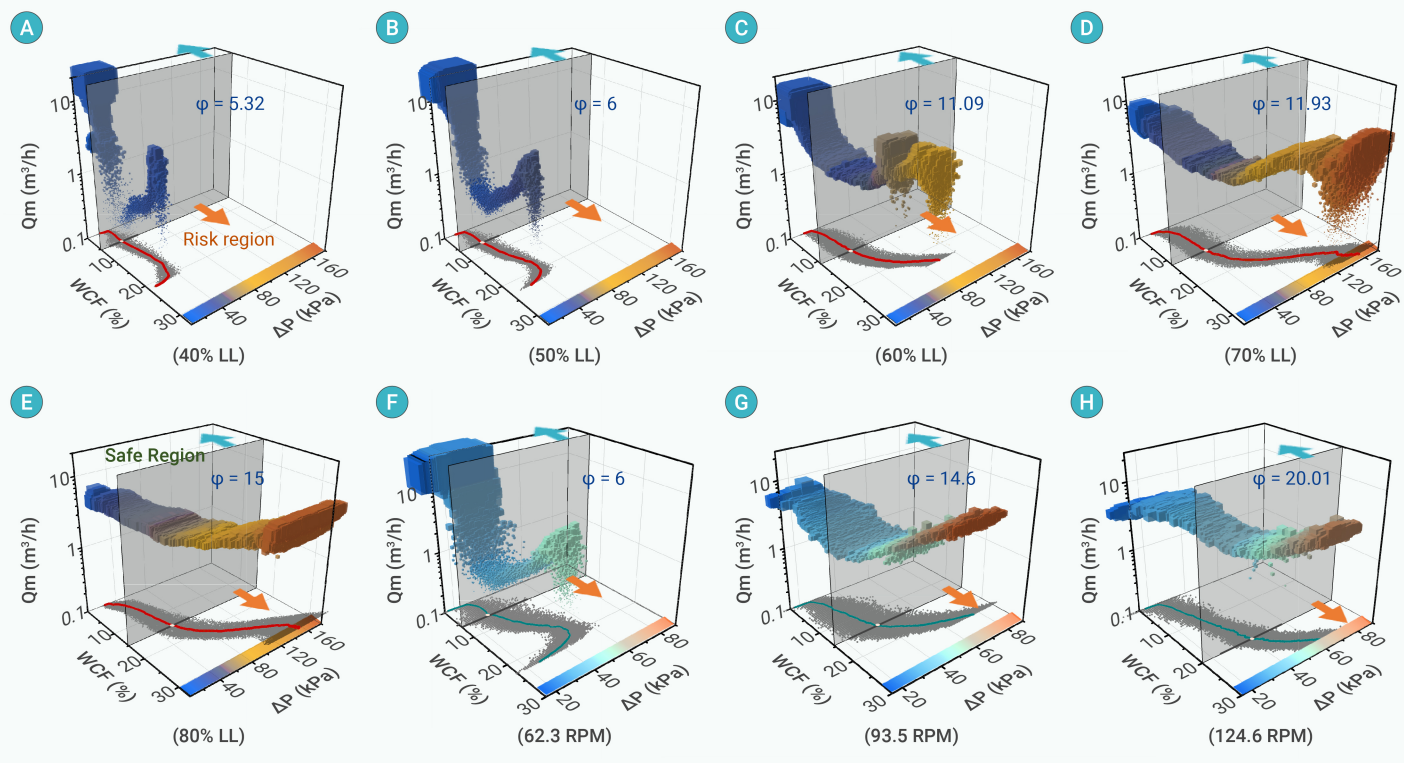


Figure 4. Three-dimensional scatter plots of the evolution of volume flow rate (Q_m) and pressure drop (ΔP) with water conversion fraction (WCF). Panels A-E illustrate liquid loading from 40% to 80%, respectively. Panels F-H illustrate pump speeds from 62.3 to 124.6 RPM, respectively. The size and color of the dots reflect the magnitude of Q_m and ΔP , respectively. The projection on the X-Y plane shows the ΔP versus WCF curve. The gray plane is the boundary between safe and risk regions. Green arrows indicate safe regions, and orange arrows indicate risk regions. ϕ is the value of WCF at the boundary.

