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Digital Twin-Based Pump Station Dynamic Scheduling for Energy-Saving Optimization in Water Supply System

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Abstract

In urban water supply systems, pump stations are the hubs for making the complete systems operate regularly as well as the main energy-consuming units. In order to address the current problems of water supply systems, such as high energy consumption and low efficiency of the pump station operation, large fluctuations of liquid levels of the clean water reservoirs, and poor response and adaptability to disturbance events, a digital twin (DT)-based full-process dynamic pump station scheduling method for energy-saving optimization in water purification plants was proposed in this study. To be specific, the DT technology was introduced to monitor production disturbance in real time, trigger the rescheduling process in time, and make a fast response to disturbance events during production, so as to provide technical and methodological support for unattended pump stations. The results of experiments revealed that an average energy-saving rate of 9.78% could be achieved by using the proposed method on the premise of ensuring the full-process dynamic water balance. In addition, the method could maintain high efficiency during the operation of the pumps, and guarantee the safety and stability of the pump stations.

1 Introduction

1.1 Significance of pump station operation optimization

According to statistics, without considering financial costs and depreciation and amortization of fixed assets, electricity costs constitute 65% of the total operating costs of urban water supply systems (Blinco et al., 2014), and the energy consumption of pumps accounts for 75% of the electricity costs of urban water supply systems (Chen et al., 2021). Compared to the optimization of hardware equipment including frequency conversion transformation and pump impeller cutting (Papagiannis et al., 2018), optimizing the operation of pump units is a low-cost investment. Nowadays, the scheduling strategies of pump stations in water purification plants are mostly derived from the manual experience of controllers (Bonvin *et al*., 2017), which cause high electricity consumption per thousand tons of water (Coelho and Andrade-Campos, 2014; Ghaddar *et al*., 2015). Therefore, it is urgent to advance the energy efficiency ratio of pump stations (Reis *et al*., 2023).

1.2 Literature review

Due to the uncertainty of residential water use and the complexity of water supply network modeling, addressing the pump station scheduling problem is very challenging (Mala Jetmarova *et al*., 2017). Currently, most scholars focus on two aspects, namely, multi-objective modeling and algorithm optimization. In terms of the research on multi-objective modeling, Barán et al. (2005) proposed a pump scheduling optimization model with four objectives to be minimized, which were electric energy cost, maintenance cost, maximum power peak, and level variation of a water reservoir. A multi-objective optimization model for energy cost and maintenance cost was given by Zhuan *et al.* (2013). And a multi-objective optimization model in terms of operating cost and greenhouse gas was proposed by Stokes et al. (2014). Also, Makaremi et al. (2017) proposed a multi-objective optimization model involving the operating cost and the number of pump switches.

In terms of the research on algorithmic optimization, López-Ibáñez *et al.* (2008) proposed the application of ant colony optimization (ACO) in the pump scheduling optimization. An optimization method with particle swarm optimization (PSO) was put forward by Tang et al. (2014). Also, an optimization method combining the genetic algorithm (GA) and the EPANET2 simulator was given by Marchi et al. (2017). Luna et al. (2019) proposed an optimization method based on GA relying on knowledge-based mechanisms, such as the mechanism introducing known feasible solutions and selective variation into the initial population. Savsani et al. (2020) proposed an optimization method relying on biogeography-based optimization (BBO). Based on GA, Cimorelli et al. (2020) proposed a new representation method

of decision variables, and the results exhibited that it could further improve the performance of GA. Turci et al. (2020) proposed a self-adaptive and improved multi-population nature-inspired optimization algorithm for pump station scheduling. Chen et al. (2021) proposed an optimization method adopting non-dominated sorting genetic algorithm II (NSGA-II). Yan et al. (2022) put forward an optimization method on the basis of multi-objective particle swarm optimization (MOPSO).

In the above research, optimization methods for the pump station scheduling of the water supply systems were designed, which reduced energy consumption of pumps to some extent. However, full consideration was not given to the dynamic balance among the water intake pump station, the clean water reservoir and the water supply pump station, and systematic thinking was absent. Besides, during the actual production, there are operational failures of centrifugal pumps involved. Therefore, it is necessary to take equipment availability into consideration in the optimization of pump station scheduling.

1.3 Contribution and organization

To fill this research gap and provide a more sound and feasible pump station scheduling solution for water supply systems, a dynamic pump station scheduling method based on the full-process water balance was proposed in this paper. By adopting digital twin (DT) (Tao et al., 2019) technology, on the one hand, all kinds of data required for production scheduling, such as real-time data and historical data, can be accurately obtained, ensuring the real-time performance of pump station scheduling. On the other hand, the operating state of centrifugal pumps can be monitored online based on the DT data (DD). Through the continuous interaction and feedback between reality and virtuality, the scheduling solution can be adjusted in time, and production disturbance can be dealt with in time. On the premise of ensuring the full-process dynamic water balance in the water treatment system, in this study, a multi-objective pump station scheduling optimization model with objectives of the minimum electricity consumption for pump station operation, the minimum opening and closing times of the units, the maximum operating efficiency, and the consistent remaining useful life (RUL) model of the pump units was established. Meanwhile, an optimization algorithm based on the improved GA (IGA) for solving the model was designed, so as to increase the operating efficiency of pumps and reduce the energy consumption of pump stations.

This paper is divided into five sections. In the first section, the current status of energy saving and consumption reduction of water supply systems is introduced, and the existing operation optimization methods of pump stations are analyzed. Next, in the second section, a brief description of the pump station scheduling problem is given and the corresponding model is set up. The third section demonstrates the exploration of the framework of dynamic scheduling based on DT, and the research on the equipment availability prediction and the optimization algorithm based on IGA. The fourth section shows that the effectiveness of the proposed method is verified by an example. In the fifth section, the whole paper is summarized and the future research directions are explained.

2 Pump scheduling problem modeling

2.1 Problem description

The water supply systems in water purification plants mainly go through a process starting from raw water, the water intake pump house, the water treatment building, the clean water reservoir to the water supply pump house, as shown in Fig. 1. The full-process dynamic pump station scheduling is a process of adjusting the dynamic water balance, requiring predicting the optimal water intake, liquid levels of clean water reservoirs and water supply based on the historical and real-time data, and realizing automatic control of the pump opening and closing and operating frequency on the basis of keeping the dynamic balance among the three.

To facilitate an accurate description of the problem to be solved, the notations and definitions of the relevant parameters used are presented in Table 1.

