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An integrated methodology for the supply reliability analysis of multi-product pipeline systems under pumps failure

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ABSTRACT

As the main way for the long-distance transportation of refined products, multi-products pipelines are of vital importance to the regional energy security. The supply reliability evaluation of multi-product pipeline systems can improve the effective response to unexpected disruptions and guarantee the reliable oil supply. Based on reliability theory and pipeline scheduling method, an integrated supply reliability evaluation methodology for multi-product pipeline systems is proposed in this paper and the pumps failure, of which influence is the most complex, is focused on. In the methodology, the discrete-time Markov process is adopted to describe the stochastic failure and the Monte Carlo method is used to simulate the system states transition. With the pipeline flowrate upper limits under various pumps failure scenarios optimized in advance, the maximum supply capacity to the downstream markets in each trial is calculated by the pipeline scheduling model. Three indicators are also developed to analyze the pipeline supply reliability from the holistic and individual perspectives. At last, the methodology application is performed on a real-world multi-product pipeline system in China and the supply reliability is analyzed in detail according to the simulation results. It is proved to provide a practical method for the emergency response decision-making and loss prevention.

1. Introduction

1.1. Background

As a strategic energy influencing the national economy and society stability, refined products account for 12.9% of China's total energy consumption and the demand is increasing a rate of 6.3% per year [1]. Among all the ways for refined products transportation, pipeline plays the most significant role. Its delivery amount takes up 45% of the total transportation amount. Therefore, multi-product pipelines have a great importance on the safe and reliable oil supply [2,3]. In recent years, multi-product pipelines are constructed rapidly. According to the Medium and Long-term Oil & Gas Pipeline Networks Planning [4], the total length of China's multi-product pipelines will reach 40,000 km and the basic access to cities with more than 1 million population will be realized. In this process, the pipeline system presents many new features such as large market span, complex supply relations, decentralized management, etc. This puts forward higher requirements for centralized control, safe operation, and equipment maintenance capability [5,6]. Once the supply shortage or interruption is led by pipeline accidents or unbalanced regional resource allocation, it will have a major impact on economic development and social stability [7]. In this way, the supply reliability analysis of the multi-product pipeline system is of vital importance to ensure the pipeline operation security, reliable oil supply, and improve the management level of regional energy supply chain [8,9]. Besides, the theoretical guidance and decision-making means under emergency conditions can be provided for pipeline operators, whose most important responsibility is to supply the required refined products to customers in time.

The earliest concept of reliability came from the American Aviation Commission in 1939. The definition of reliability used today was put forward in 1952, referring to the ability or probability of components, products, and systems to perform specified functions under certain conditions in a certain period of time [10]. The primary function of a multi-product pipeline is to deliver enough refined products to the local markets safely [11]. In this way, as the supply-side of downstream customers, the supply reliability of multi-product pipelines can be defined as the probability to satisfy the demands of delivery stations for

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Nomenclature

Sets and indices

$k \in K = \{1, 2, ..., k_{\max}\}$ Set of scenarios in which some pumps are normal and others fail.
$p \in P = \{1, 2, ..., p_{\max}\}$ Set of flowrate upper limits set.
$i \in I = \{1, 2, ..., i_{\max}\}$ Set of stations along the pipeline.
$a \in A = \{1, 2, ..., a_{\max}\}$ Set of flowrate intervals for piecewise linearization.
$s \in S = \{1, 2, ..., s_{\max}\}$ Set of time intervals.
$j \in J = \{1, 2, ..., j_{\max}\}$ Set of batches.
$o \in O = \{1, 2, ..., o_{\max}\}$ Set of oil types.

Input parameters

$\alpha_{k,\ i,\ p}$ Importance value of pipeline segment $(i, i + 1)$ under flowrate set p of scenario k $(0 < \alpha_{k,\ i,\ p} < 1)$.
$q_{\mathrm{Emax}\,i}$ Maximum design flowrate of pipeline segment $(i, i + 1)$ (m^3/h).
g Gravitational acceleration (m/s^2).
β, m Hydraulic loss calculation coefficients, which are related to the flow regime $(0 < m < 1)$.
$H_{i,\ k}$ Pumping head parameters.
L_i, d_i Length and inner diameter of pipeline segment $(i, i + 1)$ (m).
Z_i Elevation of station i (m).
R_{O} Refined product density for the pumps provided pressure calculation (kg/ m^3).
R_{D} Refined product density for the hydraulic loss calculation (kg/ m^3).
υ_{D} Refined product viscosity for the hydraulic loss calculation (m^2/s).
u_a, w_a Coefficients of the fitted linear equation of interval a.
$q_{\mathrm{Lmax}\,a}$, $q_{\mathrm{Lmin}\,a}$ Upper and lower limits of flowrate interval a (m^3/h).
$p_{\mathrm{Omax}\,i}$ Maximum outlet pressure of station i (MPa).
$p_{\mathrm{Imin}\,i}$ Minimum inlet pressure of station i (MPa).
$V_{\mathrm{DE}i,\ o}$ Demanding volume of delivery station i for refined product o (m^3).
τ_{P} Time length of the time interval (h).
$\gamma_{j,\ o}$ If batch j corresponds to refined product o, $\gamma_{j,o} = 1$; otherwise, $\gamma_{j,o} = 0$.
X_i Volume coordinate of station i (m).
$q_{\mathrm{Dmax}\,i}$, $q_{\mathrm{Dmin}\,i}$ Maximum and minimum delivery flowrate of station i (m^3/h).
$q_{\mathrm{Pmin}\,i}$ Minimum flowrate of pipeline segment $(i, i + 1)$ (m^3/h).
q_{Jmax}, q_{Jmin} Maximum and minimum injection flowrate (m^3/h).
$F_{\mathrm{U}s,\ k}$ If the pipeline is under scenario k in time interval s, $F_{\mathrm{U}s,k} = 1$; otherwise, $F_{\mathrm{U}s,k} = 0$.

Model variables

$q_{\mathrm{U}k,\ i,\ p}$ Flowrate upper limits of pipeline segment $(i, i + 1)$ under flowrate set p of scenario k (m^3/h).
$P_{\mathrm{N}k,\ i,\ p}$, $P_{\mathrm{O}k,\ i,\ p}$ Inlet and outlet pressure of station i under flowrate set p of scenario k (MPa).
$P_{\mathrm{F}k,\ i,\ p}$ Hydraulic loss of pipeline segment $(i, i + 1)$ under flowrate set p of scenario k (MPa).
$B_{\mathrm{QL}k,\ i,\ p,\ a}$ If flowrate upper limits set p under scenario k is selected and the flowrate of pipeline segment $(i, i + 1)$ is within interval a, $B_{\mathrm{QL}k,i,p,a} = 1$; otherwise, $B_{\mathrm{QL}k,i,p,a} = 0$.
$V_{\mathrm{AC}i,\ o}$ Actual delivered volume of delivery station i for refined product o (m^3).
$C_{\mathrm{OH}s,\ j}$ Upper coordinate of batch j at the start time of time interval s (m^3).
$Q_{\mathrm{NJ}s,\ j}$ Injection flowrate of batch j in time interval s (m^3/h).
$Q_{\mathrm{PF}s,\ i}$ Flowrate of pipeline segment $(i, i + 1)$ in time interval s (m^3/h).
$Q_{\mathrm{DO}s,\ i,\ j}$ Delivery flowrate of batch j at station i in time interval s (m^3/h).
$B_{\mathrm{DO}s,\ i,\ j}$ If batch j is delivered at station i in time interval s, $B_{\mathrm{DO}s,i,j} = 1$; otherwise, $B_{\mathrm{DO}s,i,j} = 0$.
$B_{\mathrm{PA}s,\ i,\ j}$ If the upper coordinate of batch j has exceeded station i at the start time of time interval s, $B_{\mathrm{PA}s,i,j} = 1$; otherwise, $B_{\mathrm{PA}s,i,j} = 0$.
$B_{\mathrm{FT}s,\ i,\ j}$ If batch j is flowing through station i in time interval s, $B_{\mathrm{FT}s,i,j} = 1$; otherwise, $B_{\mathrm{FT}s,i,j} = 0$.
$B_{\mathrm{FA}s,\ i,\ j}$ If the upper coordinate of batch j is within segment $(i, i + 1)$ in time interval s, $B_{\mathrm{FA}s,i,j} = 1$; otherwise, $B_{\mathrm{FA}s,i,j} = 0$.
$B_{\mathrm{ID}s,\ i}$ If pipeline segment $(i, i + 1)$ is shut down in time interval s, $B_{\mathrm{ID}s,i} = 1$; otherwise, $B_{\mathrm{ID}s,i} = 0$.
$B_{\mathrm{SP}s,\ k,\ p}$ If flowrate upper limits set p under scenario k is selected in time interval s, $B_{\mathrm{SP}s,k,p} = 1$; otherwise, $B_{\mathrm{SP}s,k,p} = 0$.

various refined products punctually.

1.2. Related work

The multi-product pipeline system is composed of a series of components such as pipelines, pumps, oil tanks, etc. The normal operation of each component plays an important role in realizing the system's function. Many researches have been conducted on these equipment units' mechanical reliability evaluation, which is to calculate the indicators such as availability, failure probability, etc. [12–14]. This is the basis for the supply reliability analysis of multi-product pipeline systems. For the failure probability prediction of underground pipelines under rare failure events, Kong et al. [15] proposed a novel framework to implement the Subset Simulation and compared with Monte Carlo simulation (MCS) to prove the efficiency. Based on the corrosion rate, structural integrity analysis results, and the number of defects and failure data, Dundulis et al. [16] put forward an integrated framework for the failure probability estimation of natural gas pipelines. Abyani et al. [17] conducted a comparative study on the reliability analysis of internally corroded pipelines using MCS and Latin Hypercube Sampling (LHS) methods. For the single corrosion defect, three failure mechanisms were considered, while for the multiple corrosion defects, only local burst was studied. Aiming at the mechanical reliability analysis of centrifugal pumps with small maintenance data, Zhu et al. [18] used the least square method and MCS to estimate the Weibull distribution parameters and calculated the reliability index and operation rules. Ferreira et al. [19] established a framework for the preliminary analysis of equipment failure data and applied it to petroleum refinery pumps to estimate the failure mode and plan the maintenance management. Due to the lack of basic events failure data and other uncertainties, Shi et al. [20] combined the traditional fault tree analysis with the improved analysis hierarchy process and fuzzy set theory to evaluate the fire and explosion probability of oil tanks. For the reliable and accurate calculation of the likelihood of storage tank accidents, Guo et al. [21] proposed an improved similarity aggregation method based Fuzzy Bayesian network model, which could determine the proportion of the main influencing factors and the key causes of the accidents.

