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Deeppipe: A hybrid intelligent framework for real-time batch tracking of multi-product pipelines

Jianqin Zheng[a], Jian Du[a], Yongtu Liang[a,*], Bohong Wang[b], Miao Li[c], Qi Liao[a], Ning Xu[a]

[a] National Engineering Laboratory for Pipeline Safety/ MOE Key Laboratory of Petroleum Engineering/ Beijing Key Laboratory of Urban Oil and Gas Distribution Technology, China University of Petroleum-Beijing, Fuxue Road No. 18, Changping District, Beijing 102249, PR China

[b] School of Petrochemical Engineering and Environment, Zhejiang Ocean University, Zhoushan 316022, PR China

[c] South China Branch, PipeChina Co., Ltd., Guangzhou 510620, PR China

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ABSTRACT

To improve the economy and meet the demand for transporting different oil products, multi-product pipelines are utilized to transport multi-products in sequence in the same pipelines. It is fundamentally important for operators in stations to know the accurate location of the head of each batch interface, to swing the valve at a station, and deliver oil products with minimal contamination. However, it is difficult to determine the location of the batch interface accurately, due to the complex hydrothermal conditions and mixed oil segment. In this paper, a hybrid intelligent framework is proposed to track the real-time batch interface of multi-product pipelines. The batch injection judgment module is applied to determine whether there is a new product batch injected in the pipeline. Applying the upstream and downstream flowrate, the volume calculation model is proposed to track the real-time location of each batch interface. Considering the deviation between the estimated location and the actual location of the batch interface, a self-learning modified model is proposed to compensate for the tracking errors. Taking a real-world multi-product pipeline network in China as an example, the accuracy and efficiency of the proposed model are verified. The results suggested that the hybrid intelligent framework outperforms other comparative methods, with minimal tracking errors being 3.79 min

1. Background

1.1. Introduction

Pipelines are the most effective method to transport refined oil from refineries and wharves to cities over a long distance, with more economy, safety, and greater transport capacity than railways and highways (Liang et al., 2012a). The pipelines are hardly affected by weather conditions, which results in the stable and continuous operation of pipelines (Liang et al., 2012b). Nevertheless, the demand for each product fluctuates frequently and is relatively small, and constructing a pipeline for each product respectively requires a higher cost. As a consequence, a multi-product pipeline transports different oil products in sequence to not only satisfy the demand for different delivery stations, but decrease the cost of pipeline construction (Liao et al., 2018a), and thus contribute to an efficient multi-product supply chain (Wang et al., 2019).

Multi-products are transported in batches in a pipeline, which leads to many batch interfaces needing to be tracked (Zhang and Li, 2009). Tracking batches manually causes

* Corresponding author.
E-mail address: liangyt21st@cup.edu.cn (Y. Liang).

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quality accidents and untimely download of batches, influencing the normal supply of markets, resulting from its inaccuracy and inefficiency (Harbert, 2008). To meet the demand of the market and optimize the scheduling plans of delivery stations, it is crucial to obtain the location of all the batches within one pipeline in real time (Milano et al., 2018). At present, the pipeline companies install density meters in the inlet and outlet of delivery stations, aiming to detect batch interface when the product batch arrives at the station, but lacking detection tools between the pipeline segment to acquire the location of the batch interface. However, this method cannot predict arrival time before the product batch has not arrived at the station yet. Tracking batches in multi-product pipelines in real-time means acquiring the location of the head and tail of each product batch at any given time. According to the real-time batch tracking, when the product batch is approaching the station, station operators will make delivery plans in advance and swing the valve to deliver the product to the right tank or the end-customer with minimal contamination when the batch product arrives at the station.

The flowrates of pipeline segments are different due to the delivery and injection of the stations, resulting in the variation of the pipeline inside diameter. The pipelines are not always liquid full, so the actual volume of products in the pipeline is hard to know. In addition, the amount of oil volume contained within the pipeline will change as the operating temperature (Farah et al., 2005) and pressure (Desamala et al., 2016) change. When transporting multi-product batches in sequence in a pipeline, a mixed oil segment will form between the adjacent batches, influencing the accurate determination of batch interface location (Yuan et al., 2021).

According to the above-mentioned content, the difficulty of tracking batch accurately can be summarized as follows:

(1) The hydraulic system of the pipeline network changes dynamically, and no equipment is installed between the pipeline segment to detect the batch interfaces.
(2) It is hard to quantify the effect of mixed oil and operating parameters (temperature and pressure) on batch interface location based on the real operating state.

1.2. *Related work*

In the past few years, some scholars had conducted research to analyze and study batch migration in multi-product pipelines. One common method is numerical simulation, which describes the changes in hydraulic parameters of a multi-product pipeline. Considering that the reliable calculation of batch tracking requires operational information, such as temperature, pressure, flow rate, and some fluid physical properties, Liebenberg et al. (2008) proposed a commercial numerical simulator to simulate batch flow. The proposed numerical simulator is utilized to analyze the dynamic flow parameters and construct their impact on the batch tracking model, aiming to improve the accuracy of the estimated time of arrival at stations. Ma et al. (2010) analyzed the batch delivery process in a multi-product pipeline, the results indicate that the diffusion and dispersions that occurred on the interface affect the volume of interfaces. Then, a numerical simulator of dynamic hydraulic flow is proposed to formulate batch planning. Blažič et al. (2004) simultaneously considered fluid density, pressure, and velocity of the medium in the pipeline model to simulate multi-batch pipelines. Although the numerical simulation approach can simulate batch movement and dynamic hydraulic flow, the real-time location of the batch interface is hard to be calculated based on the numerical simulation method, which is time-consuming for long-distance pipelines.

To track the product batch in multi-product pipelines in real-time accurately, some scholars developed Batch Tracking System (BTS) to determine the location of the batch interface based on mathematical models. Huber (1981) established a real-time transient model to determine temperature, pressure, density, and flow profiles for the pipeline, to track batches in the pipeline and perform leak detection. Kirschstein (2018) proposed a scheduling model for a multi-product pipeline to solve the economic lot scheduling problem by considering the times, sequences, and sizes of batch injection. Harbert (2008) summarized the method of batch cutting. The traditional manual approach contains many disadvantages, including inaccuracy interface cutting and high time cost. In contrast, new developments in automation techniques led to the establishment of the Precision Batch Cutting (PBC) system, which is applied to improve the decision-making and accuracy of a batch cut process. Zhang and Li (2009) established a mathematical model to analyze the flow rate changes with batch interface moving in pipelines. The results indicated that the flow rate changes with the batch interface and the distance of the batch interface moved through in pipeline. Milano et al. (2018) developed BTS to make the station operators know the location of all the batches moved through the pipeline in real time. They also explained that the assumptions on which the software is based are not always entirely true. Although the BTS can obtain the location of batch interfaces in the pipeline, the calculation process is based on the single-volume transporting model which neglects the impact of hydrothermal change and the development of mixed oil on real product interface migration. Consequently, it is necessary to conduct further research to improve calculation precision of BTS.

Though the approaches mentioned above make great progress in batch tracking of multi-product pipelines, the limitations can be concluded as follows:

(1) Some studies focused on the theoretical study and cannot be served as engineering applications for on-site multi-product pipelines.

(2) The real-time batch tracking methods are mainly based on a simple volume calculation process for different oil products, but the precision needs further improvement.

When transporting different oil products, a mixed oil section will unavoidably occur between the adjacent batches (Chen et al., 2021). To track the migration of product batches, the station operators regard the head of the mixed oil segment as the head of the batch interface. Therefore, the formation and development of mixed oil will influence the accuracy of batch tracking in multi-product pipelines. Furthermore, the volume of oil products changes with the temperature and pressure (Cazarez-Candia and Vásquez-Cruz, 2005). The thermal expansion of the oil product makes its volume increase with temperature (Al-Marhoun, 1985). The compressibility of the oil product causes its volume to decrease with increasing pressure (Wright, 1967). In addition, the pipeline capacity is influenced by temperature and pressure.