Table 1
Notations used in formulating the problem

Definition	
Basic parameters	
T	A scheduling period (1 T = 1 day)
N	Total power of pump station
m	Number of constant-speed pumps
n	Number of variable-speed pumps
a_i, b_i, c_i	Characteristic curve parameters of the i^{th} constant-speed pump
Q_{sum}	Urban daily water demand
Q_i	Flow rate of the i^{th} constant-speed pump
a_j, b_j, c_j	Characteristic curve parameters of the j^{th} variable-speed pump
Q_j	Flow rate of the j^{th} variable-speed pump
L	Deviation between the maximum value and the minimum value of the RUL of $m+n$ centrifugal pumps
L_{max}	Maximum RUL value of $m+n$ centrifugal pumps
L_{min}	Minimum RUL value of $m+n$ centrifugal pumps
R	Opening and closing times of all pumps in 1 T
$R_{(t,k)}$	State variable of the k^{th} pump in the t session (0 or 1)
$R_{(t+1,k)}$	State variable of the k^{th} pump in the $t+1$ session (0 or 1)
η	Product of operating efficiency of $m+n$ centrifugal pumps
η_i	Operating efficiency of the i^{th} centrifugal pump
H	Deviation between the actual liquid level and the predicted liquid level of the clean water reservoir at t
H_t	Actual liquid level of the clean water reservoir at t
H_{t-pre}	Predicted liquid level of the clean water reservoir at t
Decision variables	

Definition	
s_i	Operating state of the i^{th} constant-speed pump (0 means "closed" and 1 means "open")
s_j	Operating state of the j^{th} variable-speed pump (0 means "closed" and 1 means "open")
r_j	Speed ratio of the j^{th} variable-speed pump

2.2 Mathematical model

The purpose of pump station operation optimization is to rationally match centrifugal pump units, improve operating efficiency of pumps and reduce energy consumption of pump stations on the premise of ensuring the dynamic water balance of the water supply systems in water purification plants and smooth operation of centrifugal pumps within a scheduling period, namely T. The objectives of pump station operation optimization are as follows.

$$\min N = \sum_{t=1}^{T}\{\sum_{i=1}^{m} s_i \left(a_i + b_i Q_i + c_i Q_i^2\right) + \sum_{j=1}^{n} s_j \left(a_j r_j^3 + b_j Q_j r_j^2 + c_j Q_j^2 r_j\right)\}$$

1

$$\min L = \sum_{t=1}^{T} |L_{max} - L_{min}|$$

2

$$\min R = \sum_{t=1}^{T} \sum_{\mathrm{k}=1}^{m+n} (|\, R_{(\mathrm{t}+1,k)} - R_{(t,k)}\,|)$$

3

$$\max \eta = \prod_{i=1}^{m+n} \eta_i$$

4

$$\min\, H = \sum_{t=1}^{T} |H_t - H_{t-pre}|$$

5

Among them, Eq. (1) represents the minimum total electric energy consumption of the pump station, and Eq. (2) indicates the consistent RUL of centrifugal pumps. Eq. (3) means the minimum opening and closing times of the pump station. Eq. (4) is the maximum product of operating efficiency of all centrifugal pumps. Eq. (5) represents the minimum difference between the actual liquid level and the predicted liquid level of the clean water reservoir.

2.3 Constraints

In terms of the pump station scheduling premised on the full-process dynamic water balance, the following constraints need to be satisfied:

(1) The total flow rate constraint:

The sum of water supply from $m+n$ pumps should be equal to the predicted value of water demand: $Q_{\mathrm{p}}=\sum_{t=1}^{T}(\sum_{i=1}^{\mathrm{m}}Q_{\mathrm{i}}+\sum_{j=1}^{n}Q_{\mathrm{j}})$.

(2) The pressure constraint at the pump station outlet:

When the pumps are connected in parallel, the heads at the outlets of all pumps are equal, that is, $H_1=H_2=\cdots=H_{m+n}$.

(3) The speed ratio constraint of variable-speed pumps:

In order to stabilize the operation and prevent cavitation, variable-speed pumps usually have a minimum operating speed limit. In this paper, the speed ratio range was defined as $r_j \in$ [0.75, 1].

(4) The flow rate constraint of constant-speed pumps:$Q_{imin} \le Q_i \le Q_{imax}$

Based on the *Q*-η characteristic curve, the ranges of 10% at both sides of the rated efficiency point of the constant-speed pumps (*i.e.*, the highest efficiency point of the pumps) are taken as the interval [Q_{imin}, Q_{imax}]. The pump efficiency within the interval is greater than 80%.

(5) The flow rate constraint of variable-speed pumps:$Q_{jmin} \le Q_j \le Q_{jmax}$

According to the *Q*-η characteristic curve, when the speed ratio is 0.75 or 1, the ranges of 10% at both sides of the highest efficiency point of the pumps are selected, of which the maximum and minimum values are taken as $Q_{j\max}$ and $Q_{j\min}$.

3 The framework of dynamic pump station scheduling based on DT

As the new generation of information technologies such as the Internet of Things, cloud computing and artificial intelligence develop rapidly, the DT technology has been widely advanced (Tao et al., 2019). DT, as a technology integrating reality and virtuality, aims at creating a high-fidelity virtual model for each physical entity (PE) in order to simulate its state and behavior, and it has the ability to optimize and predict (Tsega *et al.*, 2020). In recent years, the workshop production scheduling centered on DT is advancing quickly (Li et al., 2023; Schuh et al., 2020; Guo et al., 2020). In light of that, in this paper, the DT technology was applied to the pump station scheduling optimization problem, and a DT-based full-process dynamic pump station scheduling method for energy-saving optimization was proposed, as shown in Fig. 2. The detailed scheduling process is explained as follows:

Step 1: Virtual entities (VE) should be consistent with PE. The model is calibrated by checking the real-time communication among PE, VE, services (Ss) and DD, and the model parameters of VE are corrected according to the real-time data of PE to ensure the consistency of VE and PE in the scheduling period.

Step 2: A scheduling solution is generated. The real-time data (operation duration, vibration signals, *etc.*) and historical data (daily water consumption, weather, holidays, vibration signals, *etc.*) of PE are obtained before scheduling, and then, a solution of full-process pump station joint scheduling is formulated (Fig. 4).