As a unified system that has large geographical extension, multi-product pipelines usually operate complicatedly and will be influenced by multiple uncertainties, including changeable market demand, oil supply fluctuations, unexpected equipment breakdowns, etc. [22]. To deliver various refined products to different downstream markets, the multi-batch sequential transportation process is adopted and multiple stations for injection and delivery are set along the pipeline. At the same time, because of the time-varying demands and frequent injection/delivery operations, the pipeline hydraulics varies complicatedly during operation [23]. In this way, the accurate calculation of pipeline supply capacity, which is essential to perform the supply reliability analysis, must depend on the pipeline scheduling. It is an operational research issue and determines the injection/delivery flowrate, pumps start/stop time, and supplied amount to delivery stations in a pipeline transportation task [24]. As a classic topic in the research of multi-product pipelines, considerable efforts have been made based on the discrete/continuous time representation, for different objectives including operation costs, backorder demands, transport time, etc. [25–27].

Because of the above mentioned factors, there are few articles for the supply reliability analysis of multi-product pipelines to the best of our knowledge. Most previous related studies have focused on natural gas pipelines [28,29], water distribution systems (WDNs) [30,31], industrial plants [32,33], etc. Combining graph theory, hydro-thermal simulation, and stochastic process simulation methods, Su et al. [7] proposed a systematic comprehensive methodology for the supply reliability analysis of natural gas pipeline networks, and established an evaluation model from different perspectives. Based on reliability theory and unsteady flow simulation, Yu et al. [34] developed an integrated approach to quantify the supply capacity of natural gas pipelines, considering the influence of line pack and spare equipment. Next, Yu et al. [35] improved the proposed approach by considering the pipeline network's dynamic behavior and the demand uncertainty in a Monte Carlo trial. To enhance the computation efficiency, Chen et al. [36] used LHS and Cholesky decomposition methods to produce representative demand scenarios and came up with four heuristic regulation means to improve the natural gas pipeline supply reliability. Jensen and Jerez [37] used the Markov chain Monte Carlo (MCMC) method for the hydraulic reliability evaluation of large scale WDNs under uncertainties and the applicability was demonstrated on an actual network containing thousands of nodes. Based on the probability density evolution method, Liu et al. [38] put forward a lifecycle operational reliability assessment framework for WDNs, in which the time-dependent pipe roughness model is included to reflect the pipeline degradation process in the lifecycle. Yuyama et al. [39] established a probability model to calculate the accident probability of thermal power plants and used the Bootstrap simulation to estimate the potential risk of power supply shortage. Sabouhi et al. [40] proposed reliability evaluation models for gas and steam turbine power plants and identified the critical components through the proposed reliability-oriented sensitivity indexes to determine the efficient maintenance strategies.

Concluded from the above, the uniqueness and complexity of multi-product pipelines bring difficulties for the quantitative analysis of supply reliability, and thus, few efforts have been made. Even though the researches on other large-scale complex systems could be used for reference, the technical and operational process and the components are rather different. Therefore, aiming at this issue, this paper proposes an integrated methodology consisting of four modules: supply reliability indicators establishment, equipment failure analysis, stochastic process simulation, and supply capacity calculation. The stochastic failure simulation and the pipeline scheduling model are first coupled together to achieve the supply reliability evaluation of multi-product pipeline systems. It could also be beneficial for other large-scale

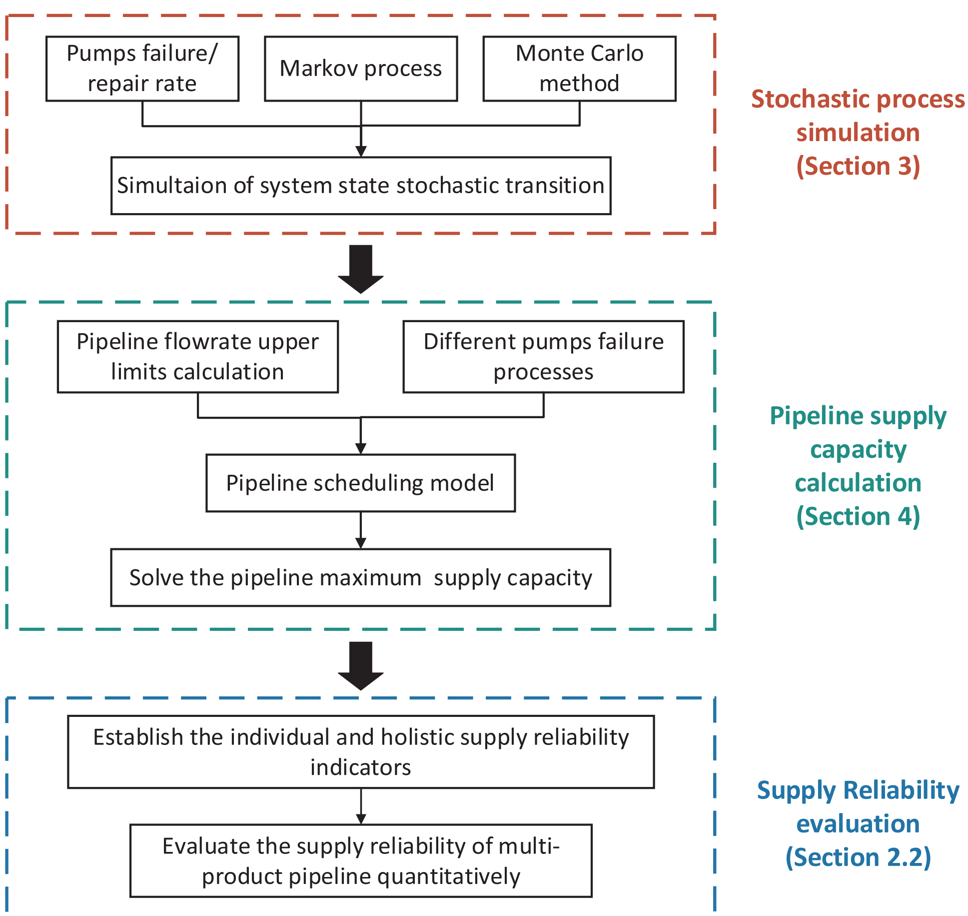

Fig. 1. The framework of the proposed methodology.

complex systems.

1.3. Contributions of this work

The contributions of this paper are listed as follows:

(1) An integrated methodology for the supply reliability analysis of multi-product pipeline systems under pumps failure is first proposed.
(2) The stochastic pumps failure is described by the discrete-time Markov process and the system states transition is simulated by the Monte Carlo method. The multi-product pipeline hydraulic and scheduling models are adopted to calculate the pipeline supply capacity.
(3) Three indicators are put forward for the supply reliability evaluation from the holistic and individual perspectives.
(4) The methodology is successfully applied to a real-world multi-product pipeline in China and the supply reliability is analyzed in detail.

1.4. Paper organization

The rest of the paper is organized as follows. Section 2 first gives the methodology framework, and then elaborates the composition, upstream/downstream link, and operation processes of a multi-product pipeline system. Three indicators are also put forward to quantify the supply reliability from the holistic and individual perspectives. In Section 3, the pumps failure and repair probability are introduced and the stochastic process of pumps failure during the pipeline operation is simulated. Section 4 gives a brief introduction on the hydraulic and scheduling models of multi-product pipelines and presents the compact forms. The specific objective functions and constraints are shown in Appendixes A and B. In Section 5, the application of the proposed methodology is performed on an actual multi-product pipeline in China. Conclusions and future works are provided in Section 6.

2. Methodology framework and pipeline supply reliability indicators

2.1. Methodology framework

The overall framework of the proposed methodology is shown in Fig. 1. It is divided into four parts: equipment failure analysis, stochastic process simulation, pipeline supply capacity calculation, and supply reliability evaluation. The previous parts are the bases of the later parts. Namely, the pumps failure is first analyzed and the stochastic process is simulated (given in Section 3). Then, based on the pipeline scheduling model introduced in Section 4, the maximum supply capacity of the pipeline under the corresponding failure condition are obtained. According to the statistics of the calculated pipeline supply capacity, the holistic and individual supply reliability of the pipeline can be evaluated systematically based on the indicators proposed in Section 2.2.

As mentioned, the multi-product pipeline system contains many types of equipment (i.e., pumps, oil tanks, pipelines, etc.). If some of them are under failure conditions, it will have a great impact on the completion of the refined products delivery task for the entire pipeline system. Among all of these equipment, the effect of pumps failure on pipeline transportation is the most complex, since it will result in part of the pipeline transportation capacity loss, which involves the pipeline hydraulics and is hard to be calculated directly. So the supply reliability analysis of multi-product pipeline systems under pumps failure is first focused in this paper because of its complexity, but the proposed framework is not limited to pumps failure. It is general and can be applied to other equipment failure. When other equipment failure needs to be considered, the failure analysis of the corresponding equipment can be added to the equipment failure analysis part. After the failure rate is obtained, the stochastic process is simulated and the supply capacity under corresponding failure scenarios can be calculated. With the solving results, the established indicators are used for the reliability analysis. Meanwhile, the framework could also be used for reference in the reliability evaluation of other large-scale complex systems by changing the multi-product pipeline scheduling model used in this paper to the mathematical models applicable to those systems. Since the commercial software or heuristic rules are often adopted to obtain the results of system performance, the proposed methodology, in which the mathematical model is adopted, may provide new methods for these systems. Even though the technical process of these systems are different, the framework structure could be beneficial.

2.2. Supply reliability indicators of multi-product pipeline

As shown in Fig. 2, a representative multi-product pipeline system consists of the initial (injection) station (i.e., IS), delivery stations (i.e., DSs), pump stations (i.e., PSs), and pipeline segments. Since refined products are mainly from refineries, ports, and large-scale depots, the initial station is upstream connected with these sources directly. Different kinds of refined products, which are divided into several batches in advance, are injected from the initial station into the pipeline sequentially and distributed to the delivery stations. The delivery stations are usually situated near the local downstream markets. This process is called the primary distribution, in which the pipeline is the main transportation way, while other modes (e.g., railway, barge and truck) serve as the supplements. To offset the hydraulic loss of refined products flowing in the pipeline, multiple pump stations are constructed along the pipeline. In a pump station, the pumps with different flowrate ranges and pumping heads are set up serially. According to different hydraulic conditions of the pipeline, different pumps combination schemes will be selected to ensure the safe and economic operation. Since different kinds of refined products must not be mixed, at least one dedicated oil tank should be available for the storage of each kind of refined product at the each delivery/injection station. Meanwhile, it can be seen from Fig. 2 that the pipeline diameter decreases gradually. This is because some of the fluid is delivered midway and the pipeline flowrate will reduce.