Recently, the rapid development of intelligent algorithms and data science, such as machine learning models, has aroused awareness in the industrial process. The data-driven

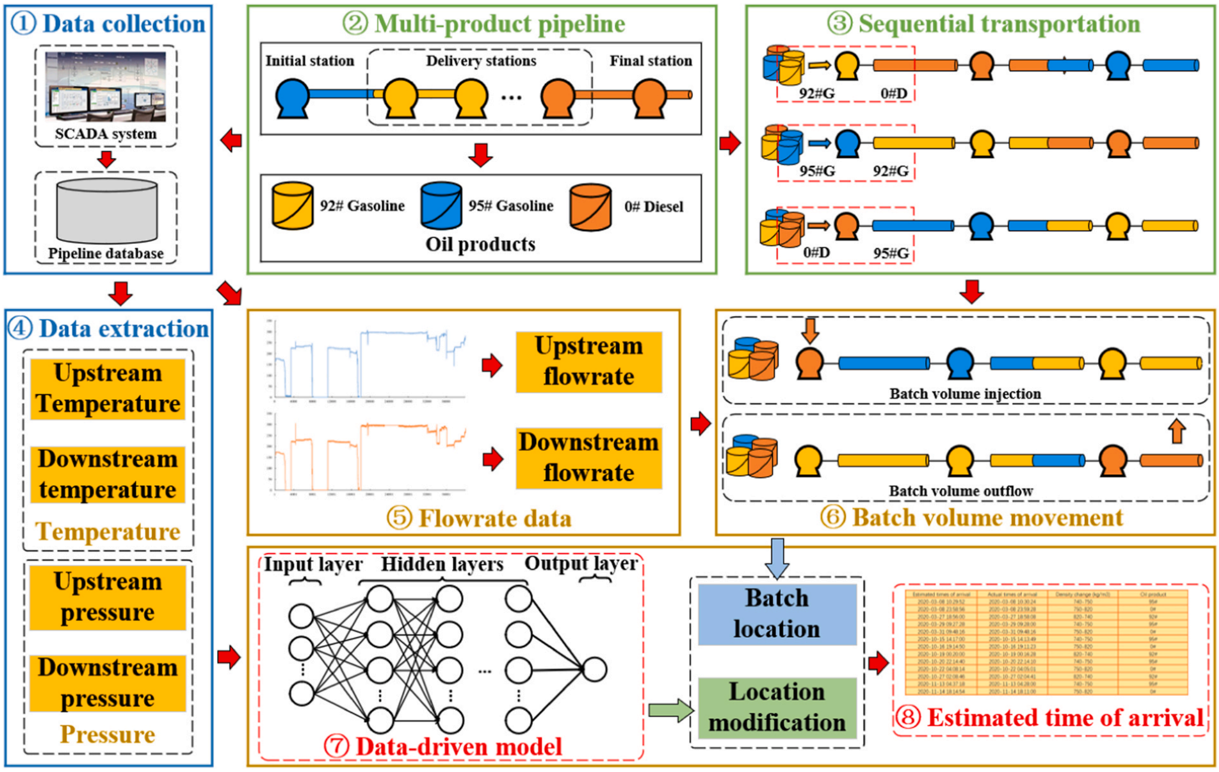


Fig. 1 – The flowchart of this work.

models learn the mapping relationship by approximating the complex function of available data, which brings more accurate results than traditional model-driven models. In the past few years, data-driven models are widely applied for multi-product pipelines, for instance, the prediction of leakage parameters (Zheng et al., 2021c), the operation condition recognition (Zheng et al., 2021a), the shutdown pressure prediction (Zheng et al., 2021b), and unsteady operation condition recognition (Wang et al., 2022). Despite the great application of data-driven models, there still exist limitations in data-driven models, such as overfitting on the small amount of data, poor model interpretability, and unclear physical meaning (Glassey and Von Stosch, 2018). Consequently, the hybrid modeling method which incorporates data-driven and mechanism processes are gradually becoming a research hotspot in the current modeling field (Schweidtmann et al., 2021). Schäfer et al. (2020) reviewed hybrid mechanistic data-driven approaches for reduced dynamic modeling. The application of the proposed model on distillation columns was discussed. Gray and Schmidt (2018) analyzed building air temperature and predicted energy consumption by designing a hybrid model, which integrated gaussian process regression algorithm to compensate for the predicted errors of the mechanism model. Dai et al. (2020) employed a simplified mechanical model to estimate furnace temperature, then, the data-driven model which considers time-series characteristics is constructed to compensate for the predicted errors of the physical model. Asgari et al. (2021) approximated the complex mapping function of different parameters by establishing a neural network, and thermal fluid transport equation is integrated to calculate air temperature. Lee et al. (2018) reviewed the main advances in the machine learning for process system engineering. von Stosch et al., (2014 revisited the commonly used hybrid semi-parametric models and parameter identification approach and their application in industry problems.

It is proved from the above discussion that the method which incorporates data science and mechanism process is receiving increasing awareness in engineering problems. As shown in Fig. 1, considering that the batch migration in a multi-product pipeline contains a mechanism process, and a large amount of operating data is stored in Supervisory Control and Data Acquisition (SCADA) system in the meantime. As a consequence, to track the location of batch interface accurately, this paper proposes a novel hybrid intelligent framework for real-time batch tracking of multi-product pipelines. Firstly, the operating data of the multi-product pipeline in the SCADA system is collected to construct the database. Based on the flow characteristics of oil products in a sequential transportation pipeline, the volume calculation model is established according to the batch volume injection and outflow. Subsequently, the upstream and downstream flowrate are utilized to calculate the real-time location of the batch interface. Considering that the hydrothermal conditions and mixed oil affect the batch volume, the upstream and downstream temperature and pressure are applied to modify the batch location by training the data-driven model. Eventually, the corresponding estimated times of arrival at stations also could be obtained.

1.3. *Contributions*

The contributions of this work can be concluded as follows:

(1) A novel systematic batch tracking framework is proposed to track the locations of batch interfaces in real time.
(2) Coupling pipeline operating mechanism, a hybrid calculation method is developed, which considers the influences of mixed oil, temperature, pressure, and flow fluctuation on batch migration.
(3) To improve the accuracy of batch tracking, the real-time operating data is incorporated with data-driven

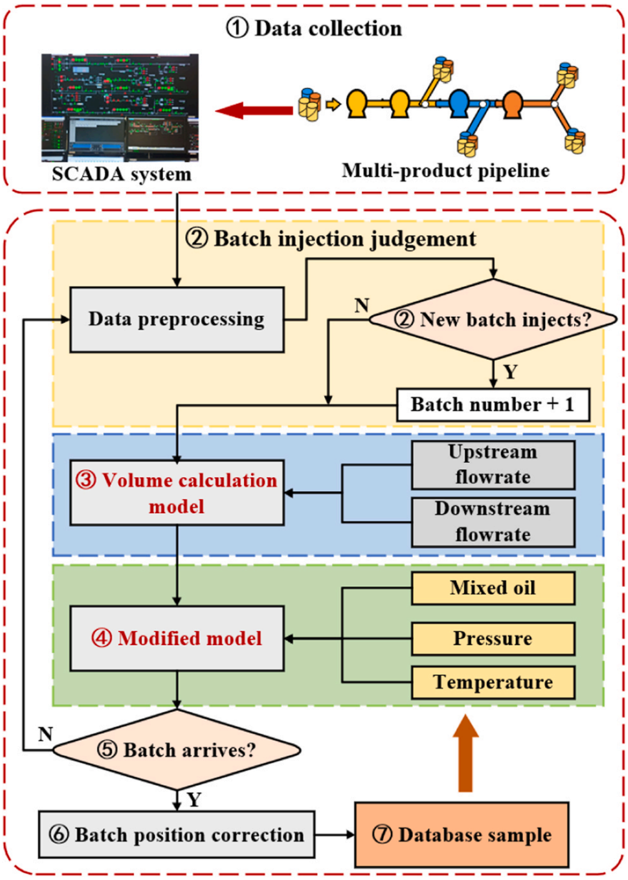


Fig. 2 – The basic architecture of the proposed intelligent framework.

algorithms to establish a modified model to compensate for tracking errors.

The rest of this paper proceeds as follows. In Section 2, the architecture of the hybrid framework for batch tracking is introduced in detail, and the function of each module in the hybrid framework is recommended separately. Then, a real-world multi-product pipeline network is taken as an example to verify the accuracy and efficiency of the proposed framework in Section 3. Eventually, the conclusion and future work are provided in Section 4.

2. Hybrid intelligent framework

In this section, a hybrid intelligent framework for tracking batch interface in the multi-product pipeline is proposed. The basic architecture of the hybrid framework is shown in Fig. 2. The proposed hybrid framework contains several sections, namely data collection, data preprocessing, batch injection judgment, volume calculation, self-learning modified model, and batch arrival judgment.