Step 3: Equipment availability prediction is performed. The vibration signals of the equipment in the next four hours are simulated *via* the VE, and the equipment anomaly detection method based on root mean square (RMS) and kurtosis (Fig. 5) is used to check the equipment state and predict the equipment availability.

Step 4: Generate a rescheduling scheme. If the equipment is not available, the entire process pumping station joint scheduling method is triggered again to generate a rescheduling scheme. Otherwise, the rescheduling process is not triggered.

Step 5: The scheduling solution is verified. The scheduling solution is transmitted to the virtual workshop for simulation, which can help to find potential conflicts in the solution before implementation. After verification, the control command from the virtual workshop is fed back to the physical workshop and it is made to maintain synchronization with the expected plan.

Step 6: Knowledge is accumulated. After the scheduling is completed, all the elements, processes, businesses and other relevant information generated during the scheduling process are stored in the DT database to guide the subsequent scheduling work.

3.1 Composition and operation mechanism of DT pump station

DT pump stations mainly consist of PE (here referred to as the physical pump station), VE (here referred to as the virtual pump station), connection (CN), Digital Twin Data (DD) and Ss (here referred to as smart services), as shown in Fig. 3. Among them, the physical pump station is the collection of objective physical entity resource objects including humans, equipment, materials, methods and environments, which provide the operating environment for the physical pump station. The virtual pump station is a virtual mapping of the physical pump station, which simulates and analyzes a variety of production activities in the physical space. CN works as the link between the physical pump station and the virtual pump station, realizing the two-way connection, two-way interaction and two-way drive between them. DD is the core driving force of DT, which covers the real-time data generated by the physical pump station during the production and operation process and the simulation data obtained via the virtual pump station simulation under different working conditions. Smart services are dynamically predicting and optimizing the production and operation of the pump stations through the two-way real mapping and real-time interaction between the physical pump station and the virtual pump station, in order to realize the optimal operating state. The smart services include online monitoring of the pump station operation and the pump state, prediction of the RUL of pumps and the water demand, pump station scheduling optimization, emergency response, etc.

In order to maintain the dynamic balance among the water intake, the liquid level of the clean water reservoir and the water supply, an operation mechanism of the full-process pump station joint scheduling in the water purification plant was designed in this paper, as shown in Fig. 4. Firstly, the daily water demand was predicted by time series (Zhou et al., 2022). Subsequently, by using the least squares method, the hourly liquid level of the clean water reservoir on the next day was predicted. Next, the water supply was substituted into the pipeline characteristic curve equation as an input parameter in order to calculate the outlet pressure. Later, the RUL of pumps was predicted by adopting the equipment RUL model (Zhou et al., 2023). Finally, the parameters, including water intake, inlet pressure, water supply, outlet pressure, and RUL of the pumps, obtained from the reverse calculation of the liquid level of the clean water reservoir were respectively substituted into the pump station scheduling model to calculate the optimal pump opening solution of the water intake pump house and the water supply pump house.

3.2 Anomaly detection method based on RMS and kurtosis

Under the condition of unattended pump stations, due to disturbance factors such as equipment performance degradation, changes of working conditions and load adjustment, the offline scheduling model cannot respond to the application scenarios in time where the equipment suddenly changes during water production. Therefore, it is necessary to quantify the change of the equipment operating state to realize online equipment anomaly detection.

Because of the simple calculation and easy implementation, a lot of research and applications related to time-frequency domain statistical indicators based on vibration signals are presented in the aspects of equipment fault prediction and health management (Xu et al., 2020). In addition, kurtosis and RMS have respective advantages and disadvantages. For example, kurtosis exhibits a better characterization ability of time variability, while RMS possesses better robustness to noise. Thus, on the basis of time-frequency domain statistical indicators, an equipment anomaly detection method based on RMS and kurtosis was proposed in this paper, as shown in Fig. 5. The specific steps are as follows:

(1) According to the original vibration signal, the kurtosis and RMS of the vibration signals before t_i are calculated.

(2) The normal range of kurtosis and RMS before t_i is calculated, namely, [$-\sigma$, $\mu+\sigma$], where σ and μ represent the standard deviation and mean value of vibration signals, respectively.

(3) If three consecutive points of Kur_t and RMS_t are all beyond the normal range, the two points before t_i are selected as the equipment fault time points. Otherwise, Step (1) is redone.

3.3 DT-based availability prediction

DT-based availability prediction refers to detecting equipment availability online through the comparison of the vibration signals collected by PE and those simulated by VE. In this method, the data of PE are represented as $X = \{x_t\}_{t=1}^{T}$, where x_t is the vibration signal at *t*, and the data of VE are set as $Y = \{y_t\}_{t=1}^{T}$ and $Z = \{\{\mathrm{z}_i | 1 \le i \le n\}\}_{t=1}^{T}$, where y_t is the corresponding simulation value of x_t at *t*, and z_i represents other additional simulation results, such as the stress level and temperature distribution of parts, and *n* means the number of components.

As shown in Fig. 6, at *t*, parameters are selected from *X* and *Y* to respectively represent the data of PE and VE, expressed as $D_{PE} = \{x_1, x_2, x_3, \ldots, x_t\}$ and $D_{VE} = \{y_1, y_2, y_3, \ldots, y_t\}$. If the deviation value between D_{PE} and D_{VE} is within the predefined threshold, T_p, that is, $|D_{PE} - D_{VE}| < T_p$, PE and VE are considered to be consistent. In this case, the data of VE can be used to monitor the equipment operating state by the anomaly detection method (Fig. 5). If the equipment works normally, the neural network method (Zhou et al., 2023) is used to perform the RUL prediction based on the feature data extracted from the data of PE and VE. If $|D_{PE} - D_{VE}| \ge T_p$, PE and VE are inconsistent. To find the cause of the inconsistency, the value, D_{HIS}, in the historical data is introduced to judge the state of the equipment. If the values, D_{VE} and D_{HIS} are close, then the deviation is caused by PE, and PE is considered abnormal. Otherwise, the deviation is caused by the model failure of VE and PE is considered normal, then the VE parameters should be corrected. According to the prediction results, if the equipment works normally, it is available. If not, maintenance time needs to be reserved, during which the equipment is unavailable.

3.4 Optimization algorithm

The pump switching problem involves discrete and continuous variables, and the number of variables increases with the number of centrifugal pumps (Patel *et al.*, 2020). Traditional GA, a point search method, is likely to lead to the local optimum instead of ensuring the global optimum. Further, it is difficult to solve the conflicts between different objectives as researched herein. Therefore, an IGA to solve the pump station scheduling problem was designed in this paper. The algorithm flow is shown in Fig. 7.