The supply reliability of multi-product pipeline systems is quantified using three indicators, namely, DS_i, RS_o, and PS. DS_i focuses on the demand satisfaction degree of delivery station i and can be calculated as

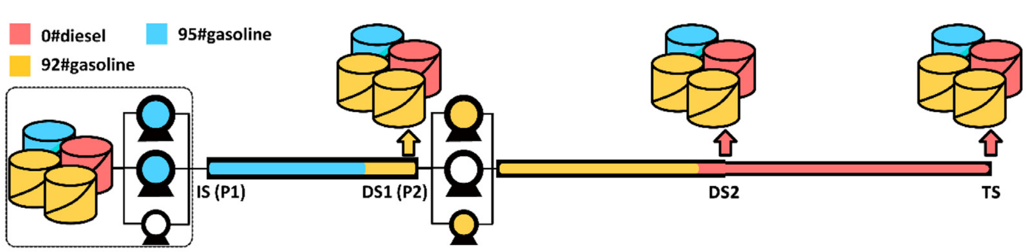

Fig. 2. Schematic diagram of the multi-product pipeline system.

the ratio of the actual delivered volume to its demanding volume (i.e., Eq. (1)). RS_o represents the completion of the delivery task for a certain kind of refined product o. As shown in Eq. (2), it is equal to the ratio of the actual delivered volume to the total demanding volume of this kind of refined product. The above two indicators can be regarded as the individual perspective for evaluating the supply reliability, that is, to pay attention to the supply status of a single station and one kind of refined products. At the same time, from the holistic perspective, the pipeline's capacity to achieve its overall function (i.e., the safe and reliable delivery of refined products to the downstream markets) in the mission time is also essential for the quantitative supply reliability analysis. It can be expressed as the ratio of total transported volume to total demanding volume (shown in Eq. (3)).

$$DS_i = \frac{\sum_{o\in O} V_{ACi,o}}{\sum_{o\in O} V_{DEi,o}} \tag{1}$$

$$RS_o = \frac{\sum_{i\in I} V_{ACi,o}}{\sum_{i\in I} V_{DEi,o}} \tag{2}$$

$$PS = \frac{\sum_{i\in I}\sum_{o\in O} V_{ACi,o}}{\sum_{i\in I}\sum_{o\in O} V_{DEi,o}} \tag{3}$$

where $V_{DEi,\ o}$ represents the demanding volume of delivery station i for refined product o and$V_{ACi,\ o}$ is the actual delivered volume.

Different than the natural gas pipeline network and water distribution system, the multi-product pipeline is not directly connected with customers and the supply flowrate is not strictly required. In this way, the indicator which describes the shortage duration, is not that meaningful to the multi-product pipeline supply reliability analysis. On the other hand, as a unique feature of multi-product pipelines, multiple kinds of refined products are transported simultaneously. Due to the different physical properties and the various demands, the satisfaction degree of each kind of refined product may be different in the case of pumps failure. Therefore, for a more comprehensive analysis of the multi-product pipeline supply reliability, the indicator RS_o, which has never been taken into account in previous related studies, must be presented in this paper.

3. Stochastic process of failure conditions

3.1. Pumps failure analysis

The unit failure rate can be estimated by historical data statistics and failure mechanism modeling methods. Historical data statistics is to obtain failure data by recording the equipment's historical failure time, numbers, causes, etc. or conducting reliability tests, and then establish historical failure databases. Based on the unit structure and external environment, failure mechanism modeling is to obtain the limit state function by setting up the strength and load model for the equipment and predict its performance degradation trend [41]. Compared with pipeline segments, the failure rate of equipment units in the multi-product pipeline system is relatively stable during operation and the historical maintenance record and failure data are easy to obtain. In this way, to highlight the research focus of this paper, the pumps failure rate estimation is implemented by the historical data statistics method.

The failure rate (usually denoted by λ) refers to the frequency of a system or unit failure [42]. For the pumps which is repairable after failure, as shown in Eq. (4), the failure rate can be obtained from the Mean time between failures (MTBF), if it is assumed constant for a period of time (often used for complex units / systems).

$$\lambda = \frac{1}{\mathrm{MTBF}} \tag{4}$$

In this paper, the pump is considered to have only two states: normal running and failure. The degradation state, in which partial function is retained, is not taken into account. The normal/interruption status of all pumps in the pipeline system constitutes a scenario. Under different scenarios, the pumping capacity varies a lot. The reparability of pumps is also considered in this paper. After a pump fails at a certain time, it may be restored and put back into service in the latter pipeline operation. The repair rate μ is equal to the reciprocal of the Mean time to repair (MTTR), if the repair time is exponentially distributed.

$$\mu = \frac{1}{\mathrm{MTTR}} \tag{5}$$

3.2. Stochastic process simulation

A multi-product pipeline system includes multiple pumps locating at different stations. The stochastic states transition of these components leads to the complex operation conditions changes of the entire system. To describe the stochastic process of system evolution mathematically, Markov process is adopted. The operation state of the pipeline system in the next time step is determined only by the current state and is independent of the previous transition process, which conforms to the basic hypothesis of Markov process. Since the stochastic process can be observed both in discrete and continuous time, Markov process is divided into two types: discrete and continuous time [43]. This is consistent with the time representation methods of the multi-product pipeline supply capacity calculation model. Considering that the model is based on the discrete-time representation, the stochastic transition of the system's operation states is also described by the discrete-time Markov process (i.e., Markov chain), so that the pumps failure/repair conditions during pipeline operation can be directly substituted into the model to obtain the supply capacity.

The transition probability is constant and the state transition process is the homogeneous Markov chain. p_{ij} (i.e., Eq. (6)) represents the single-step transition probability of homogeneous Markov chain, namely, the probability that the system transfers from state i at time step to state j at time step $n + 1$ [43]. The schematic diagram of state transition is shown in Fig. 3.

$$p_{ij} = P[X(n+1) = j | X(n) = i] \tag{6}$$

Considering all possible states N of the system, the state transition probabilities in a time step can be written into a $(N \times N)$ matrix A, which is shown in Eq. (7). It has two properties (i.e., Eqs. (8) and (9)).

$$A = \begin{array}{c|cccc} i/j & 1 & 2 & \cdots & N \\ \hline 1 & p_{11} & p_{12} & \cdots & p_{1N} \\ 2 & p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ N & p_{N1} & p_{N2} & \cdots & p_{NN} \end{array} \tag{7}$$

$$0 \le p_{ij} \le 1 \qquad i, j \in \{1, 2, \cdots, N\} \tag{8}$$

$$\sum_{j=1}^{N} p_{ij} = 1 \qquad i \in \{1, 2, \cdots, N\} \tag{9}$$

As mentioned above, one pump has two states, that is, normal running and failure. The state transition of one pump can be displayed

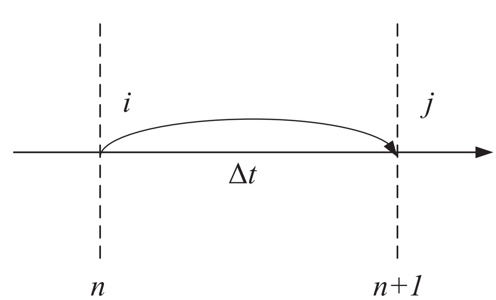

Fig. 3. Schematic diagram of the system states transition.

as Fig. 4. The system operation state is composed of the states of each pump, and thus, the system states transition is more complicated. To simulate the stochastic process of the system states transition, which is described as a Markov chain, Monte Carlo simulation is employed [44]. The detailed steps are stated as bellow and the flowchart is shown in Fig. 5. As show in Eq. (10), the stopping criterion of Monte Carlo simulation can be determined based on the coefficient of variation of the reliability indicators [45–47].

$$\frac{S_I}{E_I} \leq \delta \qquad i \in \{1, 2, \cdots, N\} \tag{10}$$

where E_I refers to the estimate of the indicator's expected value; S_I represents the standard deviation of the estimate; δ is the coefficient of variation (stopping criterion).

The simulation steps are as follows:

(1) Set time horizon T, time step Δt, and the total number of Monte Carlo trials N_M.
(2) Set the system initial state, in which all pumps are running normally.
(3) Simulate the stochastic transition of the system operation state in the mission time: according to the system state at time $(n-1)\Delta t$ and the transition probability matrix A, sample the system state at time $n\Delta t$ repeatedly until $n\Delta t = T$. Integrate the sampling results of all time steps to form a system failure scenario.
(4) Based on the failure scenario, obtain the maximum supply capacity of the pipeline using the established model presented in Section 4.
(5) Calculate the pipeline supply reliability indicators according to the model solving results.
(6) Repeat steps (2) ~ (4) for N_M times and evaluate the supply reliability of the multi-product pipeline system quantitatively according to the simulation results.

4. Multi-product pipeline supply capacity calculation model

In this section, to calculate the maximum supply capacity of the multi-product pipeline under pumps failure conditions, a pipeline scheduling model is established, taking the minimum deviation between actual delivery and demand as the objective function. Due to the low solving efficiency of the model considering the hydraulic related constraints directly, two mixed integer linear programming (MILP) models are proposed. The first one is to calculate the maximum allowed pipeline flowrate under different pumps failure conditions. As the main power equipment, when part of pumps fail, the provided energy will be reduced and the normal flowrate upper limit will also be reduced. If the pipeline still operates at the original flowrate, the refined products will not reach the latter stations and the underpressure accidents may be led. In this way, the flowrate upper limits for each pumps failure scenario should be optimized in advance. The pressure and pump-related constraints of the pipeline are also addressed in the first model. Based on the solving results of the first model, the second model is adopted to calculate the actual maximum supply to downstream delivery stations after the stochastic process of pumps failure is simulated in each Monte Carlo trial. This model needs to deal with other actual processing constraints, such as batch moving, injection/delivery, etc., to ensure the pipeline operation safety and refined products quality. The mathematical formulation of the two models are given in Appendixes A and B respectively. The compact forms are shown as follows:

$$\begin{aligned}
&\min_{v_P, c_Q, b_H} f_1(v_P, c_Q, b_H)\\
&\text{s.t. } \psi_P(v_P) = 0\\
&\phi_P(v_P, c_Q, b_H) \leq 0
\end{aligned} \tag{11}$$

where f_1 represents the objective function of the first model, namely, the maximum pipeline flowrate upper limits; v_P is the vector of pressure variables; c_Q is the vector of flowrate upper limits (variables in the first model and parameters in the second model); b_H is the vector of binary variables related to hydraulic constraints; ψ_P refers to the equality hydraulic constraints (i.e., Eqs. (A.2)-(A.3), (A.7)), while ϕ_P represents the inequality hydraulic constraints (i.e., Eqs. (A.4)-(A.6), (A.8)-(A.9)).