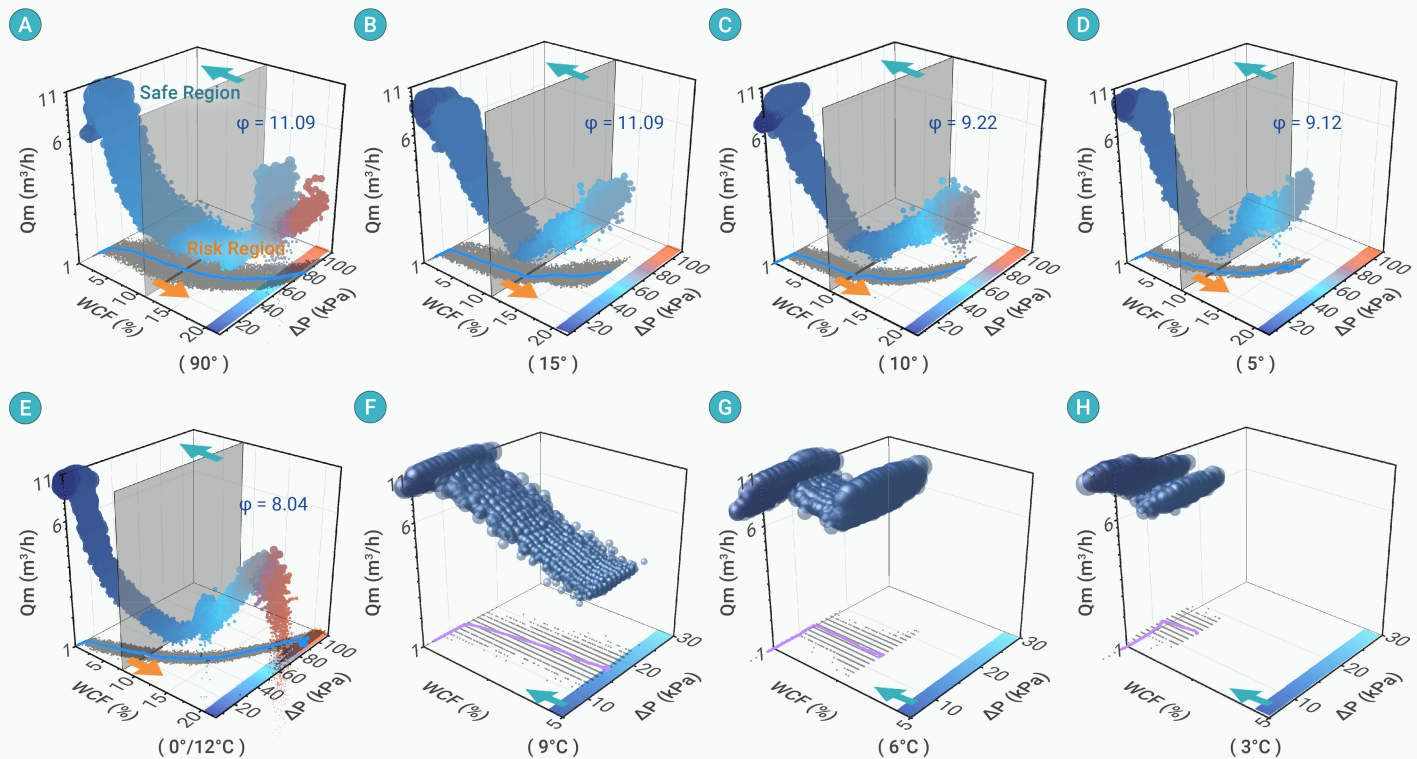


Figure 5. Three-dimensional scatter plots of the evolution of Q_m and ΔP with WCF. Panels A-E illustrate pipe inclinations from 0° to 90°, respectively. Panels F-H illustrate subcooling from 3 to 12 °C, respectively. The size and color of the dots reflect the magnitude of Q_m and ΔP , respectively. The projection on the X-Y plane shows the ΔP versus WCF curve. The gray plane is the boundary between safe and risk regions. Green arrows indicate safe regions, and orange arrows indicate risk regions. ϕ is the value of WCF at the boundary.

liquid phase. Although the hydrate formation reduced the volume flow rate, the liquid was still flowable at this stage. At Stage II, the hydrate particles