In this algorithm, the strategy of NSGA-II (Makaremi et al., 2017) was referred to address the multi-objective problem by looking for the non-dominated solutions, and the dominance relationship matrix shown in Eq. (6) was established

according to the dominance relationship between individuals produced in the process of running the algorithm. Later, the probability of each individual in the population being selected at each iteration was calculated by Eq. (7), and the non-dominated solutions obtained were stored in the archive set. Thus, the conflicts between different objectives could be effectively dealt with. Meanwhile, in order to improve the optimization ability of the algorithm, self-adaptive design was conducted on the algorithm exhibited in Fig. 7. In the design, when the archive set was found not updated after several iterations, it indicated that the algorithm search was stagnant. Then, the search range of the algorithm was expanded by reducing the crossover probability and increasing the variation probability and the number of variation points, in order to help the algorithm jump out of the local optimum.

$$RR = \begin{pmatrix} rr_{11} & rr_{12} & \cdots & rr_{1n} \\ rr_{21} & rr_{22} & \cdots & rr_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ rr_{n1} & rr_{n2} & \cdots & rr_{nn} \end{pmatrix}$$

6

$$Prob_h = \frac{\sum_{k=1}^{n} rr_{hk}}{\sum_{h=1}^{n}\sum_{k=1}^{n} rr_{hk}}$$

7

Where, rr_{hk} represents the dominance relationship between the h^{th} individual and the k^{th} individual in the population, n represents the number of individuals in the population, and $Prob_h$ stands for the probability that the h^{th} individual in the population is selected during the selection operation. If $h = k$, the value of rr_{hk} is 0.5. If the k^{th} individual is dominated by the h^{th} individual and h is not equal to k, the value of rr_{hk} is 1. If the k^{th} individual dominates the h^{th} individual, the value of rr_{hk} is 0. If the two individuals do not dominate each other, the value of rr_{hk} is 0.5.

The specific operation steps of the algorithm are as follows:

Step 1: By fitting the data of experiments, the flow rate-efficiency (*Q*-η), flow-head (*Q*-*H*) and flow-power (*Q*-*N*) characteristic curves (Equations (10)-(21) shown in Section 4.1) at the rated rotational speed are obtained. Through the *Q*-η characteristic curve, the ranges of 10% at both sides of the rated efficiency point (*i.e.*, the highest efficiency point of the pumps) are taken as the interval corresponding to the flow rate values of the constant-speed pumps and the variable-speed pumps, namely, $[Q_{\min}, Q_{\max}]$.

Step 2: On the basis of the change law of water consumption and water supply pressure in City A, a scheduling period (one day) is generally divided into six sessions. Thus, the rows of two-dimensional chromosomes is 6, then the ranges of water demand (*Q*) and the outlet pressure (*H*) in different sessions during the scheduling period are determined.

Step 3: According to the *Q*-*N* characteristic curve, the relevant parameters of the fitness functions (Equations (1)-(5)) and the constraints are set.

Step 4: The initial population with the size of *n* is obtained by random generation, and the maximum number of iterations is set as genMax.

Step 5: The fitness value of chromosomes is calculated. After selection, the chromosomes are recombined to gain a new population. Subsequently, the crossover and variation operators are performed according to the data of the archive set, so as to obtain the implementation solutions to the opening of constant-speed and variable-speed pumps, as well as the optimal speed ratio. And the solutions are stored in the two-dimensional array of 6**J*.

Step 6: Termination condition judgment is conducted. If the termination conditions are not met, Step 5 will be redone. If the termination conditions are met, Step 7 will be the next step.

Step 7: The optimized solution and related data are output, and the algorithm ends.

4 Case study

4.1 Case description

For the purpose of this study, one water treatmnet plant in China, in the city of Suzhou, was utilized to develop pump station dynamic scheduling model. The water treatmnet plant, in Fig. 8, takes the Taihu Lake as the water source and adopts regional water supply mode.The water supply pump house of this water treatmnet plant was taken as an example in this paper. Practical application research on pump station scheduling was carried out with the relevant theories and methods proposed. The data and parameters related are shown in Table 2.

Table 2
Parameters related to the water supply pump house of the water purification plant

Pump Model	Pump Type	Pump No.	Rated flow	Rated head	Rated efficiency
ASP500-620ACD	Constant-speed	1#, 2#	2,707.34 m³/h	37.08 m	88.5%
ASP700-680ACD	Constant-speed	3#, 4#	4,809.26 m³/h	28.12 m	93.09%
ASP500-620ACD	Variable-speed	5#, 6#	2,707.34 m³/h	37.08 m	89.29%
ASP700-860ACD	Variable-speed	7#, 8#	5,241.18 m³/h	40.66 m	91.37%

(1) The pipeline characteristic curve

When the fluid flows in the pipeline, the flow resistance grows in proportion to the square of the flow. The same pump connected to diverse pipe network systems presents different operating characteristics due to the different pipe resistance. The pipeline characteristic curve can be expressed as Eq. (8):

$$H = H_{st} + S_1 Q + S_2 Q^2$$

8

Where H_{st} stands for the pressure at the end of the pipe network. S_1 and S_2 denote the pipeline resistance coefficients. *H* and *Q* refer to the water supply pressure and flow rate of the secondary pump station, respectively.

According to the analysis of the actual outlet flow rate, outlet pressure, pressure at the end of the pipe network and other data of the B water purification plant in City A, curve fitting was conducted through the least squares method, and

the outlet pipeline resistance characteristic curve of the water purification plant was gained as follows:

$$H = 0.175 + 5 \times 10^{-4}Q + 3 \times 10^{-8}Q^2$$

9

(2) The centrifugal pump characteristic curve

Currently, in the pump station of some water purification plant, constant-speed pumps and variable-speed pumps work jointly. The relevant parameters are exhibited in Table 2. Due to the great difference between the actual condition and the theoretical condition of the pump station characteristic curve, in this paper, through experiments, the relationship between *Q-H*, *Q-η* and *Q-P* were determined and the centrifugal pump characteristic curve was obtained by curve fitting with the least squares method (Hong et al., 2019), as shown in Equations (10)-(21). In addition, the ranges of 10% at both sides of the rated efficiency point (*i.e.*, the highest efficiency point of the pumps) were taken as the high efficiency section of the centrifugal pumps. The pump efficiency in this interval was greater than 80%.