$$\begin{aligned}
&\max_{v_Q, v_A, v_C, b_S} f_2(c_T, c_Q, v_Q, v_A, v_C, b_S)\\
&\text{s.t. } \psi_Q(c_T, v_Q, v_A) = 0\\
&\psi_B(b_S) = 0\\
&\phi_Q(v_A, v_Q, c_Q, b_S) \leq 0\\
&\phi_C(v_C, v_Q, b_S) \leq 0\\
&\phi_B(b_S) \leq 0
\end{aligned} \tag{12}$$

where f_2 is the objective function of the second model, namely, the maximum supply capacity of the pipeline (the minimum deviation between actual supply and demand); c_T is the vector of time parameters; v_Q is the vector of flowrate variables; v_A is the vector of injection/delivery volume in an oil delivery task; v_C is the vector of batch volume coordinates, which is used for the tracking of batch locations; b_S is the vector of binary variables related to pipeline scheduling, e.g. whether a station is receiving a kind of refined product, whether a batch is flowing through a station and so on; ψ_Q represents the equality flowrate constraints (i.e., Eqs. (B.3), (B.23), (B.26)), while ϕ_Q indicates the inequality flowrate constraints (i.e., Eqs. (B.2), (B.4)-(B.5), (B.19)-(B.20), (B.24)-(B.25)); ϕ_C represents the inequality constraints for the calculation of batch volume coordinates (i.e., Eqs. (B.7), (B.11), (B.16)-(B.18)); ψ_B refers to the equality constraints for the logical relationships between binary variables (i.e., Eqs. (B.12)-(B.15), (B.21)), while ϕ_B represents the inequality constraints for the logical relationships between binary variables (i.e., Eqs. (B.6), (B.8)-(B.10), (B.22)).

Since the above two models are both MILP models, the existing commercial solvers based on branch and bound algorithm can be adopted to get the solutions efficiently. In this paper, MATLAB R2015a is used to implement the model programming and GUROBI 8.1.0 is employed as the MILP solver

5. Results and discussion

5.1. Pipeline basic data

The proposed methodology for the supply reliability analysis of multi-product pipelines is applied on a real case in China. All input parameters are from the on-site oil company and pipeline operators. The pipeline is 375.5 km with 4 delivery stations (DS1-DS4) and 1 injection station (IS) in total. The injection station is also the initial station and connects with the upstream refinery directly. The delivery stations are distributed along the pipeline and near the downstream markets. The basic parameters of the pipeline are shown in Table 1. Three kinds of refined products (92# gasoline, 95# gasoline and 0# diesel) are transported sequentially in batches. The density and viscosity are shown in Table 2. Stations IS and DS1 are pump stations (PS1 and PS2). The pump parameters are shown in Table 3. There is one standby pump in the two pump stations respectively. If some of the pumps fail, the standby units can be used for emergency. The operational parameters (i.e., flowrate and pressure limits) of each station are

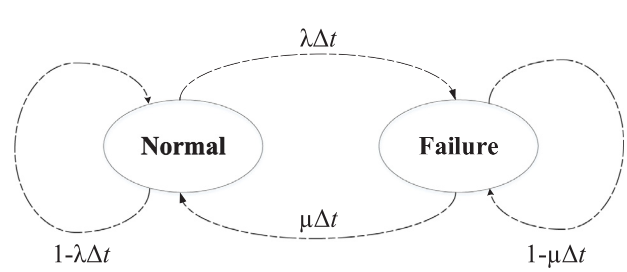

Fig. 4. Schematic diagram of the pumps state transition.

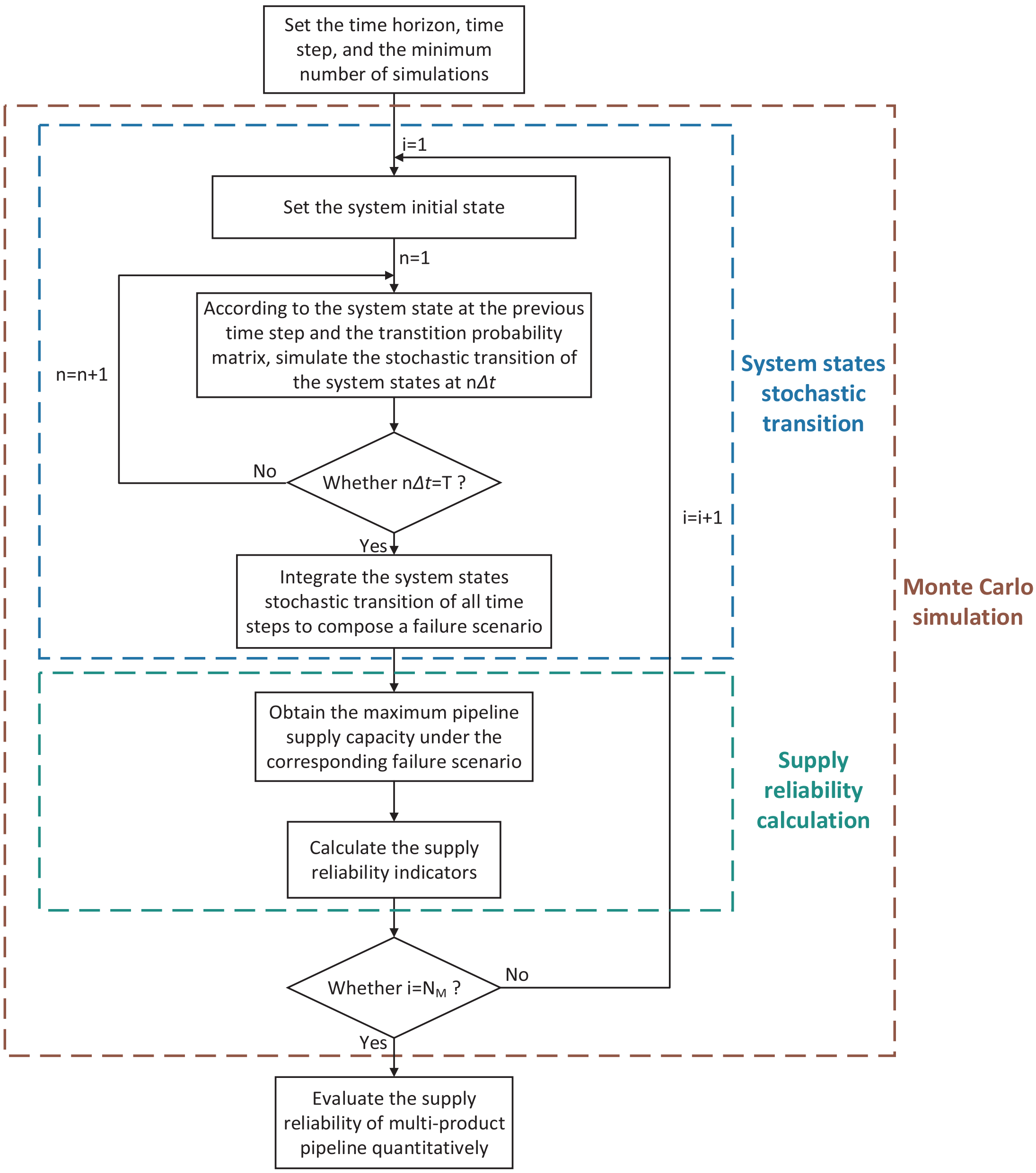

Fig. 5. Flowchart for the detailed steps of Monte Carlo simulation.

Table. 1
Pipeline basic parameters.

Pipeline segment	Length(km)	Inner diameter (mm)	Terminal station altitude (m)
IS-DS1	130.4	492.2	7
DS1-DS2	139.5	492.2	111
DS2-DS3	66.9	441.2	53
DS3-DS4	38.7	441.2	51

Table. 2
Physical properties of refined products.

Refined products	Density(kg/m^3)	Kinematic viscosity ($\times 10^{-6}$m^2/s)
0# diesel	845	6.11
92# gasoline	740	2.05
95# gasoline	750	1.07

Table. 3
Pump parameters.

Pump station	Pump	Pumping head parameters(m)
PS1	P1–1	330
	P1–2	330
	P1–3	160
	P1-S	160
PS2	P2–1	360
	P2–2	360
	P2–3	180
	P2-S	180

given in Table 4. Taking a delivery task in October 2019 as the application case, the demand of each delivery station is shown in Table 5. Compared with 95# gasoline, the market demand for 92# gasoline and 0# diesel are higher. Meanwhile, DS1 and DS4 require more refined products than DS2 and DS3. Table 6 displays the injection sequence and volume of each batch. Since the physical properties of 95# gasoline are

Table. 4
Flowrate and pressure limits of each station.

Station	Injection/ delivery upper limits (m^3/h)	Injection/ delivery lower limits (m^3/h)	Inlet pressure lower limits (MPa)	Outlet pressure upper limits (MPa)
IS	1100	300	/	7.0
DS1	950	100	0.5	7.0
DS2	600	100	0.6	7.0
DS3	600	0	0.1	7.0
DS4	600	0	0.1	/

Table. 5
Oil demands of delivery stations.

Delivery station	0# diesel (tonne)	92# gasoline (tonne)	95# gasoline (tonne)
DS1	21,000	16,000	8000
DS2	11,500	13,000	7000
DS3	18,500	16,000	4000
DS4	10,000	13,000	6000

Table. 6
Injection sequence and amount of each batch.

Batch number	Injection amount (tonne)	Oil type
BA1	0	0# diesel
BA2	25,000	92# gasoline
BA3	25,000	95# gasoline
BA4	33,000	92# gasoline
BA5	61,000	0# diesel

very different than 0# diesel, more mixed oil will be generated if they are next to each other. In this way, 92# gasoline is divided into two batches to prevent 95# gasoline from being seriously contaminated. Batch BA1 refers to the existed oil in the pipeline before the operation, and thus, its injection volume is 0. According to the historical maintenance and failure record of the pipeline pumps in 2014–2019, the failure and repair probability of a pump is determined as 1.7×10^{-4}/h and 2.1×10^{-2}/h respectively. The convergence criterion is set to 0.01, and 100,000 Monte Carlo trials are conducted accordingly to calculate the pipeline supply capacity and assess the supply reliability under various pumps failure conditions.