At first, the input operating data (pressure, temperature, and flowrate) is preprocessed to meet the demands of the subsequent calculation process. The procedures of data preprocessing include summarizing data to a regular time interval and calculating the inlet and outlet flowrate of delivery stations. After the input data is prepared, the new batch injection judgment is carried out to determine whether a new batch is injected into the pipeline. The new batch injection judgment is mainly based on the density fluctuation for a period. Then, the batch injection volume is calculated based on upstream and downstream flowrate. The location of the batch interface can be determined according to the batch volume. Considering that the batch volume is influenced by the mixed oil, temperature, and pressure, a self-learning modified model is proposed to deal with the batch tracking errors of the volume calculation model based on the pipeline operating data. Subsequently, the batch location in real-time of multi-product is applied to compare with the length of the pipeline segment, aiming to determine whether the product batch has arrived at the station. However, there exists a slight deviation between the estimated time and actual time of arrival at stations. Therefore, when the density change has been identified that the product batch interface arrives at the station, the location of the batch interface should be corrected to the station location. The deviations are utilized to update the database along with the corresponding operating data. After that, the database is gradually enriched, which further improves the accuracy and generality of the self-learning modified model.

2.1. *Data preprocessing*

It is necessary to conduct data preprocessing for the original operating data to satisfy the calculation of the batch tracking model. Considering that, the operating data in the SCADA system contains many repeated time nodes, it is significant to summarize the data to fixed time intervals and remove duplicate time nodes. In this work, the time interval of operating data is determined as 10 s. Due to the missing or damaged flow meters, some delivery stations lack inlet or outlet flowrate, which has an impact on the accuracy of the volume calculation model. As a consequence, the missing flowrate is calculated based on the equilibrium state, as shown in Eq. (1).

$$Q_{inlet} - Q_{delivery} = Q_{outlet} \tag{1}$$

where Q_{inlet} represents the inlet flowrate of stations (m^3/h), $Q_{delivery}$ is the delivery flowrate of stations (m^3/h), Q_{outlet} represents the outlet flowrate of stations (m^3/h).

2.2. *Batch injection and arrival judgment*

After acquiring the operating data, the total number of product batches injected into the multi-product pipeline should be determined. The main difference between different oil products is that the density of oil products varies from each other. For the delivery stations, the densimeters are installed in stations to monitor the density changes. Therefore, the new batch injection judgment can be conducted according to the density data and valve status.

For the multi-product pipeline network, the oil product can be injected into the pipeline through the initial station. When a new batch is injected, the density data will change, and it can be identified by the batch injection judgment module. To prevent misjudgment caused by density fluctuation, the valve status of the oil tank in the initial station is monitored to judge the batch injection along with the density identification module.

As shown in Fig. 3, to judge the batch arrival at the station, the time and density data are initialized, and the density data in time T is read from the SCADA system. Then, the density in time (T + dT) is employed to compare with density in time T, where *rc* represents the density change threshold. If the density fluctuation exceeds the set threshold, to avoid

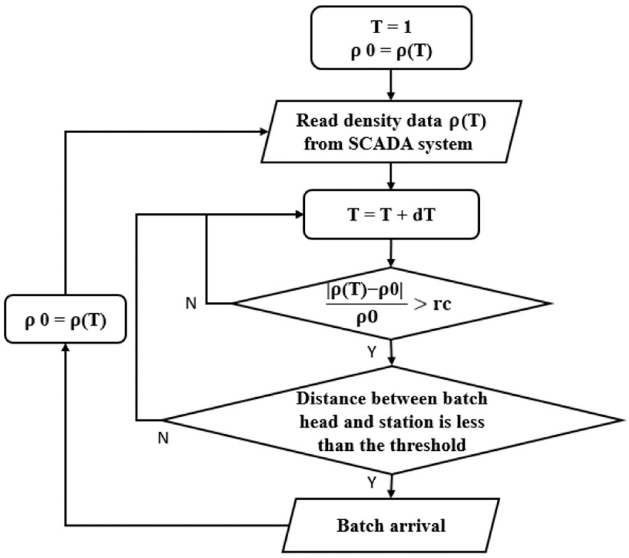


Fig. 3 – The flowchart of batch arrival judgment.

misjudgment, it is necessary to determine the location of the upstream batch head. Namely, the distance between the location of the upstream batch head and the station is calculated to confirm whether an oil batch has arrived at the station or not due to hydraulic disturbance. If the judgment condition is satisfied, it is proved that there is new batch arrival at the station. The density data will be initialized to identify the next product batch.

2.3. *Volume calculation model*

After detecting the new batch injection, it is required to calculate the injection batch volume to obtain the location of the batch head in real time. The measuring instruments of flowrate are the basis of trade between transporters, producers, and consumer markets (Amina and Ahmed, 2017). To improve the measurement accuracy of delivery flowrate, the mass flowmeters are applied to delivery stations. The unit of mass flowrate in delivery stations is t/h. Different from delivery flowrate, the measuring of inlet and outlet flowrate in stations does not require high accuracy due to expensive instruments. The measuring of inlet and outlet flowrate in stations applies the ultrasonic flowmeters, which is essentially a volume flowrate (Liao et al., 2018b). As one of the fastest-growing technologies in the field of instruments for industrial measurement, condition monitoring, and process control, ultrasonic flowmeters are widely utilized in flowrate measurement of liquids, gases, and multiphase mixtures (Lynnworth and Liu, 2006).

According to the above-mentioned content, the delivery flowrate of stations is always mass flow, while the inlet and outlet flowrates of stations are both volume flowrates. For this reason, before calculating the injection volume, it is important to unify the flowrate units, as depicted in Eq. (2).

$$Q_{delivery} = \frac{1000 \cdot \widehat{Q}_{delivery}}{\rho_{batch}} \tag{2}$$

where $Q_{delivery}$ represents the processed delivery flowrate of stations (m^3/h), $\widehat{Q}_{delivery}$ represents the original delivery flowrate of stations (t/h), and ρ_{batch} denotes the density of oil product (kg/m^3).

After the input operating data is prepared, the volume calculation model is established to determine the location of each batch interface. The basic principle of batch volume calculation is volume equilibrium. This means that, how much volume of product batch is injected upstream or flowed out downstream, how much volumes of product batch in the pipeline will move forward. The methods of batch volume calculation include upstream volume injection and downstream volume outflow. Upstream volume injection is mainly based on the upstream flowrate while downstream volume outflow is based on the downstream flowrate. The mathematical formulas of the batch volume calculation are represented as follows:

$$V_t^{inject} = V_{t-1}^{inject} + Q_{upstream} \cdot dT \tag{3}$$

$$V_t^{outflow} = V_{t-1}^{outflow} + Q_{downstream} \cdot dT \tag{4}$$

$$L_t = \frac{V_t^{inject} + V_t^{outflow}}{2 \cdot S_{pipe}} \tag{5}$$

where (V_t^{inject}, V_{t-1}^{inject}) and ($V_t^{outflow}$, $V_{t-1}^{outflow}$) denote the injection volume and volume outflow in time t and $t-1$ (m^3), respectively. $Q_{upstream}$ and $Q_{downstream}$ are upstream and downstream flowrate (m^3/h). S_{pipe} represents the cross-sectional area of the pipeline (m^2). L_t is the location of batch interface in time t (m).

2.4. *Self-learning based modified model*

After obtaining operating data from the SCADA system, the volume calculation model is utilized to determine the location of the batch interface in real time. However, due to the variation of temperature and pressure, the volume of oil products and the pipeline is not a fixed value and will change with the environmental conditions. This brings deviations between the calculated location and the actual location of the batch interface. During transportation, the operating data changes constantly and irregularly, which results in a highly nonlinear and non-fixed deviation. Furthermore, the mixed oil segment forms during batch product transportation, influencing the calculation of batch interface migration.

For this reason, a self-learning based modified model is proposed to compensate for batch tracking errors of the volume calculation model, as shown in Fig. 4. At first, the upstream and downstream flowrate data, as well as the product density data extracted from the SCADA system, are imported into the volume calculation model to track the location of the batch product interface in real-time. The detailed process of batch interface calculation can be found in Section 2.3. With the migration of the batch interface, the estimated time of arrival stations can be determined when the location of the batch interface is equal to the length of the pipeline segment. Meanwhile, the station operators acquire the actual time of arrival stations according to the density changes. To this end, the batch tracking errors can be calculated based on the difference between the calculated and actual time of arrival stations.