The *Q-H*, *Q-η* and *Q-P* curves and the high efficiency section of Centrifugal Pumps 1# and 2# can be expressed as:

Q-H curve: $H = 49.316 - 2 \times 10^{-6}Q^2$ (10)

Q-η curve: $\eta = 24.992 + 0.0475Q - 9 \times 10^{-6}Q^2$ (11)

Q-P curve: $P = 88.631 + 0.1287Q - 2 \times 10^{-5}Q^2$ (12)

The *Q-H*, *Q-η* and *Q-P* curves and the high efficiency section of Centrifugal Pumps 3# and 4# are expressed as:

Q-H curve: $H = 41.954 - 6 \times 10^{-7}Q^2$ (13)

Q-η curve: $\eta = 7.49 + 0.0356Q - 4 \times 10^{-6}Q^2$ (14)

Q-P curve: $P = 114.19 + 0.1432Q - 1 \times 10^{-5}Q^2$ (15)

High efficiency section:$H \in [0.175, 0.3574]$,$Q \in [3223.31, 6395.19]$

The *Q-H*, *Q-η* and *Q-P* curves and the high efficiency section of Centrifugal Pumps 5# and 6# are expressed as:

Q-H curve: $H = 49.316S^2 - 1.67 \times 10^{-6}Q^2$ (16)

Q-η curve: $\eta = 24.992 + 0.0475S^{-1}Q - 8.775 \times 10^{-6}S^{-2}Q^2$ (17)

Q-P curve: $P = 88.631S^3 + 0.1287S^2Q - 2 \times 10^{-5}SQ^2$ (18)

High efficiency section:$H \in [0.1477, 0.4450]$,$Q \in [1273.83, 3716.23]$

The *Q-H*, *Q-η* and *Q-P* curves and the high efficiency section of Centrifugal Pumps 7# and 8# are expressed as:

Q-H curve: $H = 53.008S^2 - 4 \times 10^{-7}Q^2$ (19)

Q-η curve: $\eta = 25.598 + 0.0251S^{-1}Q - 2.3975 \times 10^{-6}S^{-2}Q^2$ (20)

Q-P curve: $P = 180.3S^3 + 0.129S^2Q - 8 \times 10^{-6}SQ^2$ (21)

High efficiency section:$H \in [0.1673, 0.4815]$,$Q \in [2465.78, 7194.64]$

(3) The flow rate and pressure data of each session

The water demand prediction model (Zhou et al., 2022) was adopted to predict the daily water consumption which was 326,636 m^3. The flow rates (Q) divided into six sessions were substituted into the pipe resistance characteristic Eq. (9) to obtain the outlet water pressure (H) as shown in Table 3.

Table 3
Flow rate and pressure data of each session

Session	Flow rate (m^3/h)	Pressure/m	Session	Flow rate (m^3/h)	Pressure/m
00:00–04:00	10,573	26.93	13:00–16:00	15,103	30.13
05:00–08:00	14,193	30.19	17:00–20:00	16,252	32.10
09:00–12:00	15,378	31.23	21:00–24:00	11,160	27.46

(4) The RUL of the pump

The RUL prediction model (Zhou et al., 2023) was used to predict the RUL of the front and rear rolling bearings of the centrifugal pumps, as shown in Table 4.

Table 4
RUL of the front and rear rolling bearings of the pumps

Centrifugal Pump	Rolling Bearing	RUL/h
1#	Front 1#	1,200
	Rear 2#	1,100
2#	Front 1#	853
	Rear 2#	934
3#	Front 1#	1,378
	Rear 2#	1,243
4#	Front 1#	1,178
	Rear 2#	1,379
5#	Front 1#	1,210
	Rear 2#	979
6#	Front 1#	1,190
	Rear 2#	1,098
7#	Front 1#	1,320
	Rear 2#	1,276
8#	Front 1#	845
	Rear 2#	902

4.2 Verification of DT-based dynamic scheduling

Verification of the multi-objective pump station scheduling optimization model based on the IGA was conducted in this section. After the relevant parameters of the water supply pump house (Table 2), the flow rate and pressure data table of each session (Table 3), the RUL of the centrifugal pump units (Table 4), and the characteristic functions of the centrifugal pumps (Equations (10)-(21)) were all substituted into the fitness functions (Equations (1)-(5)), the pump opening solution of the pump station was calculated based on the IGA, as shown in Fig. 9. In order to verify the effectiveness of the algorithm, the pump opening solution based on the IGA was compared with the pump opening solution obtained by the general scheduling method in this paper, as shown in Table 5.

Table 5
Comparison of energy consumption and efficiency before and after pump station optimization under normal conditions

Session	opening and closing solution		Power/kW		Efficiency/%		Energy-saving rate/%
	Before optimization	After optimization	Before optimization	After optimization	Before optimization	After optimization	
1	10001010	00001110	875.23	**825.4**	66.89	**70.24**	5.69
2	10101010	10001110	1,561.98	**1,273.63**	59.50	**59.94**	18.46
3	10100011	10000111	1,602.97	**1,433.11**	61.18	**62.52**	10.59
4	10101010	10000111	1,523.91	**1,375.62**	60.14	**63.52**	9.73
5	10100011	10000111	1,745.11	**1,559.79**	62.22	**63.48**	10.62
6	00001110	00001110	931.33	**897.82**	64.53	**65.09**	3.59

As shown in Table 5, the operating efficiency of pumps after optimization was higher than that before optimization, and the average energy-saving rate of the pump solution after optimization reached 9.78%. The same pump opening solution was used for water supply before and after optimization in Session 6, but due to the larger accurate speed ratio after optimization, the energy-saving rate correspondingly rose. It could be known from Fig. 10(a) that during a scheduling period, the opening and closing times of the pumps after optimization significantly decreased. The opening and closing times of the pumps before optimization were 12 in total, while the opening and closing times of the pumps after optimization were 6. In Fig. 10(b), in a scheduling period, the operation duration of Pump 6# after optimization was longer than that of Pump 5#, while the operation duration of Pump 6# before optimization was shorter than that of Pump 5#. From Table 4, it could be seen that the RUL of Pump 6# was larger than that of Pump 5#, indicating that the solution after optimization met the objective of the consistent RUL proposed in this paper. To sum up, the decision-making solution after optimization is more scientific and reasonable, and can realize the objective of energy-saving and optimal operation of the water supply pump house.