5.2. Case study

5.2.1. Flowrate upper limits calculation

According to the MILP model shown in Appendix A, the pipeline flowrate upper limits under various pumps failure scenarios can be calculated in advance. The number of flowrate upper limits set $p_{\max}$ is valued as 3 and the maximum design flowrate of the pipeline is set as $1100m^3/h$. Since each pump station is equipped with a stand-by pump, of which pumping head is the same as that of 3# pump, the scenario where only 3# pump fails can be regarded as the normal running state. In this way, a pump station has five states, as shown in Table 7. The maximum provided pressure of each pump station under different states is also given. The pipeline has two pump stations, and the failure condition of the pipeline is the combination of PS1 and PS2. Therefore, the pipeline system has 25 states in total. Considering the pressure limits of the pipeline, the flowrate upper limits for all possible states are solved and the main results are shown in Table 8.

Table. 8
Pipeline flowrate upper limits under the main states.

State	P	Flowrate upper limits (m^3/h)			
		IS-DS1	DS1-DS2	DS2-DS3	DS3-DS4
1 (S1,S2)	1	1079	816	816	816
	2	1079	816	816	816
	3	1100	813	800	800
2 (S2,S1)	1	904	816	816	816
	2	940	800	800	800
	3	1085	758	700	700
3 (S1,S3)	1	900	813	813	813
	2	929	800	800	800
	3	1100	728	700	700
4 (S1,S4)	1	800	765	765	765
	2	900	720	720	720
	3	1000	700	643	643
5 (S2,S2)	1	904	816	816	816
	2	940	800	800	800
	3	1085	758	700	700
6 (S3,S1)	1	800	781	781	781
	2	900	736	736	736
	3	922	758	700	700
7 (S4,S1)	1	720	720	720	720
	2	720	720	720	720
	3	720	720	720	720

5.2.2. Assessment results of multi-product pipeline supply reliability

The stochastic process of pumps failure is simulated 10^5 times by the Monte Carlo method described in Section 3. Based on the calculated flowrate upper limits, the maximum supply capacity as well as the corresponding scheduling plan of the pipeline in each trial can be obtained by the mathematical model presented in Appendix B. With the solving results, the pipeline supply reliability indicators are worked out. The total calculation time is 11.85 h. The coefficients of variation range from 0.0032(RS_1)to 0.0070(DS_4). The statistics of pipeline supply and delivery stations demand satisfaction are displayed in Table 9. Tables 10, 12, and 13 show the minimum and average supply capacity and the average supply degree from the holistic and individual perspectives. The minimum and average supplied amount and the average demand satisfaction degree of each refined product at each delivery station are shown in Fig. 6 and Fig. 7 respectively. To illustrate the pipeline supply reliability in more detail, the cumulative distribution functions (CDF) of the proposed three indicators are shown in Fig. 8 and Fig. 9.

As shown in Table 9, the holistic supply and individual demand satisfaction degree (i.e., PS and DS_i) are divided into 14 intervals. The lowest interval reaches 0.6–0.7 and DS_4 falls into this interval 3 times. Since most supply and demand satisfaction degrees are concentrated between 0.9 and 1, the range is divided more densely to display the statistics more clearly. For the holistic supply degree PS, it is equal to 1 > 98,000 times, which proves that the pipeline can complete the oil delivery task successfully and preform its function well in most cases. The lowest holistic supply degree is within 0.93–9.94. This demonstrates that a great decline in the pipeline supply capacity will not occur, even under extreme pumps failure conditions, and the pipeline can transport refined products to downstream stations safely. As for the individual demand satisfaction degree DS_i, their frequency of equaling

Table. 7
The possible states of a pump station.

State	S1	S2	S3	S4	S5
Pumps failure condition	Normal	1# or 2# pump fails	1#,3# or 2#,3# pumps fail	1# and 2# pumps fail	1#,2#, and 3# pumps fail
The maximum provided pressure of P1 and P2 (m)	820/900	650/720	490/540	320/360	160/180

Table. 9
Statistics of the pipeline supply and the delivery stations demand satisfaction.

The holistic supply and individual demand satisfaction degree	Frequency PS	DS_1	DS_2	DS_3	DS_4
1	98,759	99,466	99,428	99,449	99,168
[0.99,1)	227	234	179	245	100
[0.98,0.99)	974	100	140	86	18
[0.97,0.98)	5	61	93	88	105
[0.96,0.97)	18	52	6	11	69
[0.95,0.96)	1	46	53	21	9
[0.94,0.95)	10	35	14	30	137
[0.93,0.94)	6	3	15	65	36
[0.92,0.93)	/	/	69	1	203
[0.91,0.92)	/	1	1	1	127
[0.90,0.91)	/	1	1	/	2
[0.80,0.90)	/	1	1	3	20
[0.70,0.80)	/	/	/	/	3
[0.60,0.70)	/	/	/	/	3

Table. 10
Results of the holistic supply capacity for the pipeline.

Station	Minimum supply capacity (tonne)	Average supply capacity (tonne)	Average supply degree (%)
IS	134,408.6	143,973.9	99.9808

1 is higher than PS. This is because even if the oil supply is not fully completed, the shortage is only reflected in one or a few stations, and the demand of other stations can be fully met. When PS is equal to 1, the oil delivery for all downstream stations must be reliable ($DS_i = 1$). It can also be found that DS4 station is more frequent with low supply degrees, which indicates that the oil supply to the last station is more likely to be insufficient. This is because DS4 is the farthest from the initial station, and it is more difficult to deliver enough refined products when unexpected failures occur.

Table 10 shows the minimum and average supply capacity and the average holistic supply degree of the pipeline. Since the maximum supply capacity is equal to the planned transport amount (the actual transport amount in most trials), it is not displayed. The average supply shortage is 26.1 tonnes, which equals the total demand minus the average supply capacity. Compared with the total demand, the average supply shortage is very small. This means that under stochastic pumps failure, the pipeline can almost achieve the continuous and reliable delivery of refined products normally. The average supply degree of the pipeline reflects the expected completed ratio of the oil delivery task. It is calculated based on the holistic supply degree PS obtained from each Monte Carlo trial. As for the minimum supply capacity, it is nearly 10,000 tonnes less than the required amount. The corresponding pump state transition is shown in Table 11. As we can see, the pumps at PS1 and PS2 run normally in the first 14 time intervals. Starting from the 15th time interval, the two pumps with higher pumping head at PS1 fail in succession. Since they locate at the initial station, their failure will result in a significant reduction in the pipeline flowrate upper limits. In this way, the total supply capacity also declines greatly and becomes the minimum one among all trials.

Table 12 shows the minimum and average supply capacity and the average supply degree of different stations. It can be found that the average demand satisfaction degree of stations closer to the initial station is generally higher. This is because it takes more energy to transport refined products further away. The provided energy is limited under pumps failure conditions and the fluid in the pipeline passes through the front stations first. In this way, the demand for stations far from the initial station is less likely to be met. As for stations DS2 and DS3, the average demand satisfaction degree of DS2 is a bit higher than that of DS3. This is because DS3 has a lower elevation than DS2. It consumes less energy for the oil flowing from DS2 to DS3 and the pressure will even increase at certain flowrates. At the same time, the delivery requirement of DS2 is a bit higher than that of DS3. In this way, the delivery operation of DS2 is not as flexible as DS3. The average shortage of DS1-DS3 is concentrated in 4–5 tonnes, while the average shortage of DS4 is more 10 tonnes. This also illustrates that the demand satisfaction of DS4 is the most vulnerable in the event of pumps failure. The sum of the average shortage of all delivery stations is equal to the supply shortage of the pipeline system, which proves the correctness of the statistical results. The sum of the minimum supplied amount of all stations is lower than the minimum pipeline supply capacity. This is because the minimum supplied amount of all stations is not in the same trial and will not be reached simultaneously.

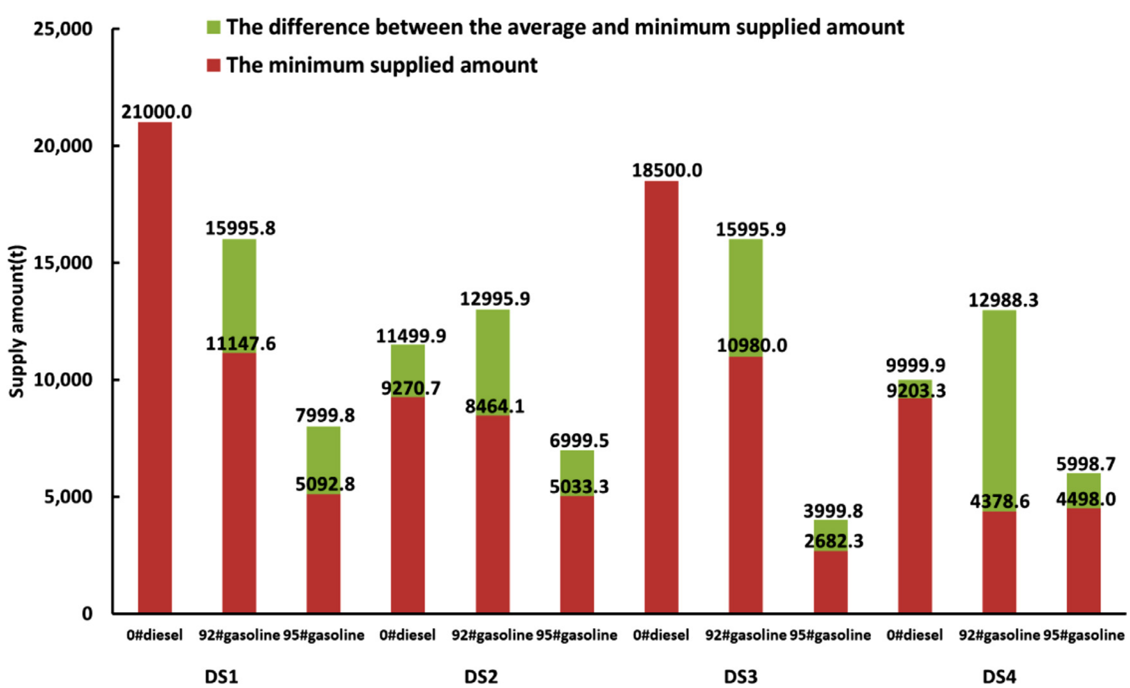

Fig. 6. The minimum and average supplied amount of each refined product for different delivery stations.