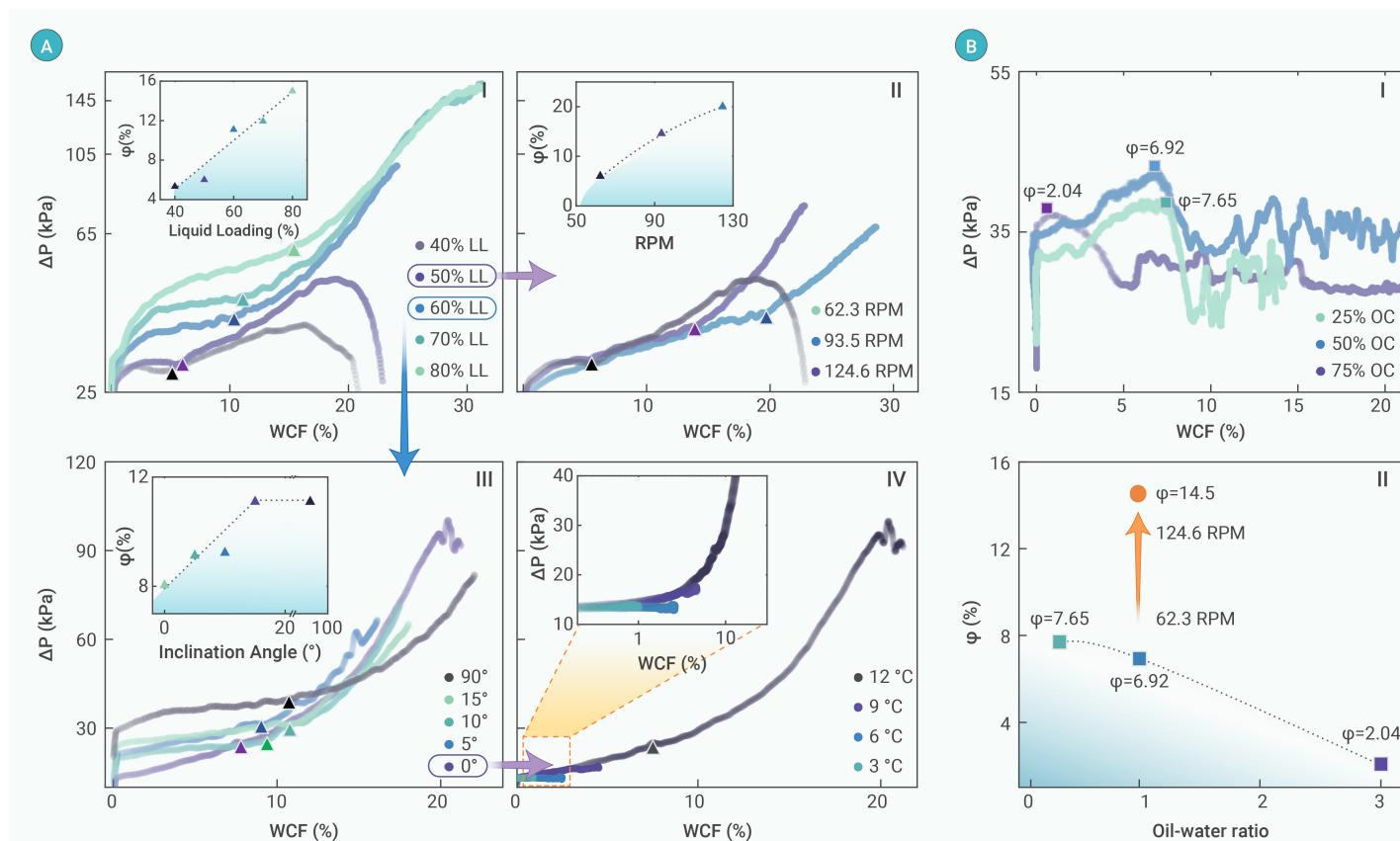


Figure 6. Evolution curves of ΔP with WCF in five systems (A) Panels I-IV represent the LL, pump speed, pipe inclination, and subcooling system, respectively. The dotted line in the inset shows the relationship between ϕ and the independent variables. The green area under the dotted line represents the safe region. (B) Panel I illustrates the evolution of ΔP with WCF with various OWR. OC denotes the oil content in the liquid phase. Panel II shows the ϕ versus OWR relationship.

reached the critical concentration. Particles aggregate with each other and encapsulate free water to form wet agglomerates. Hydrate slurry became non-Newtonian and gradually lost fluidity and continuity, eventually depositing at the pipe bottom. The transition of rheology caused the dramatic increase in ΔP and the deposition of slurry caused the final decay in Q_m . Higher LL had higher hydrate carrying capacity but required a stronger flow driving force (Figure 6A-I). The differential pressure inflection point, i.e., the critical point of hydrate concentration, was regarded as the blockage indicator.