In the actual production, there are rescheduling needs in the pump stations due to some sudden faults or disturbance. In order to compare and analyze the rescheduling scenarios, it was assumed that Pump 7# was unavailable due to the maintenance plan or faults between 13:00 and 16:00, then the system automatically set Pump 7# as unavailable. The Gantt chart of operation results is shown in Fig. 11.

Table 6
Comparison of energy consumption and efficiency of the pump station rescheduling under disturbance

Session	Pump station opening and closing solution		Power/kW		Efficiency/%		Energy-saving rate/%
	Before optimization focusing on disturbance	After optimization focusing on disturbance	Before optimization	After optimization	Before optimization	After optimization	
4	10101001	10001101	1,523.91	**1,355.97**	56.14	**57.35**	11.02
5	10110001	10100101	1,846.75	**1,723.31**	58.49	**57.62**	6.68
6	00001101	00001101	931.33	**897.82**	64.53	**65.09**	3.59

When the variable-speed pump fails, in the general scheduling solution, the proportional-integral-derivative (PID) algorithm (constant pressure control) is adopted to start the constant-speed pump first, but this scheduling solution may not be optimal. In Table 6, in the case of disturbance, the general scheduling solution (before optimization) and the rescheduling solution (after optimization) were analyzed and compared. The results revealed that the energy-saving rate and operating efficiency of the rescheduling solution were higher than that of the general scheduling solution. According to the comparison and analysis of Table 5 and Table 6, the energy-saving effectiveness of optimal solution in Session 4 after disturbance was better than that of the optimal solution before disturbance, because when Pump 7# failed, the opening and closing times of Pump 7# were no longer considered. It could be known from Fig. 12(a) that during a scheduling period, the opening and closing times of the pumps after optimization decreased. The opening and closing times of the pumps before optimization were 12 in total, while the opening and closing times of the pumps after optimization were 10. According to Fig. 12(b), after optimization, the operation duration of Pump 6# was also longer than that of Pump 5# in a scheduling period.

Through comprehensive analysis and comparison, in the two scenarios of conventional scheduling and disturbance scheduling, the optimization results of the DT-based dynamic pump station scheduling model for energy-saving optimization proposed in this paper are better than those of the general method, and the proposed model is feasible in the engineering application.

4.3 Proving the superiority of the algorithm

To measure the performance of the algorithm studied, it was compared with the ACO (Hashemi et al., 2014), Artificial Bee Colony (ABC) (Bagirov et al., 2013), and PSO (Yan et al., 2022; Jafari-Asl et al., 2020).

Figure 13 presents the convergence curve of the IGA and other meta-heuristic algorithms. When electricity consumption was used as an evaluation indicator, the IGA was superior to other meta-heuristic algorithms in the aspect of fitness evaluation.

Table 7
Comparison of fitness values between the IGA and other meta-heuristic algorithms

Algorithm	Electricity consumption per thousand tons of water (KWH/Kt)	Average efficiency	Total opening and closing times
IGA	90.19	64.13	6
ACO	90.59	63.84	6
PSO	90.71	63.67	6
ABC	91.11	62.34	6

In a scheduling period, according to Table 7, the IGA proposed in this paper performed the best in terms of the total power and average efficiency of pump units. As all heuristic algorithms bring up the same pump opening and closing solution, the total opening and closing times of pumps were basically consistent. Figure 14 demonstrates the comparison of equipment operation durations, and the results of the four algorithms were basically consistent. Figure 15 shows the comparison of the liquid level fluctuations of the clean water reservoir. The liquid level of the clean water reservoir calculated by the IGA proposed in this paper had the highest consistency with that by the water balance method. To sum up, the optimization algorithm proposed in this paper has a better optimization effectiveness than other meta-heuristic algorithms in the literature.

5 Conclusion

Pump scheduling is one of the most significant tasks of the water supply system, constituting a major part of its operation costs (Bagirov et al., 2013). In this paper, DT technology was applied to the rapid response to the disturbance caused by dynamic events during production, thus safeguarding the unattended pump stations. At first, the DT-based dynamic scheduling framework was discussed. Then, the equipment availability prediction module and the optimization method based on the IGA were studied. Finally, the effectiveness of the proposed method was verified by a case analysis.

However, the proposed method still has some limitations. Firstly, the virtual model in the DT needs to keep consistent with the physical model, requiring that the virtual model in the DT should be continuously corrected and updated iteration by iteration on the basis of the real-time data. Secondly, the consistency judgment of the virtual model and physical model in the DT only takes vibration signals as the influence factor. In the future, experts in different fields may be required to build a complete and detailed DT, covering various models and data of the whole pump station. Thirdly, due to the complexity of water supply network modeling, the microscopic model of the pipe network is not considered in the current research results (Marchi et al., 2017), which can affect the accuracy of the pump unit scheduling solution. Furthermore, information security is also a key issue, which must be considered before applying this method to larger scale practice.

Future work mainly includes further verification of the advantages of the DT-enhanced dynamic scheduling method in the aspects of real-time property and reliability and the comparison of the proposed DT-enhanced dynamic scheduling method and the existing data-driven scheduling method. The advantages and disadvantages of the two methods should be analyzed in order to provide instructions for future applications in different scenarios.

Declarations

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Author Contributions Sheng-Wen Zhou: Original draft writing and Visualization, Shun-Sheng Guo: Reviewing and Editing, Wen-Xiang Xu: Conceptualization, Supervision and Methodology, Bai-Gang Du: Data analysis, Jun-Yong Liang: Data Collection and Visualization, Lei Wang: Editing, Yi-Bing Li: Reviewing.

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Availability of data and materials Authors will share data when needed.

Ethical Approval Compliance with Ethical Standards Conflict.

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Consent to Publish The participant has consented to the submission of the case report to the journal.

Competing Interests 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.