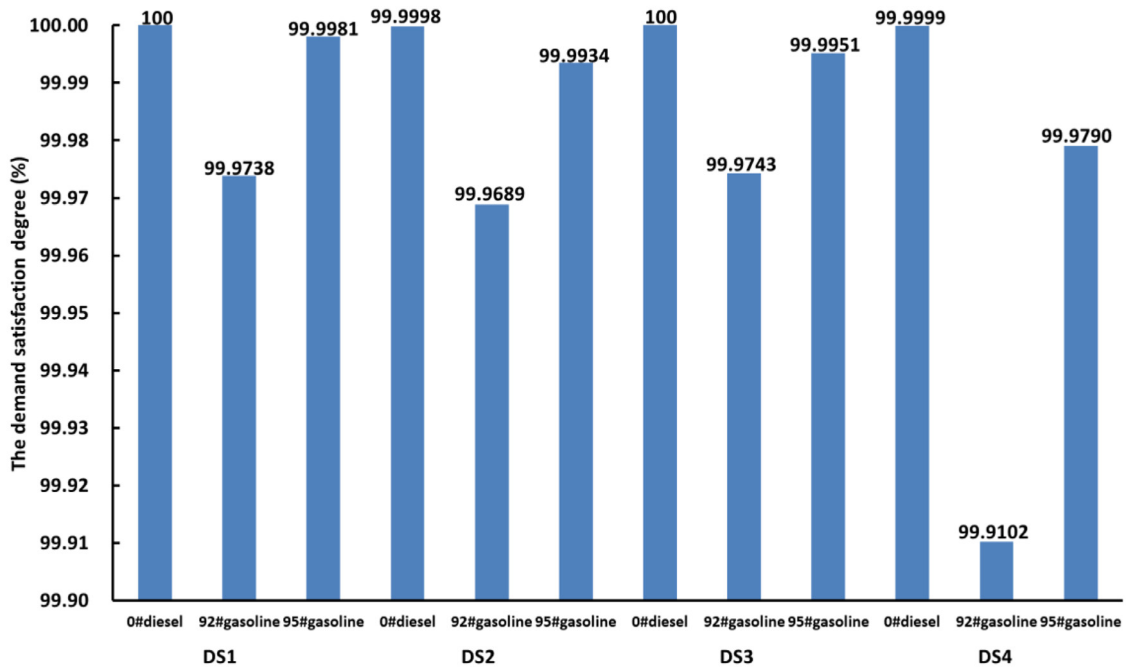

Fig. 7. Average demand satisfaction degree of different stations for each refined product.

Table 13 displays the minimum and average completed amount and the average completion degree for each refined product. As it is shown, the average completed amount of 0# diesel and 95# gasoline is almost equal to the required amount. The average shortage is 0.1 tonne and 2.1 tonnes respectively. Compared with these two refined products, the shortage of 92# gasoline reaches 23.9 tonnes, which is relatively high. It indicates that the delivery of 92# gasoline is not as reliable as other refined products under stochastic pumps failure. This can also be concluded from the average completion degree. The average completion degree of 0# diesel and 95# gasoline is much higher that of 92# gasoline, which is related to the initial condition of the pipeline and the batch injection sequence. Since the pipeline is filled with 0# diesel at the initial time, all stored oil must be delivered so that later batches can be injected and delivered. In this way, the average completion degree of 0# diesel is the highest. As for 95# gasoline, it is located between the two batches of 92# gasoline. In most cases, it also needs to be pushed out of the pipeline (completely delivered) so that the next two batches can be operated. In addition, the required amount of 95# gasoline is much less than that of 92# gasoline, so it is easier to complete. With regard to 92# gasoline, it is divided into two batches. The previous batch will be delivered completely, while the latter batch is not easy to be totally delivered. As for the minimum completed amount, the sum of all refined products is less than the minimum supply capacity of the pipeline, which is in the same way as Table 12. The minimum

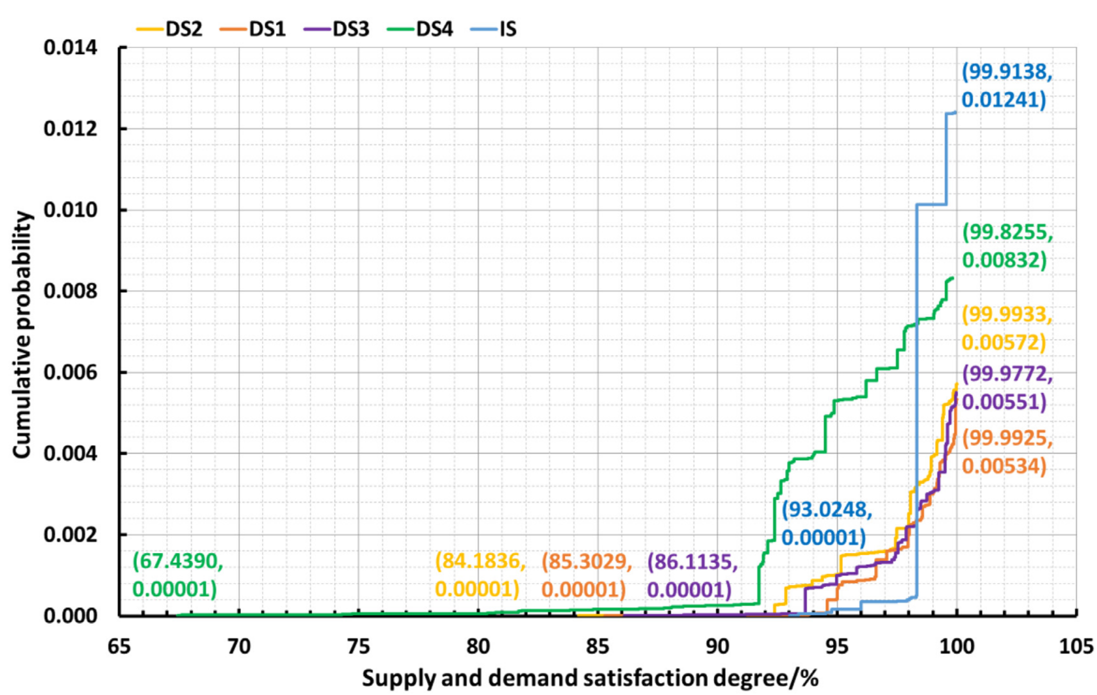

Fig. 8. The holistic supply and individual demand satisfaction degree represented by CDF.

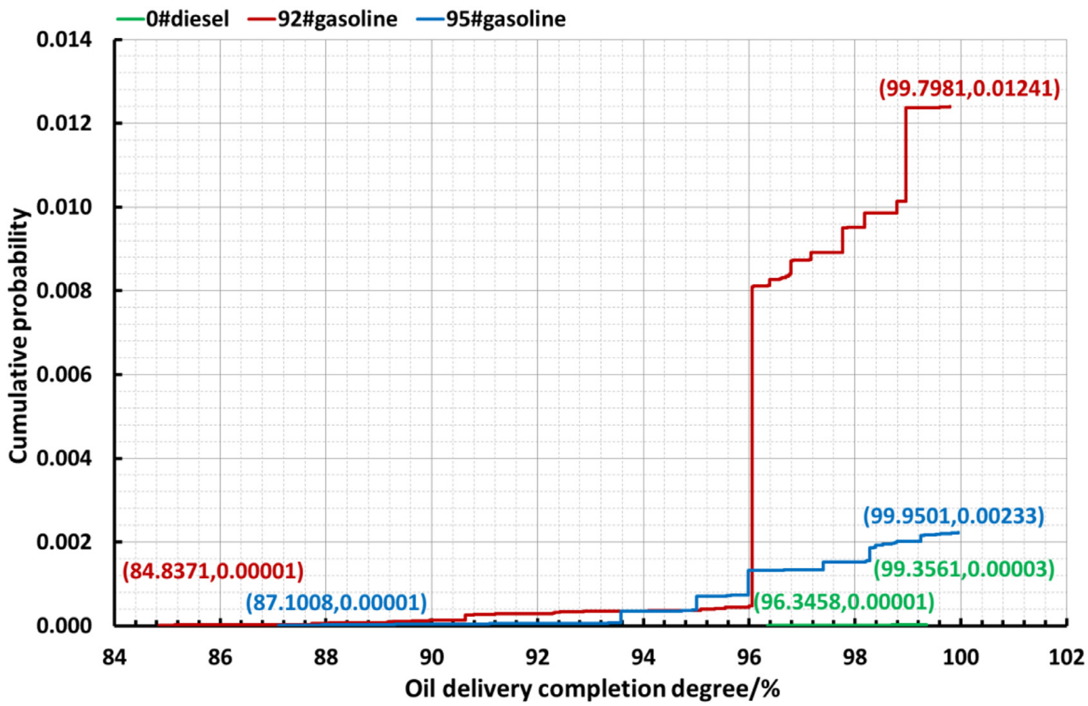

Fig. 9. The oil delivery completion degree represented by CDF.

Table. 11
Pump state transition.

Time interval number	Pumps state PS1	PS2	Time interval number	Pumps state PS1	PS2
1	S1	S1	14	S1	S1
2	S1	S1	15	S2	S1
3	S1	S1	16	S2	S1
4	S1	S1	17	S4	S1
5	S1	S1	18	S4	S1
6	S1	S1	19	S4	S1
7	S1	S1	20	S4	S1
8	S1	S1	21	S4	S1
9	S1	S1	22	S4	S1
10	S1	S1	23	S4	S1
11	S1	S1	24	S4	S1
12	S1	S1	25	S4	S1
13	S1	S1			

Table. 12
Results of the individual demand satisfaction for each delivery station.

Station	Minimum supplied amount (tonne)	Average supplied amount (tonne)	Average demand satisfaction degree (%)
DS1	38,766.8	44,995.7	99.9897
DS2	26,755.6	31,495.5	99.9849
DS3	33,480.0	38,495.7	99.9881
DS4	19,982.7	28,987.0	99.9533

completed amount of 0# diesel is relatively high. This is because the completed amount of 0# diesel is equal to the basic amount (pipeline storage oil) plus the fluctuating amount and the basic amount is high ($67{,}499 \times 0.845 = 57{,}037$ tonnes). The basic amount of 92# gasoline (25,000 tonnes) is low. About 87% of 95# gasoline is pushed out of the pipeline and the remaining 13% is left at the end of the pipeline in the worst case.

Fig. 6 shows the minimum supplied amount (in red) and the difference between the average and minimum supplied amount (in green). As can be seen, the minimum supplied amount of 0# diesel at DS1 and DS3 is equal to the average. This means that under no conditions will the two stations be short of diesel. With respect to the other two stations, even if the diesel supply is not always sufficient, the maximum shortage is not large. As for the 92# gasoline supply, the maximum shortage is generally large, which is consistent with Table 13. Among all stations, the maximum shortage of DS4 is the highest and other stations are approximately the same. Regarding the maximum shortage of 95 # gasoline, the difference between all stations is not great, mainly between 65% and 75% of the demand.

The detailed average demand satisfaction degree of each station for each refined product is presented in Fig. 7. It can be found that DS1-DS3 have roughly the same change trend in the demand satisfaction degree for each refined product, with 92# gasoline being the least, followed by 95# gasoline and finally 0 diesel (almost all equal to 100%). As for DS4, the average demand satisfaction degree of diesel is almost the same as the first three stations, but the average demand satisfaction degree of gasoline (especially 92# gasoline) is reduced a lot. This leads to a great reduction in the total average demand satisfaction degree of DS4.