Considering that the temperature and pressure possess a great impact on the accuracy of the volume calculation model, the upstream and downstream temperature and pressure are incorporated to modify batch tracking. During the transportation of one batch in a pipeline segment, the period is several hours or days, but the temperature and pressure fluctuate within a certain range. Therefore, assuming the temperature and pressure data conform to the specific distribution, such as normal distribution. The

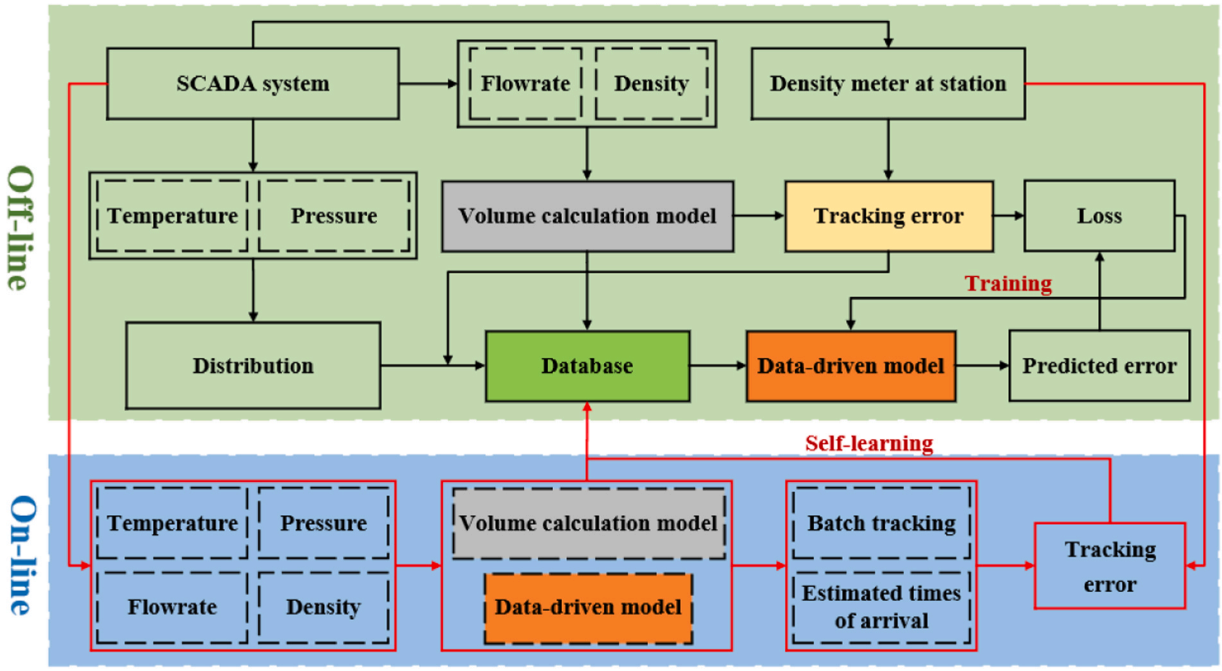


Fig. 4 – The architecture of the self-learning based modified model.

average value and variance can be extracted from the data sequence of temperature and pressure. In this way, the average, variance, and batch tracking errors can be applied to construct an error modification database.

Considering that there exists a complex nonlinear relationship between batch location and hydrothermal parameters (pressure and temperature), the data-driven model is employed to predict the batch tracking errors to modify the batch tracking errors calculated by the volume calculation model, which will be used to modify the estimated time of arrival stations. For the proposed data-driven model, the average value and variance of historical temperature and pressure are taken as input variables, and the batch tracking errors of the volume calculation model are taken as output variables correspondingly. The mean squared errors (MSE) between predicted error and actual batch tracking error are applied to construct the loss function, and the historical operating data is employed to train the data-driven model. The data-driven model uses the temperature and pressure as the input and uses the errors as the output, aiming to explore the correlations between influencing factors and tracking errors. This modeling process is consistent with mechanism intuition. When the loss function tends to converge, the predicted model of batch tracking errors is obtained. Based on the above off-line training process, the data-driven model is established, which predicts batch tracking errors according to the operating parameters.

After obtaining the trained data-driven model, the online batch tracking results can be modified based on the operating data in real time. The real-time operating data of the multi-product pipeline is used to extract temperature, pressure, flowrate, and density data. Then, the real-time location of the batch interface is estimated by the volume calculation model, and the batch tracking error is predicted to modify the deviation between the actual location and the estimated location of the batch interface in real time. During the real-time transportation of oil products, plenty of batch tracking errors between estimated times and actual times of arrival stations will be recorded. The data-driven model is trained using the updated operation data to make the lower values of tracking errors. To this end, the database will be enriched and applied to improve the accuracy and generality of the data-driven model via a self-learning process.

In this work, the artificial neural network (ANN) is selected as the data-driven model to predict the deviation. The ANN is a powerful approximation tool of the nonlinear function. The relationship between input variables and output variables can be learned by ANN. The basic architecture of the ANN is depicted in Fig. 5. The ANN contains three different sections, namely the input layer, output layer, and hidden layers. Each layer consists of several nodes. Generally speaking, an ANN includes one input layer and one output layer, but the number of hidden layers can be determined by the underlying problem. The activation functions are applied in the neural network layer, such as Sigmoid, rectified linear unit (ReLU) (LeCun et al., 2015), and hyperbolic tangent (Tanh) (Wang et al., 2020). The optimization algorithm will be applied to minimize the loss function of ANN, such as Stochastic Gradient Descent (SGD) (Bottou, 2010) and adaptive moment estimation (Adam) (Tong et al., 2022).

3. Case study

In this section, a real-world multi-product pipeline network is taken as an example to evaluate the accuracy and efficiency of the proposed hybrid intelligent framework. The tracking errors of the proposed hybrid framework are compared with previous work to illustrate the superiority of the hybrid framework. A comparison of the volume calculation model and hybrid modified model is carried out to testify to the performance of the self-learning modified model.

3.1. *Basic data*

In this work, a novel intelligent framework is proposed for real-time batch tracking in a multi-product pipeline network. To verify the performance of the proposed framework, it is

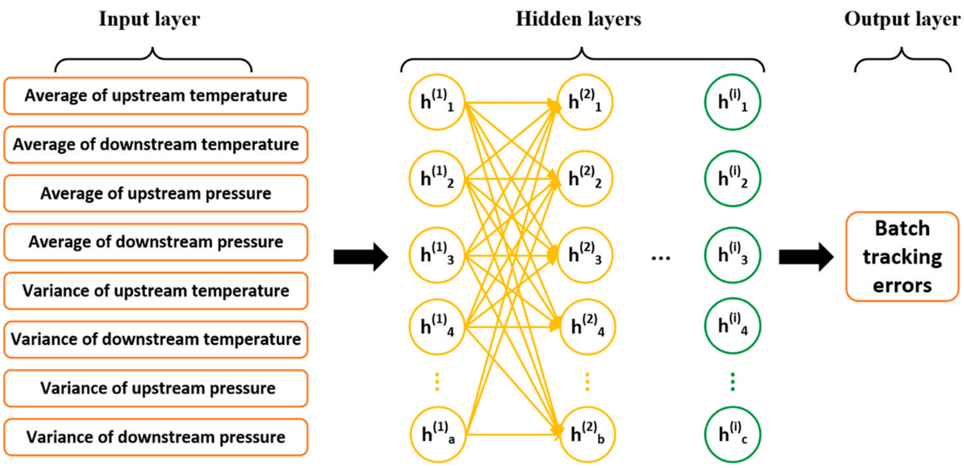


Fig. 5 – The basic architecture of ANN.

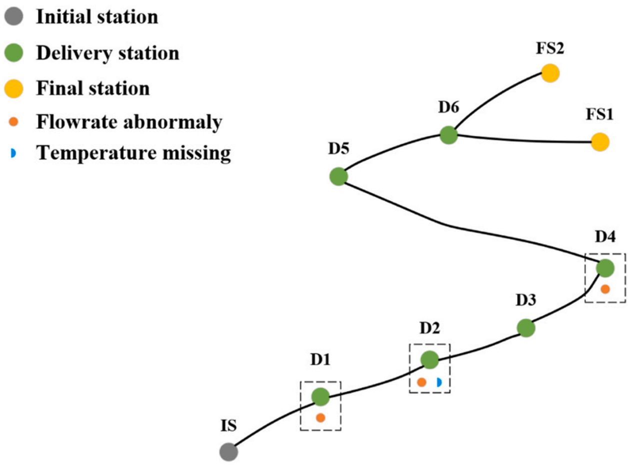


Fig. 6 – The schematic diagram of the studied multi-product pipeline network.

Table 1 – Information overview of each station.

Pipeline segment	Volume calculation model		Modified model
	Volume injection	Volume outflow	
IS-D1	√	×	√
D1-D2	×	×	×
D2-D3	√	√	×
D3-D4	√	×	√
D4-D5	×	√	√
D5-D6	√	√	√
D6-FS1	√	√	√
D6-FS2	√	√	√

Table 2 – The basic information of the studied pipeline.