References

1. Blinco, L.J., Simpson, A.R., Lambert, M.F., et al., 2014.Genetic algorithm optimization of operational costs and greenhouse gas emissions for water distribution systems. Procedia. Eng. 89, 509–516. https://doi.org/10.1016/j.proeng.2014.11.246.
2. Chen, W., Tao, T., Zhou, A., et al., 2021. Genetic optimization toward operation of water intake-supply pump stations system. J. Clean. Prod. 279, 0959–6526. https://doi.org/10.1016/j.jclepro.2020.123573.
3. Papagiannis, F., Gazzola, P., Burak, O., Pokutsa, I., 2018. Overhauls in water supply systems in Ukraine: a hydro-economic model of socially responsible planning and cost management. J. Clean. Prod. 183, 358–369. https://doi.org/10.1016/j.jclepro.2018.02.156.
4. Bonvin, G., Demassey, S., Le Pape, C., et al., 2016. A convex mathematical program for pump scheduling in a class of branched water networks. Appl. Energy. 185, 1702–1711. https://doi.org/10.1016/j.apenergy.2015.12.090.
5. Coelho, B., Andrade-Campos, A., 2014. Efficiency achievement in water supply system-A review. Renew. Sustain. Energy. Rev. 30, 59–84. https://doi.org/10.1016/j.rser.2013.09.010.
6. Ghaddar, B., Naoum-Sawaya, J., Kishimoto, A., Taheri, N., Eck, B., 2014. A Lagrangian decomposition approach for the pump scheduling problem in water networks. Eur. J. Oper. Res. 241, 490–501. https://doi.org/10.1016/j.ejor.2014.08.033.
7. Ana L. Reis, Marta A.R. Lopes, A. Andrade-Campos, Carlos Henggeler Antunes, 2023. A review of operational control strategies in water supply systems for energy and cost efficiency. Renew. Sustain. Energy. Rev. 175, 113140. https://doi.org/10.1016/j.rser.2022.113140.
8. Mala-Jetmarova, H., Sultanova, N., Savic, D., 2017. Lost in optimisation of water distribution systems? A literature review of system operation. Environ. Model. Softw. 93, 209–254. https://doi.org/10.1016/j.envsoft.2017.02.009.
9. Barán, B., von Lücken, C., Sotelo, A., 2005. Multi-objective pump scheduling opti- misation using evolutionary strategies. Adv. Eng. Softw. 36, 39–47. https://doi.org/10.1016/j.advengsoft.2004.03.012.

10. Zhuan, X., Xia, X., 2013. Optimal operation scheduling of a pumping station with multiple pumps. Appl. Energy. 104, 250–257. https://doi.org/10.1016/j.apenergy.2012.10.028.
11. Stokes C.S., Maier H.R., Simpson A.R., 2014. Water distribution system pumping operational greenhouse gas emissions minimization by considering time-dependent emissions factors. J. Water. Resour. Plan. Manag. 141, 04014088. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000484.
12. Makaremi, Y., Haghighi, A., Ghafouri, H.R., 2017. Optimization of pump scheduling program in water supply systems using a Self-Adaptive NSGA-II; A review of theory to real application. Water. Resour. Manag. 31, 1283–1304. https://doi.org/10.1007/s11269-017-1577-x.
13. Lo´pez-Ib´an˜ez, M., Prasad, T.D., Paechter, B., 2008.Ant Colony Optimization for Optimal Control of Pumps in Water Distribution Networks. J. Water. Resour. Plan. Manag. 134, 337–346. https://doi.org/10.1061/(asce)0733-9496(2008)134:4(337).
14. Tang, Y., Zheng, G., Zhang, S., 2014. Optimal control approaches of pumping stations to achieve energy efficiency and load shifting. Int. J. ELEC. POWER. 55, 572–580. https://doi.org/10.1016/j.ijepes.2013.10.023.
15. Marchi, A., Simpson, A.R., Lambert, M.F., 2017. Pump operation optimization using rule-based controls. Procedia. Eng. 186, 210–217. https://doi.org/10.1016/j.proeng.2017.03.229.
16. Luna, T., Ribau, J., Figueiredo, D., 2019. Rita Alves, Improving energy efficiency in water supply systems with pump scheduling optimization. J. Clean. Prod. 213, 342–356. https://doi.org/10.1016/j.jclepro.2018.12.190.
17. Savsani, V., Patel, V., Tawhid, M., 2020. Biogeography Based Optimization for Water Pump Switching Problem. Nature-Inspired Methods for Metaheuristics Optimization: Algorithms and Applications in Science and Engineering. 16, 183–202. https://doi.org/10.1007/978-3-030-26458-1_11.
18. Cimorelli L., D'Aniello A., Cozzolino L., 2020. Boosting genetic algorithm performance in pump scheduling problems with a novel decision-variable representation. J. Water. Resour. Plan. Manag. 146, 04020023, https://doi.org/10.1061/(asce)wr.1943-5452.0001198.
19. Turci, L. de O., Wang, J., Brahmia, I., 2020. Adaptive and Improved Multi-population Based Nature-inspired Optimization Algorithms for Water Pump Station Scheduling. Water. Resour. Manage. 34, 2869–2885. https://doi.org/10.1007/s11269-020-02588-3.
20. Yan, P., Zhang, Z., Lei, X., Hou, Q., Wang, H., 2022. A multi-objective optimal control model of cascade pumping stations considering both cost and safety. J. Clean. Prod. 2022, 131–171. https://doi.org/10.1016/j.jclepro.2022.131171.
21. Tao F., Qi Q., 2019. Make more digital twins. Nature. 573, 490–491. https://doi.org/10.1038/d41586-019-02849-1.
22. Tao, F., Zhang, H., Liu, A., Nee, A.Y.C., 2019. Digital twin in industry: State-of-the-art. IEEE Trans. Ind. Inform. 15, 2405–2415. https://doi.org/10.1109/TII.2018.2873186.
23. Melesse, T.Y., Di Pasquale, V., Riemma, S., 2020. Digital Twin Models in Industrial Operations: A Systematic Literature Review. Procedia Manufacturing. 42, 267–272. https://doi.org/10.1016/j.promfg.2020.02.084.
24. Li, Y., Tao, Z., Wang, L., et al., 2023. Digital twin-based job shop anomaly detection and dynamic scheduling. Robot. Comput. Integr. Manuf. 79, 102443. https://doi.org/10.1016/j.rcim.2022.102443.
25. Schuh, G., Kelzenberg, C., Wiese, J., Kessler, N., 2020. Creation of digital production twins for the optimization of value creation in single and small batch production. Procedia CIRP. 93, 222–227. https://doi.org/10.1016/j.procir.2020.04.125.
26. Guo, H., Chen, M., Mohamed, K., et al., 2020. A digital twin-based flexible cellular manufacturing for optimization of air conditioner line. J. Manuf. Syst. 58 (PB), 65–78. https://doi.org/10.1016/j.jmsy.2020.07.012.