The same evolution pattern of dependent variables was found in the other four systems. Figure 4F-H present the evolution of Q_m and ΔP with WCF at various pump speeds. The high pump speed effectively reduced the fluctuations in Q_m and increased the value of the critical point ϕ (Figure 6A-II). The increase in pump speeds enhanced the carrying capacity of liquid for hydrate particles, delaying the occurrence of blockage. Furthermore, the hydrate blockage process was investigated with different pipe inclinations (Figure 5A-E). The complex structure of deepwater pipelines was simulated by adjusting the inclination of the flow loop (90° refers to the riser, Figure S1). On the contrary, the increase in inclination did not affect the fluctuation of Q_m . Owing to larger inclinations resulting in more energy dissipation, the riser yielded a higher pressure drop than that of 0-15° (Figure 6A-III). The value of ϕ was positively correlated with the inclination. Moreover, the evolution of Q_m and ΔP with WCF with various subcooling is presented in Figure 5E-H. Subcooling exhibited a strong effect on hydrate blockage. The lower the subcooling, the fewer the hydrates were formed. The WCF was only 1% at a subcooling of 3 °C (Figure 6 A-IV). The flow remained in the safe region for subcooling below 9 °C.

In addition, the hydrate blockage process was investigated at 50% LL with various OWR. The oil phase yielded a different evolution pattern of ΔP (Figure 6B). The characteristics of stage I ($WCF < \phi$) were identical to that of the pure water system. In stage II ($WCF > \phi$), hydrate particles were massively

deposited on the wall. The deposition resulted in a high risk of blockage due to increased frictional resistance and reduced flow area. However, owing to the limitations of the flow loop, ΔP dropped abruptly in stage II (Figure 6B-I). During hydrate formation, the mass of the liquid phase was constant. Nevertheless, hydrate growth and agglomeration consumed large amounts of free water, resulting in an increasing proportion of mineral oil in the liquid phase. Therefore, ΔP decreased when the risk of blockage started to increase in this work. The inflection in ΔP remained a valid indicator. The critical point ϕ followed an inverse relationship with the OWR. The higher the oil content, the earlier the hydrate was deposited. In addition, increasing the pump speed can inhibit hydrate deposition (Figure 6B-II).

The above results demonstrate the broad generality of the differential pressure-based hydrate blockage prediction method. The critical point ϕ stably existed in various systems. Furthermore, the hydrate blockage process develops chronologically. Theoretical analysis of the high-dimensional space consisting of multiple dependent variables is difficult. The dominant dependent variables (ΔP , Q_m , WCF) were utilized to understand the hydrate blockage process. Although being black-box models, neural networks can capture and learn the features of high-dimensional space. Therefore, all dependent variables were used in the development of the TLV model. The time before critical point ϕ was regarded as a safe region labeled with "0", and the time after was regarded as a risk region labeled with "1".

Performance evaluation

The TLV model proposed in this work was compared with five representative baseline models. LSTM-AE^{40,41} is a classical model in the field of time series anomaly detection. K-means and One-class SVM (OC SVM) are classical unsupervised machine learning algorithms commonly employed in anomaly detection work. Anomaly-Transformer⁴² and DCdetector⁴³ are two state-of-the-art (SOTA) models that specialize in multivariate time series anomaly detection and have demonstrated superior performance in previous work. It should be noted that both Anomaly-Transformer and DCdetector