Fig. 8 intuitively shows the change of the holistic and individual

Table. 13
Results of the delivery task completion for each refined product.

Oil type	Minimum completed amount (tonne)	Average completed amount (tonne)	Average completion degree of the delivery task (%)
0# diesel	58,770.7	60,999.9	99.9999
92# gasoline	49,205.3	57,976.1	99.9586
95# gasoline	21,775.0	24,997.9	99.9917

supply reliability from the perspective of probability. The vertical axis represents the cumulative probability, while the horizontal axis means the supply or demand satisfaction degree. The curves represent the cumulative distribution functions, namely, the probability that PS or DS_i is less than or equal to a certain value. Different colored numbers in the figure indicate the start and end points of the corresponding curve. In fact, the ordinate value of the traditional CDF should reach 1 at last. But in this paper, compared with 1, the cumulative probability of other values except 100% is very small. If the curve is finally drawn to 1, a great "step" will be generated at the end of the curve, and the previous part will not be effectively displayed. Therefore, the CDF curves in this paper exclude the point (100%, 1). The end points shown in the figure are the highest points except (100%, 1). Taking the CDF of PS as an example, it can be understood that the probability of the holistic supply degree being less than 99.9138% is 0.01241, and the probability of being equal to 100% is 0.98759. Then the probability of PS being less than or equal to 100% is 1.

As we can see in Fig. 8, the CDF of the holistic supply degree begins to rise from 93.0248%, which means that the pipeline supply degree will not be less than this value. Next, the cumulative probability remains stable at about 4×10^{-4} between 96% and 98% and has a significant "step" between approximately 98.3% and 99.5%. It can be concluded that the probability of the holistic supply degree being less than 98.3% is relatively small. Meanwhile, when the pumps failure occurs and the normal supply is interrupted, the holistic supply degree is mostly concentrated around 98.3% and 99.5%. As for the CDFs of the individual demand satisfaction degree, DS1-DS3 have roughly similar growth trends. But for DS4, the CDF curve starts to rise earlier and the end point is higher. This indicates that the possible minimum demand satisfaction degree is lower compared with other three stations and pumps failures are more likely to cause the supply shortage of DS4. This is consistent with the conclusions drawn above. Namely, DS4 is the furthest away from the injection station (IS) among all delivery stations. Once pumps failure occurs and the provided energy is limited, DS4 will be the first to be affected, because the delivery to DS4 is the most energy intensive. Besides, due to the pipeline initial condition and batch injection sequence, the 92# gasoline supply to DS4 is very vulnerable to pumps failure.

Fig. 9 shows the CDF of the delivery completion degree for the three refined products. The meaning of the vertical axis in Fig. 9 is the same as that in Fig. 8 and the horizontal axis represents RS_o. For the same reason, the point (100%, 1) is also excluded from the curves in Fig. 9. The start and end points of each curve are also marked. As we can see, the CDF of 92# gasoline starts growing earlier and ends at a much higher level, followed by 95# gasoline. The supply shortage of 0# diesel has been maintained at a very low level and the possible minimum completion degree of 0# diesel is much higher than that of the other two refined products. This proves that the supply shortage of 0# diesel is the most difficult to be led, while 92# gasoline is the most possible. The CDFs of 92# gasoline has an obvious "step" around 96%, followed by 99%, which indicates that the delivery completion degree is most likely to be concentrated in these two intervals once the incomplete delivery occurs.

From the above analysis, it can concluded that under pumps failure conditions, the multi-products pipeline can maintain a high level of supply reliability both as a whole and for individual stations/refined products. But it's also important to note that the supply shortage will be caused in some failure conditions. When the supply interruption occurs, the terminal station DS4 is the most vulnerable to supply shortage. As for different refined products, 92# gasoline is most likely to have an incomplete delivery, while 0# diesel's transportation is the most reliable. These results can provide auxiliary emergency management measures for pipeline operation managers, such as improving the availability of other transportation methods to the failure-sensitive stations, and increasing the reserve of the refined products with relatively weak supplies, etc.

6. Conclusion

In this paper, an integrated methodology for the supply reliability analysis of multi-product pipeline systems under pumps failure is proposed by integrating stochastic process simulation and pipeline scheduling together. Based on the technical and operational process of the multi-product pipeline system, three evaluation indicators are developed to quantify the supply reliability from the holistic and individual perspectives. Considering the unit reparability, the stochastic failure and recovery of pumps are described by Markov process and the stochastic transition of the system states are simulated using Monte Carlo method. To deal with the pipeline pressure and pump related issues, the pipeline flowrate upper limits under all possible states are optimized first. Then, for each trial with a different failure process, the maximum supply capacity to the downstream markets is calculated by the pipeline scheduling model. According to the simulation and model solving results, the established supply reliability indicators are calculated, which can quantitatively show the supply level of refined products.

A real-world multi-product pipeline in China is used to perform the case study. All system states are first listed and the flowrate upper limits under these states are calculated. Next, based on the statistics of the solving results in each Monte Carlo trial, the holistic and individual supply reliability are analyzed in detail. For the entire pipeline system, the reliable and continuous oil supply can be achieved in general and pumps failure will not significantly affect the pipeline transportation capacity at a high probability. With respect to different stations and refined products, the extents to which they are affected by pumps failure are quite different. For the stations and refined products which are more sensitive to pumps failure, loss prevention measures should be provided in advance to minimize the impact. In summary, the proposed methodology can provide a comprehensive supply reliability evaluation for multi-product pipeline systems and help improve the regional energy supply chain resilience. For future works, the methodology will be expanded to multi-products pipeline networks and more other failure conditions can be considered. Besides, the upstream and downstream supply-demand changes can be taken into account by combining the prediction method with the present supply reliability evaluation framework.

CRediT authorship contribution statement

Xingyuan Zhou: Conceptualization, Methodology, Investigation, Writing - original draft. **P.H.A.J.M. van Gelder:** Supervision, Writing - review & editing. **Yongtu Liang:** Funding acquisition, Supervision. **Haoran Zhang:** Resources, Formal analysis.

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 A. Mathematical formulation of the flowrate upper limits calculation model

A.1. Objective function

The objective function is to search for the maximum flowrate upper limits of each pipeline segment under different scenarios. Since it will never exceed the pipeline design flowrate, the maximum flowrate upper limits can be converted the minimum difference from the design flowrate. $\alpha_{k,\ i,\ p}$ refers to the importance of each pipeline segment under flowrate set p of scenario k. On the whole, the pipeline segments closer to the initial station will have a higher importance value and $\alpha_{k,\ i,\ p}$ will be closer to 1.

$$\min F_1 = \sum_{i\in I} \alpha_{k,i,p}(q_{\mathrm{E\,max}\,i} - q_{\mathrm{U}k,i,p}) \tag{A.1}$$

A.2. Model constraints

The following two equations are the energy balance constraints along the pipeline. Namely, the outlet pressure of station i is equal to the inlet pressure plus the provided pressure (if station i is not a pump station, its provided pressure is 0) and the inlet pressure of station $i + 1$ is equal to the outlet pressure of station i minus the hydraulic loss of pipeline segment $(i,\ i + 1)$.

$$P_{\mathrm{O}k,i,p} = P_{\mathrm{N}k,i,p} + R_{\mathrm{O}} g H_{i,k} \qquad k \in K,\ i \in I,\ p \in P \tag{A.2}$$

$$P_{\mathrm{N}k,i+1,p} = P_{\mathrm{O}k,i,p} - P_{\mathrm{F}k,i,p} \qquad k \in K,\ i < i_{\max},\ p \in P \tag{A.3}$$

The pipeline hydraulic loss is calculated by the Liebenson (Лейбензон) equation, which is derived from the Darcy-Weisbach equation and widely used in the multi-product pipelines in China . Since there is a nonlinear term in the equation, the piecewise linearization method is employed for the efficient and accurate model solving. Namely, if flowrate upper limits set p under scenario k is selected and the flowrate of pipeline segment $(i,\ i + 1)$ is within interval a, $P_{\mathrm{F}k,\ i,\ p}$ can be expressed by the following two equations.

$$P_{\mathrm{F}k,i,p} \geq R_{\mathrm{D}} g \left[\frac{\beta(u_a q_{\mathrm{U}k,i,p} + w_a)\upsilon_{\mathrm{D}}^m L_i}{d_i^{5-m}} + Z_{i+1} - Z_i \right] + (B_{\mathrm{QL}k,i,p,a} - 1)M \qquad k \in K,\ i < i_{\max},\ p \in P,\ a \in A \tag{A.4}$$

$$P_{\mathrm{F}k,i,p} \leq R_{\mathrm{D}} g \left[\frac{\beta(u_a q_{\mathrm{U}k,i,p} + w_a)\upsilon_{\mathrm{D}}^m L_i}{d_i^{5-m}} + Z_{i+1} - Z_i \right] + (1 - B_{\mathrm{QL}k,i,p,a})M \qquad k \in K,\ i < i_{\max},\ p \in P,\ a \in A \tag{A.5}$$

If the flowrate upper limit of pipeline segment $(i,\ i + 1)$ under flowrate set p of scenario k is within interval a, the upper and lower bounds of the interval need to be satisfied. Meanwhile, there must be an interval to be selected.

$$q_{\mathrm{L\,min}\,a} + (B_{\mathrm{QL}k,i,p,a} - 1)M \leq q_{\mathrm{U}k,i,p} \leq q_{\mathrm{L\,max}\,a} + (1 - B_{\mathrm{QL}k,i,p,a})M \qquad k \in K,\ i < i_{\max},\ p \in P,\ a \in A \tag{A.6}$$

$$\sum_{a\in A} B_{\mathrm{QL}k,i,p,a} = 1 \qquad k \in K,\ i < i_{\max},\ p \in P \tag{A.7}$$

The inlet and outlet pressure of each station along the pipeline should meet the required limits.

$$P_{\mathrm{O}k,i,p} \leq p_{\mathrm{O\,max}\,i} \qquad k \in K,\ i \in I,\ p \in P \tag{A.8}$$

$$p_{\mathrm{I\,min}\,i} \leq P_{\mathrm{N}k,i,p} \qquad k \in K,\ i \in I,\ p \in P \tag{A.9}$$

Appendix B. Mathematical formulation of the maximum supply capacity calculation model

B.1. Objective function

When the pipeline system is under pumps failure conditions, the pipeline's capacity to meet the demand of downstream stations is usually smaller than that under normal operating conditions. Therefore, the objective function is to minimize the deviation between the actual delivered volume and the demanding volume of each delivery station.