Pipeline segment	Pipeline length (km)	Pipeline inner diameter (mm)
IS-D1	116.8	392.2
D1-D2	94.4	392.2
D2-D3	39.9	392.2
D3-D4	48.6	392.2
D4-D5	64.8	260.3
D5-D6	32.1	207.9
D6-FS1	45.7	207.9
D6-FS2	52.8	207.8

Table 3 – The properties of oil products.

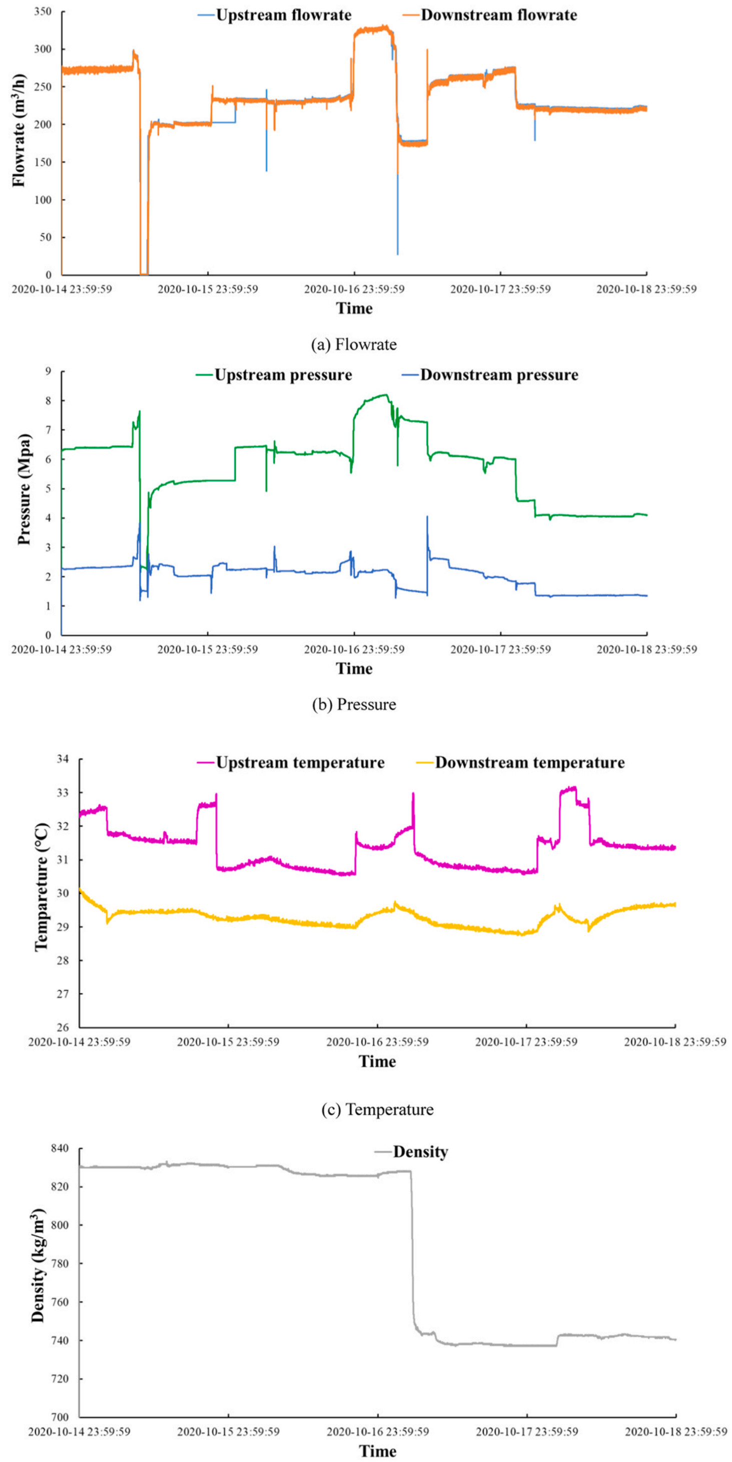
Oil product	Density (kg/m^3)	Viscosity (mm^2/s)
92# gasoline	734–738	0.74
95# gasoline	745–755	0.85
0# diesel	825–840	5.70

fundamentally significant to collect operating data from the real-world pipeline. In that case, a multi-product pipeline network in China is taken as an example to construct the basic database. The schematic diagram of the studied pipeline network is depicted in Fig. 6. The pipeline network contains 1 initial station, 6 delivery stations, and 2 final stations. The transported oil products include 92# and 95# gasoline, and 0# diesel. To reduce the amount of mixed oil and improve the transportation efficiency of multi-product pipelines, the batch sequence is usually 92#G-95#G-0#D according to actual batch planning.

In real engineering, due to the station instruments' failure and data collection issues, the operating data in some stations is insufficient. As shown in Fig. 6, the inlet and outlet flowrate of D1, D2, and D4 stations is abnormal due to the failure of instruments. Under this circumstance, the batch volume calculation of IS-D1 and D3-D4 pipeline segments can only utilize the volume injection model, and the batch volume calculation of D4-D5 pipeline segment can only utilize the volume outflow model. The estimated time of arrival station for D1-D2 cannot be calculated by using the volume calculation model. Moreover, the D2 station lacks outlet temperature, which makes the batch tracking of D2-D3 pipeline segment unable to use the self-learning based modified model to improve the tracking errors, affecting the accuracy of batch tracking in this pipeline segment. The volume calculation model and self-learning modified model applicable to pipeline segments are shown in Table 1.

The basic information of the studied pipeline network and oil products are respectively shown in Table 2 and Table 3. The delivery stations download oil products and the flowrate will decrease, which leads to the diameter-varying pipeline.

In this work, the pipeline operating data for two months from March 14, 2020, to April 14, 2020, and October 14, 2020, to November 14, 2020, is collected to construct the pipeline operating database. The time interval of the collected data is preprocessed to 10 s. The collected data contains upstream



(a) Flowrate

(b) Pressure

(c) Temperature

(d) Density

Fig. 7 – Part of the operating data in pipeline D5-D6.

and downstream oil density, flowrate, temperature, and pressure. Part of the operating data in pipeline D6-D6 is displayed in Fig. 7. From the flowrate curves (Fig. 7(a)), the pipeline flowrate varies due to the change in the transportation plan. The injection flowrate in the initial station and the delivery flowrate in the delivery stations influence the flowrate of the downstream pipeline segment. Due to the station operations, such as shutoff value, open value, pump startup, and pump stoppage, the flowrate will instantaneously fluctuate and become steady after a period. Furthermore, the upstream flowrate is slightly larger than the downstream flowrate, which may result from the temperature descent.

From the pressure curves depicted in Fig. 7(b), the downstream pressure is lower than the upstream pressure. Due to the effect of oil viscosity and pipeline wall roughness, there exists frictional resistance during transportation. For this reason, the pipeline pressure decreases gradually along the product flow direction. The pressure descent is influenced by flowrate, when the flowrate increases, the pressure descends increases at the same time. The pipeline temperature is shown in Fig. 7(c). It can be seen that the upstream temperature is larger than the downstream temperature in most instances. This is mainly caused by heat exchange. The oil product is pressurized by pumps upstream, so the temperature of the oil increases. Along the pipeline segment, due to the difference in oil temperature and soil temperature, heat conduction is inevitable. However, the upstream temperature may be smaller than the downstream temperature sometimes, due to the difference in ambient temperature during different periods. The product density curves are shown in Fig. 7(d). Because multiple types of oil products are transported in the pipeline, the properties of oil products are quite different from each other, among these, the representative one is the density differences. Due to the changes in oil products transported in the pipeline, the density comes to increase or decrease. For this reason, the density change is the main basis for station operators to judge whether the product batch arrives at stations.

3.2. *Results and discussion*

After obtaining the operating data, the volume calculation model can be utilized to determine the estimated time of batch arrival stations. Due to the data missing and data abnormality, the available calculation methods of the different pipeline segments are shown in Table 1. Then, the batch can be tracked based on the volume calculation model applying the operating data. The operating data in two months for the studied pipeline network is employed for verification of the volume calculation model. Some of the batch tracking errors based on the operating data from October to November are shown in Table 7 in Appendix. For the IS-D1 pipeline segment, the estimated times of arrival at the station are later than the actual times. This may result from the descent of pipeline temperature. The upstream temperature of IS-D1 pipeline is much larger than the downstream temperature, this will lead to a higher average pipeline temperature and the oil volume comes to expand. To this end, the actual batch is transported faster than the calculated results, causing an earlier actual time of arrival than the estimated time. The minimum value of batch interface tracking errors in IS-D1 pipeline segment is 14.73 min. A similar conclusion can be drawn in D5-D6 and D6-FS1 pipeline segments, of which the estimated times are later than the actual times of arrival.