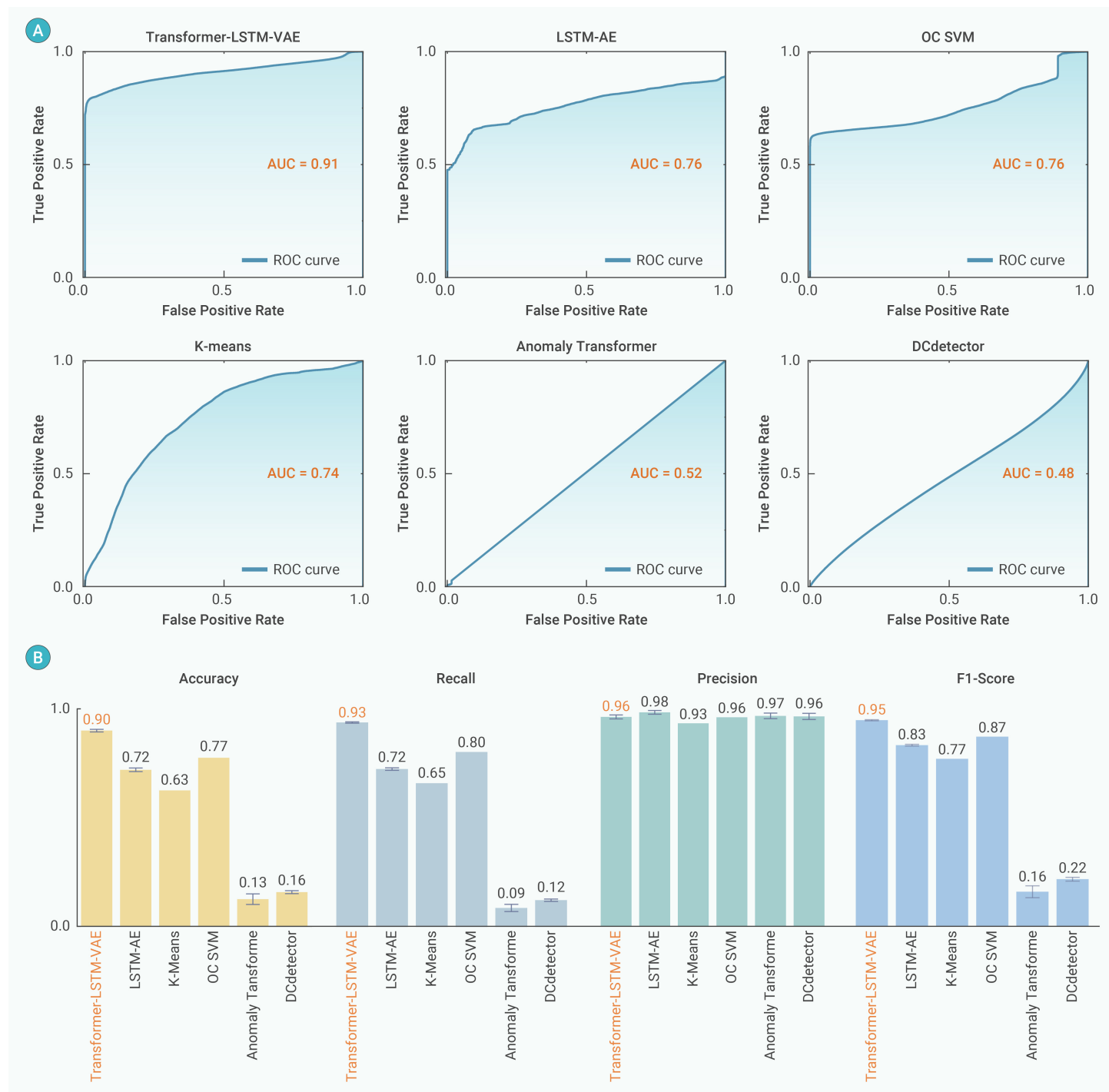


Figure 7. Performance metrics for the TLV model and five baseline models in the test (A) ROC curves for the six models. AUC refers to the area under the curve. (B) Four performance metrics for six models. All metrics were averaged over four repeated tests. Since the performance of machine learning models (K-means and OC SVM) is independent of the number of test iterations, the error bar is zero.

contain a section of the Detection Adjustment code that has been deleted from this work. Because of the lack of ground truth in actual production, Detection adjustment is impracticable and removed in our experiment.

The Receiver Operating Characteristic (ROC) curves and performance metrics of models are shown in Figure 7. Detailed confusion matrices (Figure S2) are provided in the supplemental information. ROC curve is a commonly used performance evaluation tool for binary classification models. The area under the curve (AUC) represents the performance of models. An AUC of 1 indicates perfect classification of the model, 0.5 indicates random guessing, and less than 0.5 indicates poor performance. As illustrated in Figure 7A, the AUC for the TLV model was 0.91, which was higher than that of the other five baseline models. Meanwhile, all four metrics for the TLV model were greater

than 0.9 (Figure 7B). The TLV model ranked first among all models in terms of accuracy, recall, and F1-score. As the harmonic mean of precision and recall, the F1-score can provide a comprehensive assessment of model performance. The F1-score of the TLV model developed in this study was 8 % higher than OC SVM (ranked second), indicating its advantage in hydrate blockage prediction. In contrast, although LSTM-AE has the highest precision, its recall is too low (0.72), which may cause the failure of blockage prediction.