$$\min F_2 = \sum_{i\in I} \sum_{o\in O} (V_{\mathrm{DE}i,o} - V_{\mathrm{AC}i,o}) \tag{B.1}$$

B.2. Delivery constraints

Since the pipeline delivery capacity under failure conditions must be reduced, the actual delivered volume of each delivery station is limited to be less than the demanding volume. There may be a case in which the actual delivered volume of a station is greater than the demanding volume if it is not limited. As a result, the actual delivered volume of other stations will be much smaller than the demanding volume, resulting in the supply satisfaction level further decreased. Meanwhile, the supply satisfaction level for the stations whose actual delivered volume is greater than the demanding volume have not increased. Therefore, it is necessary to set this constraint.

$$V_{\mathrm{AC}i,o} \leq V_{\mathrm{DE}i,o} \qquad i \in I,\ o \in O \tag{B.2}$$

The total delivered volume of oil o at delivery station i is equal to the sum of the delivered volume in each time interval.

$$V_{\mathrm{AC}i,o} = \sum_{s\in S}\sum_{j\in J}\gamma_{j,o}Q_{\mathrm{DO}s,i,j}\tau_{\mathrm{P}} \quad i\in I,\, o\in O \tag{B.3}$$

If batch j is delivered at station i in time interval s, the delivery flowrate should meet the upper and lower limits; otherwise, the flowrate must be equal to 0.

$$q_{D\min i} + (B_{\mathrm{DO}s,i,j}-1)M \le Q_{\mathrm{DO}s,i,j} \le q_{D\max i} + (1-B_{\mathrm{DO}s,i,j})M \qquad s\in S,\, i\in I,\, j\in J \tag{B.4}$$

$$Q_{\mathrm{DO}s,i,j} \le B_{\mathrm{DO}s,i,j}M \qquad s\in S,\, i\in I,\, j\in J \tag{B.5}$$

Only when batch j flows through delivery station i in time interval s, delivery station i can receive it.

$$B_{\mathrm{DO}s,i,j} \le B_{\mathrm{FT}s,i,j} \qquad s\in S,\, i\in I,\, j\in J \tag{B.6}$$

B.3. Batch moving constraints

The following constraint is to realize the definition of $B_{\mathrm{PA}s,\ i,\ j}$. That is, if batch j's upper coordinate has exceeded station i at the start time of time interval s, $B_{\mathrm{PA}s,\ i,\ j}$ is equal to 1; otherwise, $B_{\mathrm{PA}s,i,j}$=0.

$$X_i + (B_{\mathrm{PA}s,i,j}-1)M \le C_{\mathrm{OH}s,j} < X_i + B_{\mathrm{PA}s,i,j}M \qquad s\in S,\, i\in I,\, j\in J \tag{B.7}$$

The following three equations are to constrain the logical relationship of variable $B_{\mathrm{PA}s,\ i,\ j}$: (1) the time when batch j arrives at station i must be later than that when it arrives at station $i-1$; (2) the time when batch j arrives at station i must be later than that when batch $j-1$ arrives at station i; (3) if batch j has arrived at station i in time interval s, it must have arrived at station i in the later time intervals.

$$B_{\mathrm{PA}s,i-1,j} \ge B_{\mathrm{PA}s,i,j} \quad s\in S,\, i>1,\, j\in J \tag{B.8}$$

$$B_{\mathrm{PA}s,i,j-1} \ge B_{\mathrm{PA}s,i,j} \quad s\in S,\, i\in I,\, j>1 \tag{B.9}$$

$$B_{\mathrm{PA}s+1,i,j} \ge B_{\mathrm{PA}s,i,j} \quad s<s_{\max},\, i\in I,\, j\in J \tag{B.10}$$

Since this model is based on the discrete-time representation, the exact time of batch interfaces arriving at delivery stations must be the discrete-time nodes. Namely, if $B_{\mathrm{PA}s+1,i,j}-B_{\mathrm{PA}s,i,j}=1$, $C_{\mathrm{OH}t+1,j}$ must equal X_i on account of Eq. (B.7) and (B.10).

$$C_{\mathrm{OH}s+1,j} \le X_i + (1-B_{\mathrm{PA}s+1,i,j}+B_{\mathrm{PA}s,i,j})M \qquad s<s_{\max},\, i\in I,\, j\in J \tag{B.11}$$

If batch j's upper coordinate has reached station i (i.e. $B_{\mathrm{PA}s,i,j}$=1) and batch $j+1$'s upper coordinate (batch j's lower coordinate) has not (i.e. $B_{\mathrm{PA}s,i,j+1}$=0), it means that batch j is flowing through station i (i.e. $B_{\mathrm{FT}s,i,j}$=1). As for the last batch $j_{\max}$, if its upper coordinate has reached station i, it is flowing through the station.

$$B_{\mathrm{FT}s,i,j} = B_{\mathrm{PA}s,i,j} - B_{\mathrm{PA}s,i,j+1} \qquad s\in S,\, i\in I,\, j<j_{\max} \tag{B.12}$$

$$B_{\mathrm{FT}s,i,j\max} = B_{\mathrm{PA}s,i,j\max} \qquad s\in S,\, i\in I \tag{B.13}$$

For station .., there must be a batch flowing through in time interval s.

$$\sum_{j\in J} B_{\mathrm{FT}s,i,j} = 1 \qquad s\in S,\, i\in I \tag{B.14}$$

If batch j's upper coordinate has reached station i (i.e. $B_{\mathrm{PA}s,i,j}$=1) and has not reached station $i+1$ (i.e. $B_{\mathrm{PA}s,i+1,j}$=0), it means that batch j's upper coordinate is in pipeline segment $(i,\ i+1)$ (i.e. $B_{\mathrm{FA}s,i,j}$=1).

$$B_{\mathrm{FA}s,i,j} = B_{\mathrm{PA}s,i,j} - B_{\mathrm{PA}s,i+1,j} \qquad s\in S,\, i<i_{\max},\, j\in J \tag{B.15}$$

If batch j's upper coordinate is in pipeline segment $(i,\ i+1)$ in time interval s, its position at the start time of time interval $s+1$ is equal to that at the start time of time interval s plus the flowed volume of pipeline segment $(i,\ i+1)$ in time interval s.

$$C_{\mathrm{OH}s,j} + Q_{\mathrm{PF}s,i}\tau_{\mathrm{P}} + (B_{\mathrm{FA}s,i,j}-1)M \le C_{\mathrm{OH}s+1,j} \le C_{\mathrm{OH}s,j} + Q_{\mathrm{PF}s,i}\tau_{\mathrm{P}} + (1-B_{\mathrm{FA}s,i,j})M \quad s<s_{\max},\, i<i_{\max},\, j\in J \tag{B.16}$$

If batch j has not been injected into the pipeline (i.e. $B_{\mathrm{PA}s,1,j}$=0), its upper coordinate at the start time of time interval $s+1$ is equal to that at the start time of time interval s plus the injected volume in time interval s.

$$C_{\mathrm{OH}s,j} + Q_{\mathrm{PF}s,1}\tau_{\mathrm{P}} - B_{\mathrm{PA}s,1,j}M \le C_{\mathrm{OH}s+1,j} \le C_{\mathrm{OH}s,j} + Q_{\mathrm{PF}s,1}\tau_{\mathrm{P}} + B_{\mathrm{PA}s,1,j}M \qquad s<s_{\max},\, j\in J \tag{B.17}$$

If batch j has reached the terminal station, its upper coordinate will remain unchanged.

$$C_{\mathrm{OH}s,j} + (B_{\mathrm{PA}s,i\max,j}-1)M \le C_{\mathrm{OH}s+1,j} \le C_{\mathrm{OH}s,j} + (1-B_{\mathrm{PA}s,i\max,j})M \qquad s<s_{\max},\, j\in J \tag{B.18}$$

B.4. Pipeline flowrate constraints

If pipeline segment $(i,\ i+1)$ is active in time interval s, the flowrate need to meet the upper and lower limits; otherwise, it is equal to 0. With regard to the upper limit, it is the solving results of the MILP model in Appendix A. If the pipeline is under scenario k in time interval s, there must be a flowrate set under this scenario selected. If flowrate set p is chosen, the corresponding upper limit of pipeline segment $(i,\ i+1)$ $q_{\mathrm{U}k,\ i,\ p}$ must be satisfied in Eq. (B.19).

$$q_{\mathrm{Pmin}i} - B_{\mathrm{ID}s,i}M \le Q_{\mathrm{PF}s,i} \le \sum_{k\in K}\sum_{p\in P} q_{\mathrm{U}k,i,p}B_{\mathrm{SP}s,k,p} + B_{\mathrm{ID}s,i}M \qquad s\in S,\, i<i_{\max} \tag{B.19}$$

$$Q_{\mathrm{PF}s,i} \le (1 - B_{\mathrm{ID}s,i})M \qquad s \in S,\ i < i_{\max} \tag{B.20}$$

$$\sum_{p \in P} B_{\mathrm{SP}s,k,p} = F_{\mathrm{U}s,k} \qquad s \in S,\ k \in K \tag{B.21}$$

If the former pipeline segments are shut down, the later pipeline segments must also be idle.

$$B_{\mathrm{ID}s,i+1} \ge B_{\mathrm{ID}s,i} \qquad s \in S,\ i < i_{\max} - 1 \tag{B.22}$$

The flowrate of pipeline segment (i, i + 1) is equal to that of pipeline segment (i-1, i) minus delivery station i's flowrate.

$$Q_{\mathrm{PF}s,i} = Q_{\mathrm{PF}s,i-1} - \sum_{j \in J} Q_{\mathrm{DO}s,i,j} \qquad s \in S,\ 1 < i < i_{\max} \tag{B.23}$$

B.5. Injection constraints

If batch j is being injected in time interval s (i.e. $B_{\mathrm{FT}t,1,j} = 1$), the injection flowrate must satisfy the required limits; otherwise, it is equal to 0.

$$q_{\mathrm{J}\min} + (B_{\mathrm{FT}s,1,j} - 1)M \le Q_{\mathrm{NJ}s,j} \le q_{\mathrm{J}\max} + (1 - B_{\mathrm{FT}s,1,j})M \qquad s \in S,\ j \in J \tag{B.24}$$

$$Q_{\mathrm{NJ}s,j} \le B_{\mathrm{FT}s,1,j}M \qquad s \in S,\ j \in J \tag{B.25}$$

The injection flowrate is equal to the flowrate of pipeline segment (1, 2).

$$\sum_{j \in J} Q_{\mathrm{NJ}s,j} = Q_{\mathrm{PF}s,1} \qquad s \in S \tag{B.26}$$

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