However, the tracking errors in some other pipeline segments are negative values. For example, the estimated times of arrival in D3-D4 pipeline segment are earlier than the actual times of arrival, which results in the negative values of tracking errors. The influencing factors of batch tracking errors are complex, including the variation of temperature and pressure, the topographic relief, the transient disturbance of the hydraulic system, and the mixed oil segment. Therefore, the pipeline segments lying in different regions show various operating characteristics. For the D3-D4 pipeline segment, the later actual times of arrival may be caused by the lower average temperature. Furthermore, the operating pressure and actual product flow process could affect the actual times of arrival at the station. The minimum value of batch tracking errors for the D3-D4 pipeline segment is – 6.4 min (minus means the estimated time is earlier than the actual time of arrival), and the maximum value of batch tracking errors is – 24.53 min. For the D2-D3 and D4-D5 pipeline segments, some of the batch tracking errors are positive and some of them are negative. This may result from the dynamic hydro-thermal variation. Among them, the minimum value of batch tracking errors is 0.17 min

Table 4 – The parameters in the ANN model.

Parameters	Range	Result
Number of hidden layers	[1,4]	1
Number of hidden nodes	[5,50]	25
Learning rate	[0.1, 0.01, 0.001]	0.001
Optimizer	[Adam, SGD]	Adam
Activation function	[ReLU, Sigmoid, Tanh]	ReLU

During the period from March to April, the batch tracking results are not the same as in the period from October to November. Some of the estimated times of arrival based on the operating data from March to April are depicted in Table 8 in Appendix. For IS-D1 pipeline segment, most of the estimated times are later than the actual times of arrival at stations, leading to positive tracking errors. Only the case of the first 95#G batch shows a different result, the estimated time is 1.15 min earlier than the actual time of arrival. The minimum value of tracking errors for IS-D1 pipeline segment is – 1.15 min, and the maximum value is 23.42 min. Similar to the cases from October to November, for the cases of D5-D6 and D6-FS1 pipeline segments, the estimated times are all later than the actual times of arrival at stations. The minimum values of tracking errors for D5-D6 and D6-FS1 pipeline segments are 3.20 min and 12.00 min, respectively. The maximum values are 6.40 min and 17.33 min, respectively. For the case of D3-D4 pipeline segment, the tracking errors show similar characteristics to the case from October to November. The estimated times are earlier than the actual times of arrival at stations. The minimum value and maximum value of tracking errors for D3-D4 pipeline segment are – 0.32 min and – 6.45 min, respectively.

By testifying the performance of the volume calculation model, it is proved that the tracking errors are relatively higher only based on the mechanism model due to the complex flow characteristics of oil products. For this reason, the tracking errors should be modified for accurate batch interface tracking.

3.3. *Batch tracking via modified model*

To begin with, the batch tracking errors calculated by using the volume calculation model and operating data can be applied to establish a tracking error database. To acquire the ANN parameters, the historical operating data is divided into two datasets, including 80% of them for training the ANN model, and 20% of them to verify the performance of the ANN model. Multiple experiments are carried out to determine the suitable structure of ANN by the means of trial and error. Table 4 shows the suitable structure of ANN, the number of hidden layers is selected as 1, the hidden nodes are 25, and the learning rate is 0.001. To optimize the model hyper-parameters in the ANN model, the Adam optimizer is applied. The ReLU activation function is selected as the nonlinear activation function.

After receiving the trained ANN model, several ensemble models, e.g., decision tree (DT), random forest (RF), and extra trees (ET) are applied for model comparison. As shown in Table 5, the self-learning model based on DT acquires an 8.69 min tracking error. The self-learning model based on ET and RF achieves a reduction of 25% and 38% than that of DT. The self-learning model based on ANN obtains the lowest tracking errors. So, the ANN is selected to construct the

Model	Tracking error/min	Training time/s
DT	8.69	2.33
RF	6.55	2.54
ET	5.36	2.48
ANN	**3.79**	6.07

Table 5 – The tracking error of the hybrid intelligent framework with different models.

hybrid framework. The proposed hybrid intelligent framework is executed on Python, and the computer with Intel(R) _Core(TM)_i5–9300 H @ 2.40 GHz CPU is used to train the data-driven model.

To illustrate the effectiveness of the self-learning modified model, a comparison between the volume calculation model and volume calculation with the modified model is conducted, as shown in Fig. 8. For the IS-D1 pipeline segment, the tracking errors are relatively higher and the maximum value

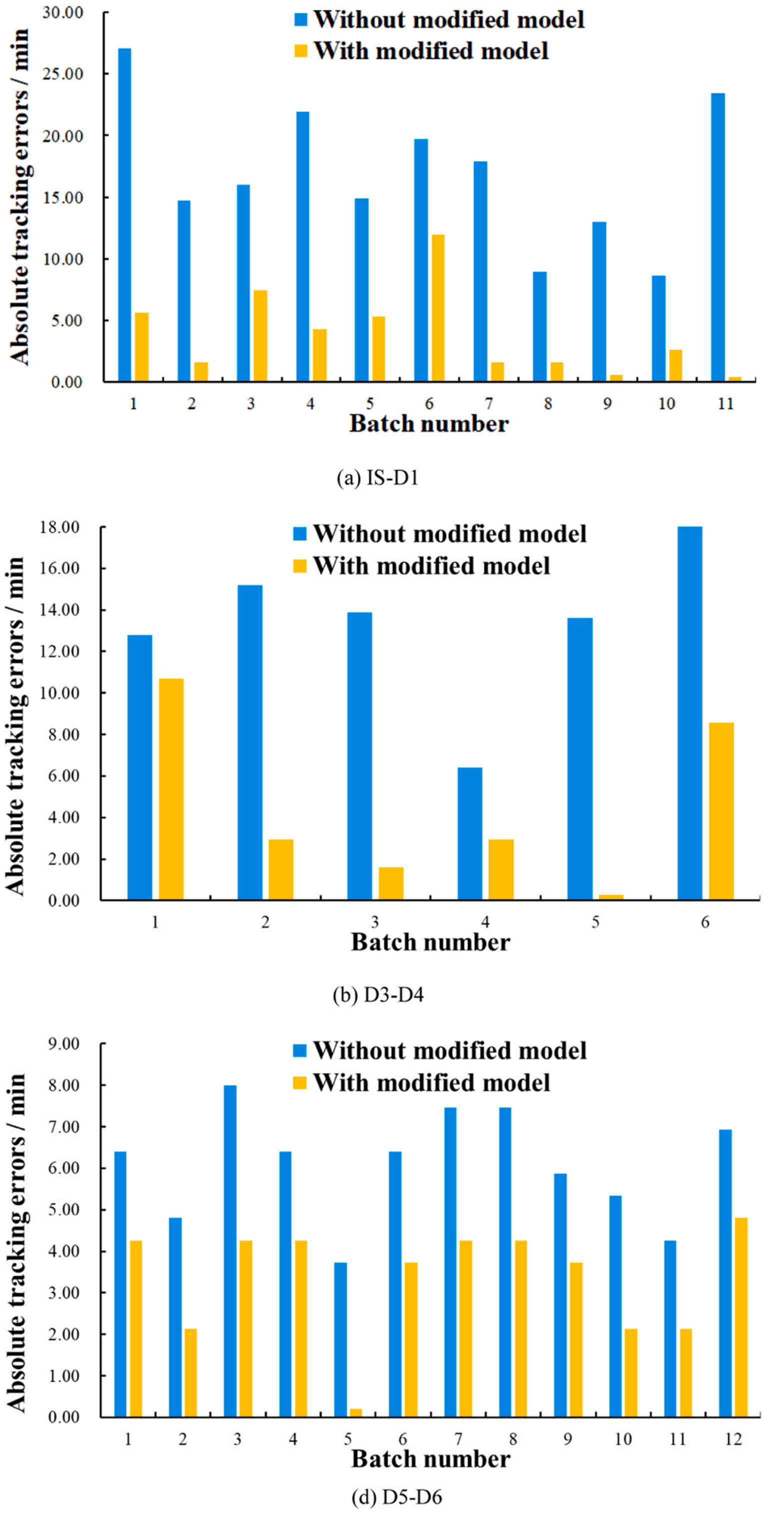


Fig. 8 – The comparison of batch tracking errors without the modified model and with the modified model.

Table 6 – The comparison of batch tracking errors on different methods.