Although the precision of the TLV model was not the highest, it struck a good balance between precision and recall, making it suitable for application. Precision represents the proportion of true blockage predicted by the model as blockage. Recall represents the proportion that can be identified as blockage by the model among true blockage. The higher the recall, the more

Table 1. Performance metrics for various combinations of encoder and decoder model

Combinations	Encoder	Decoder	Accuracy	Recall	Precision	F1-Score
L-L	LSTM	LSTM	0.8506	0.8613	0.9808	0.9172
T-T	Transformer	Transformer	0.8548	0.8679	0.9738	0.9178
T-L	Transformer	LSTM	0.8957	0.9339	0.9553	0.9472

comprehensive the model's prediction of blockages. In practical production, the loss of failing to predict blockage is much greater than that caused by false positives. Therefore, recall is more important than precision in hydrate blockage prediction. The TLV model demonstrated the highest recall and high average precision (0.962), implying its ability to accurately and comprehensively predict hydrate blockages.

The high performance of the TLV model was mainly attributed to the formulation of the physical problem and the construction of the VAE-based framework. During oil and gas transportation, hydrate blockage can induce significant fluctuations in pipeline flow parameters. The test results in Section 3.1 demonstrated that the difference in data distribution between safe and risk states can be effectively utilized to predict the formation of blockage. In addition, the ability of the VAE framework to generate latent space and its robustness, combined with the optimal encoder-decoder configuration, enables the TLV model to distinguish between normal and abnormal data.

Ablation study

In this section, ablation studies were further performed to study the impact of different design factors on the effectiveness of the whole TLV model.

Combination of encoder and decoder. The encoder and decoder models in the VAE framework were replaced to investigate the impact of various combinations on performance. Three combinations were utilized, including LSTM-LSTM (L-L), Transformer-Transformer (T-T), and Transformer-LSTM (T-L). The training and evaluation procedures were consistent with those in Section 2.4. The experimental results are presented in Table 1.

The model performance varied significantly with different combinations of encoder and decoder. The T-L combination ranked first in accuracy, recall, and F1-score with a precision of 0.95. The F1-score of the T-L was about 3% higher than that of the other two combinations. The self-attention mechanism and parallel processing capabilities of the Transformer enable it, as an encoder, to effectively capture the global dependencies within time series data. The recursive structure of the LSTM enables it, as a decoder, to preserve temporal structure when reconstructing data. The combination of Transformer and LSTM resulted in the high performance of the TLV model. Although the precision of the L-L combination was as high as 0.98, its recall was only 0.86. It indicated that the model reconstructed a portion of the abnormal data during sequence reconstruction, reflecting the low quality of the latent space and weak discrimination ability.

Uneven weight adjustment methods. The error sequence calculation method was specifically improved in this work. Two UWA methods, linear and quadratic, were proposed (see Section 2.3.3). The training and evaluation procedures were consistent with those in Section 2.4. The experimental results are presented in Table 2.

Both linear and quadratic methods demonstrated improved performance metrics compared to the normal method. The recall increased by about 5% while precision remained stable. The F1-score also increased slightly. The model's ability to predict imminent blockage was enhanced by assigning higher weights to later points within a time subsequence. The increase in the recall was as expected, ensuring the practicability of the TLV model in actual production. Nevertheless, evaluating the UWA methods with performance metrics alone is insufficient because the proportion of abnormal data is higher than that of the normal portion.

Each data set was further tested individually using the trained model. The results for the 15th (Figure 8A & C-E) and 25th (Figure 8B & F-H) data sets were visualized. Figure 8A & B illustrates the classification process of the TLV model for three weight adjustment methods. The horizontal axis represents the running time of the flow loop, and φ is the true boundary line between the safe and risk regions. The vertical coordinate and the horizontal dashed line

Table 2. Performance metrics for various weight adjustment methods.

Method	Acc	Recall	Precision	F1-Score
Normal	0.8957	0.9339	0.9553	0.9472
Linear	0.9393	0.9803	0.9572	0.9686
Quadratic	0.9397	0.9808	0.9572	0.9688

represent the error and threshold of the model output, respectively. The model classified data below the threshold as safe and vice versa. The normal method resulted in partially risk data being misclassified as safe (red triangles), indicating that the blockage was not identified until several hours after it occurred (Figure 8A & B). In contrast, the UWA methods allowed the error value to increase with hydrate formation by increasing the weight of a later time point in a time subsequence. The error curve shifted upward overall, which means the model was able to identify blockage in time. The histograms of the error values and performance metrics are shown in Figure 8C-H. The quadratic adjustment method presented the best classification results. The UWA methods improved the recall and F1-score. The early warning mechanism is invaluable for industrial applications.

The performance of the TLV model was influenced by the threshold, which was determined by the percentile. Therefore, we examined the performance of the model at different percentiles. The percentile was sampled at 5% intervals from 75-100%. The precision and recall were positively and negatively correlated with percentile, respectively, while accuracy and F1-score initially increased and then decreased with increasing percentile, peaking at 90% when the TLV model performed best (Figure S3). In gas hydrate blockage prediction, the determination of the threshold percentage requires a trade-off between precision and recall. A low percentile makes the model excessively stringent, resulting in frequent false alarms, which is not conducive to practical production. A high percentile leads to model undemanding, erroneously classifying risk signals as safe signals. The ablation experiments demonstrated that the recall and precision were balanced at a percentile of 90% in this work. Furthermore, all tests were divided into five subsystems based on the independent variables (corresponding to Section 3.1). In the evaluations of five systems, the TLV model achieved the highest F1-score among all six models, with a maximum of 0.977 and an average of 0.918 (Figure S4).

CONCLUSION

The main conclusions of this work are as follows:

1. In the oil-gas-water-hydrate multiphase flow, the evolution of differential pressure over time includes two stages: I, ΔP remains stable or rises slightly with increasing hydrate concentration; II, ΔP changes abruptly after the hydrate reaches the critical concentration (φ). Without intervention in stage II, the hydrate will eventually deposit and form a blockage. The evolution pattern of ΔP is applicable to various transport systems and flow conditions. The blockage indicator (φ) is positively correlated with LL, pump speed, and pipe inclination and negatively correlated with OWR.

2. The proposed TLV model utilizes VAE as its framework, with the Transformer and LSTM as the encoder and decoder, respectively. The TLV model strikes a good balance between prediction accuracy and recall, with an F1-score of 0.969 for predicting hydrate blockage. Its performance is significantly higher than that of two SOTA anomaly detection models. The UWA methods enhance the TLV model's ability to sense impending blockage and alerts earlier.

3. The successful application of unsupervised learning methods demonstrates that the high-dimensional variable space composed of input parameters (ΔP , T_{in} , T_{out} , Q_{TH} , ρ , WCF) contains recognized features corresponding to