Method	Means of tracking error/min	Std of tracking error/min
The BTS in reference (Milano et al., 2018)	15.00	/
Volume calculation model	10.87	6.53
Hybrid intelligent framework	**3.79**	**2.91**

is 27.1 min. The higher tracking errors bring a serious influence on the judgment of station operators on batch interface arrival at the station, leading to more processing costs for the mixed oil segment. Moreover, the stations cannot deliver oil products in time, affecting the normal supply of the consumer market. However, by combining the volume calculation model with the self-learning modified model, the tracking errors are reduced a lot. For example, the tracking errors of the 9th and 11th batches in IS-D1 pipeline segment are reduced from 12.98 min and 23.42–0.53 min and 0.40 min, respectively. In the case of D3-D4 pipeline segment, the minimum value of tracking errors with the modified model is 0.28 min while the maximum value is 10.68 min. The tracking error of 1st batch is reduced from 12.80 min to 10.68 min, whose error may mainly result from other unexpected factors, such as slack flow. In the case of D5-D6 pipeline segment, the tracking errors without the modified model are all less than 10 min. After being modified by the self-learning based ANN model, the tracking errors are reduced. All the tracking errors with the modified model are all less than 5 min, and the minimum value of tracking errors is 0.20 min

Based on the above content, the accuracy and effectiveness of the proposed self-learning modified model are verified. To further illustrate the superiority of the proposed model, the average tracking errors of different methods are calculated for method comparison, as shown in Table 6. The BTS developed by Milano et al. (2018) provides an available method to estimate the time of product batch arrival at stations. The operating data is used to verify model performance, the results show that the tracking error of the BTS is 15 min. In this work, the volume calculation model is applied to calculate the location of the batch interface, and the mean and std of tracking errors are 10.87 min and 6.53 min, indicating a large fluctuation in model accuracy. To improve the accuracy, the hybrid intelligent framework with a self-learning model is applied to modify the tracking errors, and the mean and std of the proposed method are 3.79 min and 2.91 min, which indicates that the modified model possesses the most accurate and efficient performance.

4. Conclusion

To meet the demand of supplying multi-products and reduce the economic cost, different oil products are transported in sequence in one pipeline. This leads to the difficult problem of determining the location of each batch interface, influencing delivering oil products to the right storage tank and the normal supply of the consumer market. The batch interface migration in the pipeline is affected by complex hydrothermal conditions and mixed oil segments. To track batch interface accurately, a novel hybrid intelligent framework is proposed in this paper. Incorporating the mechanism process with the data-driven algorithm, the proposed model overcomes the limitations of the conventional mechanism model which shows poor accuracy and generality. By applying the operating data to train the neural network parameters, the data-driven model learns the complex and nonlinear relationship between pipeline operating conditions and tracking errors of the mechanism model. To this end, the data-driven modify the location of batch interface calculated by mechanism according to real-time operating data, outputting more precise and efficient estimated times of batch arrival at stations compared with other methods. The average tracking error of the proposed hybrid framework is 3.79 min while the traditional volume calculation model is 10.87 min, realizing a 75% reduction in the tracking error. For engineering applications, based on the operating data in the SCADA system, the proposed hybrid intelligent framework can track the real-time location of each oil batch in multi-product pipelines to remind station operators to deliver oil products or mixed oil cutting in time.

This work proposes a hybrid intelligent framework to estimate times of batch arrival at stations. The influences of pressure, temperature, and mixed oil segment are taken into consideration. However, the influencing factors of batch migration are various, such as topographic relief and mixed oil trailing. Our future work will focus on the more accurate batch tracking method integrating these factors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See appendix Table 7, Table 8.

Table 7 – The comparison of actual time and estimated time of arrival from October to November.

Pipeline segment	Batches	Actual times of arrival	Estimated times of arrival	Tracking errors/min
IS-D1	95#G-1	2020–10–16 18:07:43	2020–10–16 18:34:49	27.10
	0#D-1	2020–10–17 22:00:15	2020–10–17 22:14:59	14.73
	92#G-1	2020–10–20 00:48:31	2020–10–20 01:04:29	15.97
	95#G-2	2020–10–22 03:45:51	2020–10–22 04:07:49	21.97
	0#D-2	2020–10–23 17:02:07	2020–10–23 17:16:59	14.87
	92#G-2	2020–10–30 09:43:27	2020–10–30 10:03:09	19.70
	95#G-3	2020–11–14 18:15:27	2020–11–14 18:33:19	17.87
D2-D3	92#G-1	2020–10–16 02:20:10	2020–10–16 02:13:39	-6.52
	95#G-1	2020–10–18 07:37:36	2020–10–18 07:39:49	2.22
	0#D-1	2020–10–19 11:19:41	2020–10–19 11:16:59	-2.70
	95#G-2	2020–10–24 03:39:43	2020–10–24 03:36:59	-2.73
	0#D-2	2020–10–26 00:43:59	2020–10–26 00:40:39	-3.33
	92#G-3	2020–11–13 15:51:11	2020–11–13 16:01:59	10.80
D3-D4	92#G-1	2020–10–16 19:06:07	2020–10–16 19:03:11	-2.93
	95#G-1	2020–10–18 22:34:07	2020–10–18 22:21:19	-12.80
	0#D-1	2020–10–20 02:04:31	2020–10–20 01:49:19	-15.20
	92#G-2	2020–10–22 07:14:55	2020–10–22 07:01:03	-13.87
	95#G-2	2020–10–24 19:06:23	2020–10–24 18:59:59	-6.40
	0#D-2	2020–10–26 15:10:23	2020–10–26 14:56:47	-13.60
	92#G-3	2020–11–14 17:53:19	2020–11–14 17:28:47	-24.53
D4-D5	92#G-1	2020–10–17 05:50:23	2020–10–17 05:22:49	-27.57
	95#G-1	2020–10–19 08:14:23	2020–10–19 08:13:09	-1.23
	0#D-1	2020–10–20 11:23:59	2020–10–20 11:24:09	0.17
	92#G-2	2020–10–22 17:19:11	2020–10–22 17:21:09	1.97
	95#G-2	2020–10–25 20:08:31	2020–10–25 20:09:49	1.30
	0#D-2	2020–10–27 00:02:23	2020–10–27 00:04:09	1.77
D5-D6	92#G-1	2020–10–17 10:25:03	2020–10–17 10:27:49	2.77
	95#G-1	2020–10–19 11:58:55	2020–10–19 12:09:29	10.57
	0#D-1	2020–10–20 16:05:03	2020–10–20 16:11:09	6.10
	92#G-2	2020–10–22 21:57:03	2020–10–22 22:07:19	10.27
	95#G-2	2020–10–26 00:10:07	2020–10–26 00:12:59	2.87
	0#D-2	2020–10–27 05:00:15	2020–10–27 05:01:29	1.23
D6-FS1	92#G-1	2020–10–18 01:02:23	2020–10–18 01:18:49	16.43
	95#G-1	2020–10–20 03:57:19	2020–10–20 04:14:09	16.83
	0#D-1	2020–10–21 05:57:35	2020–10–21 06:18:29	20.90
	92#G-2	2020–10–23 19:46:55	2020–10–23 20:07:19	20.40
	0#D-2	2020–10–27 20:00:47	2020–10–28 20:15:59	15.99

Table 8 – The comparison of actual time and estimated time of arrival from March to April.

Pipeline segment	Batches	Actual times of arrival	Estimated times of arrival	Tracking errors/min
IS-D1	95#G-1	2020–03–09 15:30:08	2020–03–09 15:28:59	-1.15
	0#D-1	2020–03–10 04:43:12	2020–03–10 04:52:09	8.95
	92#G-1	2020–03–29 04:58:40	2020–03–29 05:11:39	12.98
	95#G-2	2020–04–01 00:48:00	2020–04–01 00:56:39	8.65
	0#D-2	2020–04–01 14:14:24	2020–04–01 14:37:49	23.42
D2-D3	92#G-1	2020–03–10 09:03:28	2020–03–10 09:04:49	1.35
	95#G-1	2020–03–11 17:31:12	2020–03–11 17:24:59	-6.22
	0#D-1	2020–03–12 03:19:28	2020–03–12 03:21:19	1.85
	92#G-2	2020–04–02 00:38:56	2020–04–02 00:24:39	-14.28
	95#G-2	2020–04–03 05:20:00	2020–04–03 05:04:39	-15.35
	0#D-2	2020–04–03 14:14:24	2020–04–03 13:51:39	-22.75
D3-D4	92#G-1	2020–03–11 06:44:16	2020–03–11 06:39:09	-5.12
	95#G-1	2020–03–12 14:35:44	2020–03–12 14:31:09	-4.58
	0#D-1	2020–03–12 22:58:40	2020–03–12 22:52:19	-6.35
	92#G-2	2020–04–02 23:06:08	2020–04–02 23:05:49	-0.32
	95#G-2	2020–04–04 01:29:36	2020–04–04 01:26:09	-3.45
	0#D-2	2020–04–04 09:23:44	2020–04–04 09:23:09	-0.58
D5-D6	92#G-1	2020–3–12 08:24:32	2020–03–12 08:29:20	3.20
	95#G-1	2020–3–14 18:02:08	2020–03–14 18:10:08	6.40
	0#D-1	2020–3–15 20:22:24	2020–03–15 20:28:48	4.80
	92#G-2	2020–4–3 21:49:20	2020–04–03 21:54:40	3.73
	95#G-2	2020–4–4 20:37:20	2020–04–04 20:41:36	3.20
	0#D-2	2020–4–7 13:57:20	2020–04–07 14:04:16	5.87
D6-FS1	92#G-1	2020–03–13 14:36:19	2020–03–13 14:53:39	17.33
	95#G-1	2020–03–15 14:38:09	2020–03–15 14:50:09	12.00
	0#D-2	2020–4–4 17:46:39	2020–4–4 17:59:09	12.50

References

Al-Marhoun, M.A., 1985. Pressure-volume-temperature correlations for Saudi crude oils. Univ. Pet. Miner.