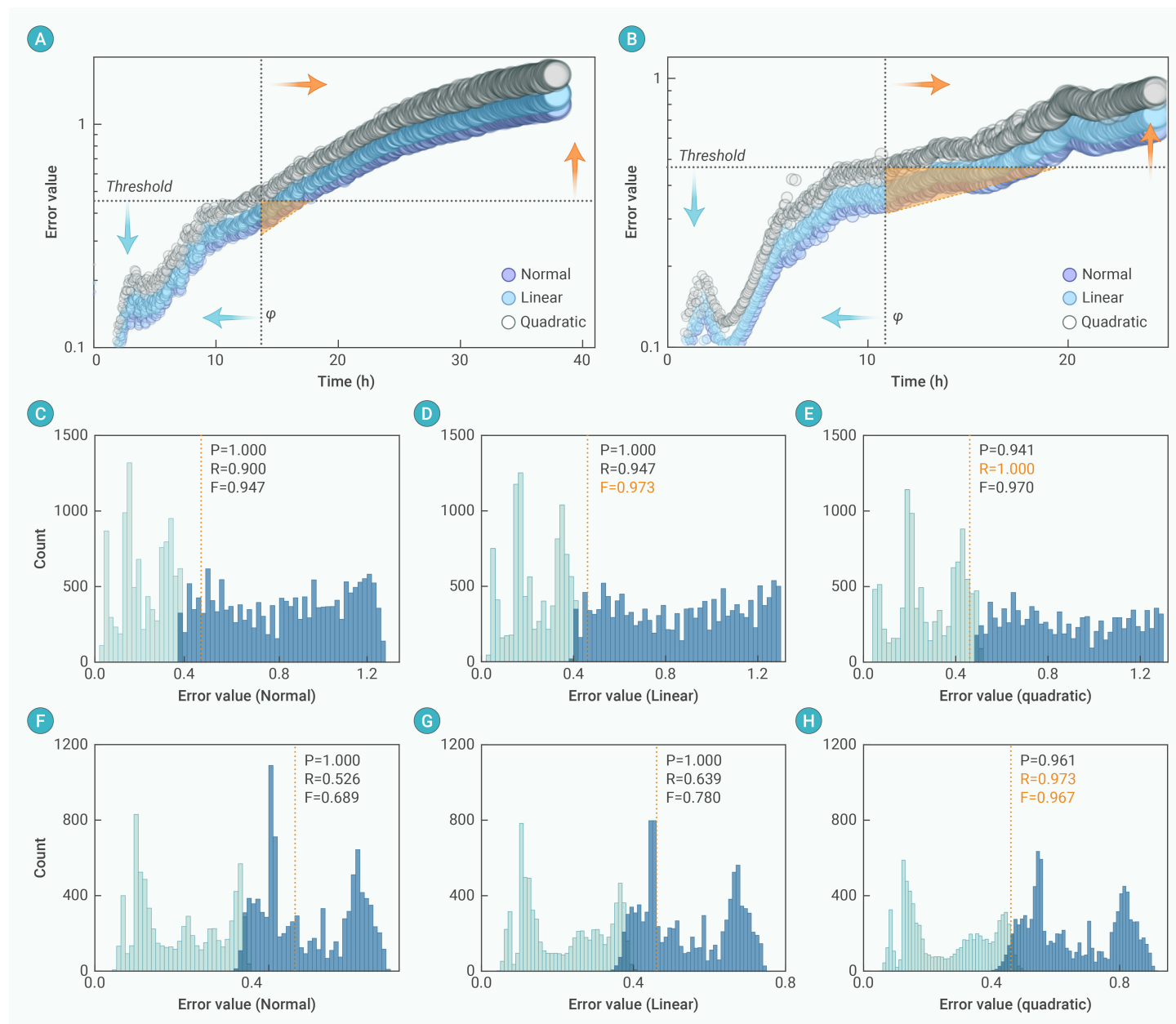


Figure 8. Visualization of the effectiveness of UWA methods (A-B) Error sequences of the fifteenth and twenty-fifth datasets. The dots represent the error value at each moment. The three colors correspond to the three weight adjustment methods. The size of the dots maps the value of the ΔP . The vertical dashed line indicates that the hydrate concentration reaches the critical value φ at this point. The horizontal dashed line indicates the threshold for the error value calculated by the TLV. Green arrows point to safe regions, and orange arrows point to risk regions. The red triangle indicates that the TLV misclassifies the risk to a safe state. (C-E) Histogram of error values for the fifteenth dataset. The normal, linear, and quadratic weight adjustment methods are represented respectively from left to right. (F-H) Histogram of error values for the twenty-fifth dataset. The green and blue columns refer to the real safe and risk regions, respectively. The red dashed line is the risk boundary calculated by the TLV. The left and right sides refer to the safety and risk zones judged by the model, respectively. P, R, and F refer to precision, recall, and F1-score, respectively.

hydrate blockage. These features can be learned by neural networks and applied to predict blockage. The architecture of the Transformer is well-suited for capturing long-term dependencies between flow parameters and time during the hydrate blockage process. Its attention mechanism enhances the model's feature extraction capabilities in high-dimensional spaces while simplifying computations. The recursive structure, cell state, and gating mechanism of the LSTM ensure that it can effectively reconstruct the time series data by utilizing the blockage laws in latent space.

The TLV model preliminarily demonstrates the broad prospects of the deep-learning method in hydrate blockage prediction. All data and models in this work are open-sourced to facilitate the development of related research (<https://github.com/IDED-TLV>). Since the TLV model relies on data regularities rather than specific values, it can theoretically be applied to any similar anomaly detection problem.

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AUTHOR CONTRIBUTIONS

J. Wang: Conceptualization, Investigation, Visualization, Methodology, Data curation, Formal analysis, Writing – original draft. B. Yang: Investigation, Software, Formal analysis, Validation, Data curation, Visualization. Kaiming Jin: Investigation, Software, Formal analysis, Validation, Data curation, Visualization. L. Zhang: Writing, Review, Editing, Methodology, Project administration, Resources. L. Wang: Investigation, Data curation, Formal analysis. B. Jiang: Writing, Review, Editing, Methodology, Project administration, Resources. H. Yao: Supervision, Project administration. Y. Song: Resources, Supervision. All authors contributed to and approved the manuscript.

DECLARATION OF INTERESTS

Yongchen Song is an Editorial Board member of The Innovation Energy and was blinded from reviewing or making final decisions on the manuscript. Peer review was handled independently of this member and their research group. The other authors declare no conflicts of interest.

DATA AND MATERIALS AVAILABILITY

Data are available from the corresponding author upon reasonable request.

SUPPLEMENTAL INFORMATION

Supplementary materials are available at: <https://doi.org/10.59717/j.xinn-energy.2025.100081>