Amina, B., Ahmed, H., 2017. An overview of thermal mass flowmeters applicability in oil and gas industry. Energy Procedia 141, 299–303.

Asgari, S., MirhoseiniNejad, S., Moazamigoodarzi, H., Gupta, R., Zheng, R., Puri, I.K., 2021. A gray-box model for real-time transient temperature predictions in data centers. Appl. Therm. Eng. 185, 116319.

Blažič, S., Matko, D., Geiger, G., 2004. Simple model of a multi-batch driven pipeline. Math. Comput. Simul. 64, 617–630.

Bottou, L., 2010. Large-scale machine learning with stochastic gradient descent. Proceedings of COMPSTAT'2010. Springer, pp. 177–186.

Cazarez-Candia, O., Vásquez-Cruz, M.A., 2005. Prediction of pressure, temperature, and velocity distribution of two-phase flow in oil wells. J. Pet. Sci. Eng. 46, 195–208.

Chen, L., Yuan, Z., Xu, J., Gao, J., Zhang, Y., Liu, G., 2021. A novel predictive model of mixed oil length of products pipeline driven by traditional model and data. J. Pet. Sci. Eng. 205, 108787.

Dai, J., Chen, N., Yuan, X., Gui, W., Luo, L., 2020. Temperature prediction for roller kiln based on hybrid first-principle model and data-driven MW-DLWKPCR model. ISA Trans. 98, 403–417.

Desamala, A.B., Vijayan, V., Dasari, A., Dasmahapatra, A.K., Mandal, T.K., 2016. Prediction of oil-water flow patterns, radial distribution of volume fraction, pressure and velocity during separated flows in horizontal pipe. J. Hydronam. Ser. B 28, 658–668.

Farah, M.A., Oliveira, R.C., Caldas, J.N., Rajagopal, K., 2005. Viscosity of water-in-oil emulsions: Variation with temperature and water volume fraction. J. Pet. Sci. Eng. 48, 169–184.

Glassey, J., Von Stosch, M., 2018. Hybrid Modeling in Process Industries. CRC Press.

Gray, F.M., Schmidt, M., 2018. A hybrid approach to thermal building modelling using a combination of Gaussian processes and grey-box models. Energy Build. 165, 56–63.

Harbert, T.R., 2008. Automation improvements in batch cutting process. Last Profit Cent. Pipelines, Int. Pipeline Conf. 623–628.

Huber, D.W., 1981. Real-time transient modem for batch tracking, line balance and leak detection. J. Can. Pet. Technol. 20.

Kirschstein, T., 2018. Planning of multi-product pipelines by economic lot scheduling models. Eur. J. Oper. Res. 264, 327–339.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. nature 521, 436–444.

Lee, J.H., Shin, J., Realff, M.J., 2018. Machine learning: Overview of the recent progresses and implications for the process systems engineering field. Comput. Chem. Eng. 114, 111–121.

Liang, Y., Li, M., Li, J., 2012a. Hydraulic model optimization of a multi-product pipeline. Pet. Sci. 9, 521–526.

Liang, Y., Li, M., Zhang, N., 2012b. A study on optimizing delivering scheduling for a multiproduct pipeline. Comput. Chem. Eng. 44, 127–140.

Liao, Q., Liang, Y., Xu, N., Zhang, H., Wang, J., Zhou, X., 2018a. An MILP approach for detailed scheduling of multi-product pipeline in pressure control mode. Chem. Eng. Res. Des. 136, 620–637.

Liao, Q., Zhang, H., Xu, N., Liang, Y., Wang, J., 2018b. A MILP model based on flowrate database for detailed scheduling of a multi-product pipeline with multiple pump stations. Comput. Chem. Eng. 117, 63–81.

Liebenberg, M., Bueno, D.E.G., Magalha˜, es, C.C., 2008. Effects of density and viscosity measurements errors at the pipeline batch tracking system. Int. Pipeline Conf. 705–710.

Lynnworth, L.C., Liu, Y., 2006. Ultrasonic flowmeters: half-century progress report, 1955–2005. Ultrasonics 44, e1371–e1378.

Ma, B., Zhou, A., Steeves, J., 2010. Pipeline batch planning to optimize storage requirements. Int. Pipeline Conf. 17–27.

Milano, G., Goyal, N., Basnett, D., 2018. Tracking Batches Accurately in a Multi-Product Pipeline With Large Elevation Changes and Prominent Slack Flow. International Pipeline Conference. American Society of Mechanical Engineers V003T004A026.

Schäfer, P., Caspari, A., Schweidtmann, A.M., Vaupel, Y., Mhamdi, A., Mitsos, A., 2020. The potential of hybrid mechanistic/data-driven approaches for reduced dynamic modeling: application to distillation columns. Chem. Ing. Tech. 92, 1910–1920.

Schweidtmann, A.M., Esche, E., Fischer, A., Kloft, M., Repke, J.U., Sager, S., Mitsos, A., 2021. Machine learning in chemical engineering: a perspective. Chem. Ing. Tech. 93, 2029–2039.

Tong, Q., Liang, G., Bi, J., 2022. Calibrating the adaptive learning rate to improve convergence of ADAM. Neurocomputing 481, 333–356.

von Stosch, M., Oliveira, R., Peres, J., Feyo de Azevedo, S., 2014. Hybrid semi-parametric modeling in process systems engineering: Past, present and future. Comput. Chem. Eng. 60, 86–101.

Wang, B., Liang, Y., Zheng, T., Yuan, M., Zhang, H., 2019. Optimisation of a downstream oil supply chain with new pipeline route planning. Chem. Eng. Res. Des. 145, 300–313.

Wang, C., Zheng, J., Liang, Y., Li, M., Chen, W., Liao, Q., Zhang, H., 2022. Deeppipe: a hybrid model for multi-product pipeline condition recognition based on process and data coupling. Comput. Chem. Eng. 160, 107733.

Wang, N., Zhang, D., Chang, H., Li, H., 2020. Deep learning of subsurface flow via theory-guided neural network. J. Hydrol. 584, 124700.

Wright, W., 1967. Prediction of bulk moduli and pressure-volume-temperature data for petroleum oils. ASLE Trans. 10, 349–356.

Yuan, Z., Chen, L., Shao, W., Zuo, Z., Zhang, W., Liu, G., 2021. A robust hybrid predictive model of mixed oil length with deep integration of mechanism and data. J. Pipeline Sci. Eng. 1, 459–467.

Zhang, F., Li, S., 2009. Batch interface and flow rate variations of products pipeline, ICPTT 2009: advances and experiences with pipelines and trenchless technology for water, sewer. Gas., Oil Appl. 423–428.

Zheng, J., Du, J., Liang, Y., Liao, Q., Li, Z., Zhang, H., Wu, Y., 2021a. Deeppipe: a semi-supervised learning for operating condition recognition of multi-product pipelines. Process Saf. Environ. Prot. 150, 510–521.

Zheng, J., Du, J., Liang, Y., Wang, C., Liao, Q., Zhang, H., 2021b. Deeppipe: Theory-guided LSTM method for monitoring pressure after multi-product pipeline shutdown. Process Saf. Environ. Prot. 155, 518–531.

Zheng, J., Liang, Y., Xu, N., Wang, B., Zheng, T., Li, Z., Liao, Q., Zhang, H., 2021c. Deeppipe: a customized generative model for estimations of liquid pipeline leakage parameters. Comput. Chem. Eng. 149, 107290.