27. Zhou, S., Xu, F., Guo, S., et al., 2023. Constructing a health indicator based on long short-term memory and using an extreme inflection point with a slope model to enhance monotonicity. J. Braz. Soc. Mech. Sci. Eng. 45, 175. https://doi.org/10.1007/s40430-022-03968-z.
28. Zhou, S., Guo, S., Du, B., Huang, S., Guo, J., 2022. A Hybrid Framework for Multivariate Time Series Forecasting of Daily Urban Water Demand Using Attention-Based Convolutional Neural Network and Long Short-Term Memory Network. Sustainability. 14, 11086. https://doi.org/10.3390/su141711086.
29. Xu, F., Huang, Z., Yang, F., et al., 2020. Constructing a health indicator for roller bearings by using a stacked auto-encoder with an exponential function to eliminate concussion. Appl. Soft. Comput. 89, 106119. https://doi.org/10.1016/j.asoc.2020.106119.
30. Patel, V.K., Raja, B.D., 2020. Comparative Performance of Recent Advanced Optimization Algorithms for Minimum Energy Requirement Solutions in Water Pump Switching Network. Arch. Comput. Methods. Eng. 28, 1545–1559. https://doi.org/10.1007/s11831-020-09429-x.
31. Hong, S., Kim, T., Lee, S., 2019. A precision pump schedule optimization for the water supply networks with small buffers. Omega-Int. J. Manage. S. 82, 24–37. https://doi.org/10.1016/j.omega.2017.12.001.
32. Hashemi, S.S., Tabesh, M., Ataeekia, B., 2014. Ant-colony optimization of pumping schedule to minimize the energy cost using variable-speed pumps in water distribution networks. Urban. Water. J. 11, 335–347. https://doi.org/10.1080/1573062X.2013.795233.
33. Bagirov, A.M., Barton, A.F., Mala-Jetmarova, H., et al., 2013. An algorithm for minimization of pumping costs in water distribution systems using a novel approach to pump scheduling. Math. Comput. Model. 57, 873–886. https://doi.org/10.1016/j.mcm.2012.09.015.
34. Jafari-Asl, J., Sami Kashkooli, B., Bahrami, M., 2020. Using particle swarm optimization algorithm to optimally locating and controlling of pressure reducing valves for leakage minimization in water distribution systems. Sustain. Water Resour. Manag. 6, 1–11, https://doi.org/10.1007/s40899-020-00426-3.

Figures

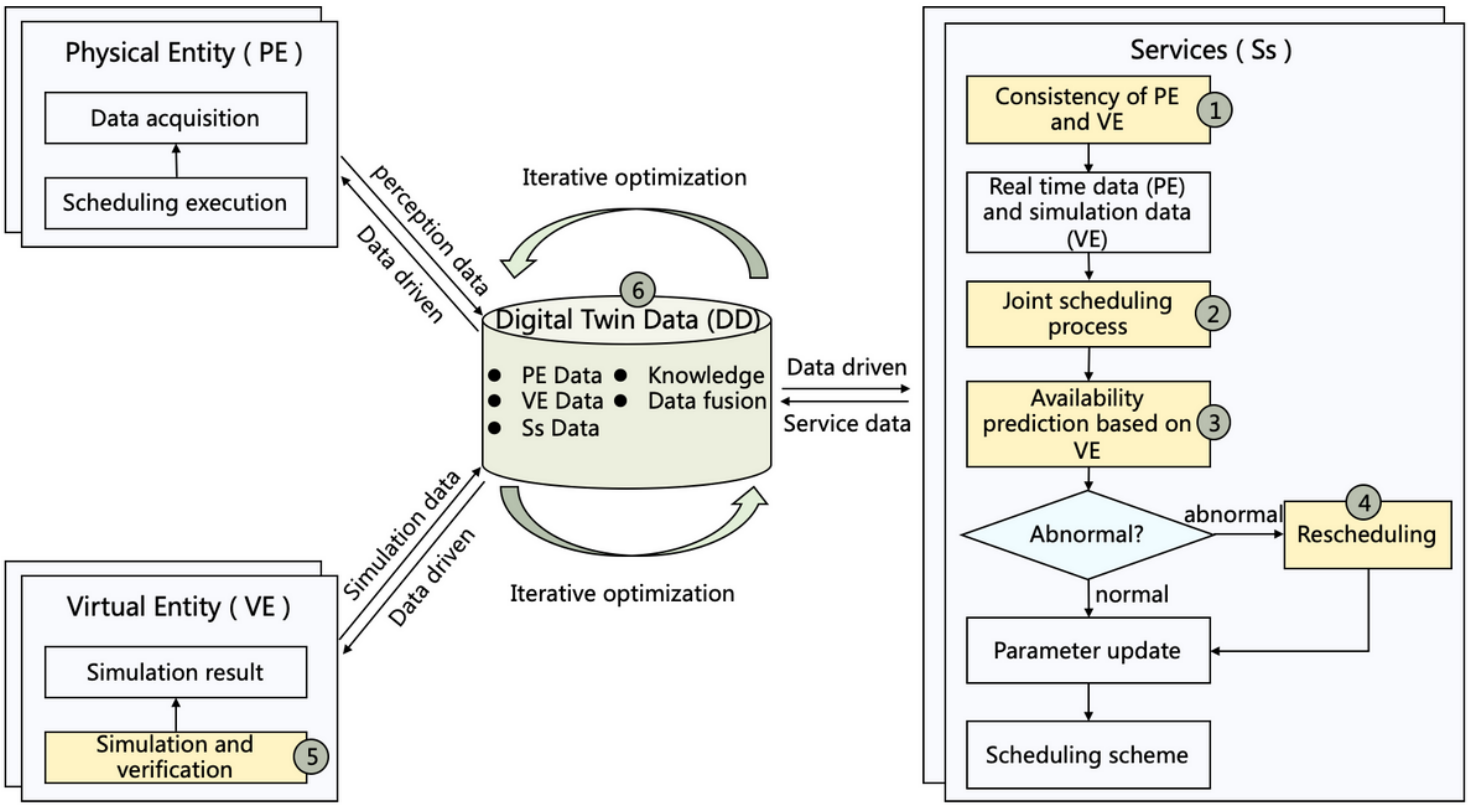


Figure 2

DT-based dynamic pump station scheduling

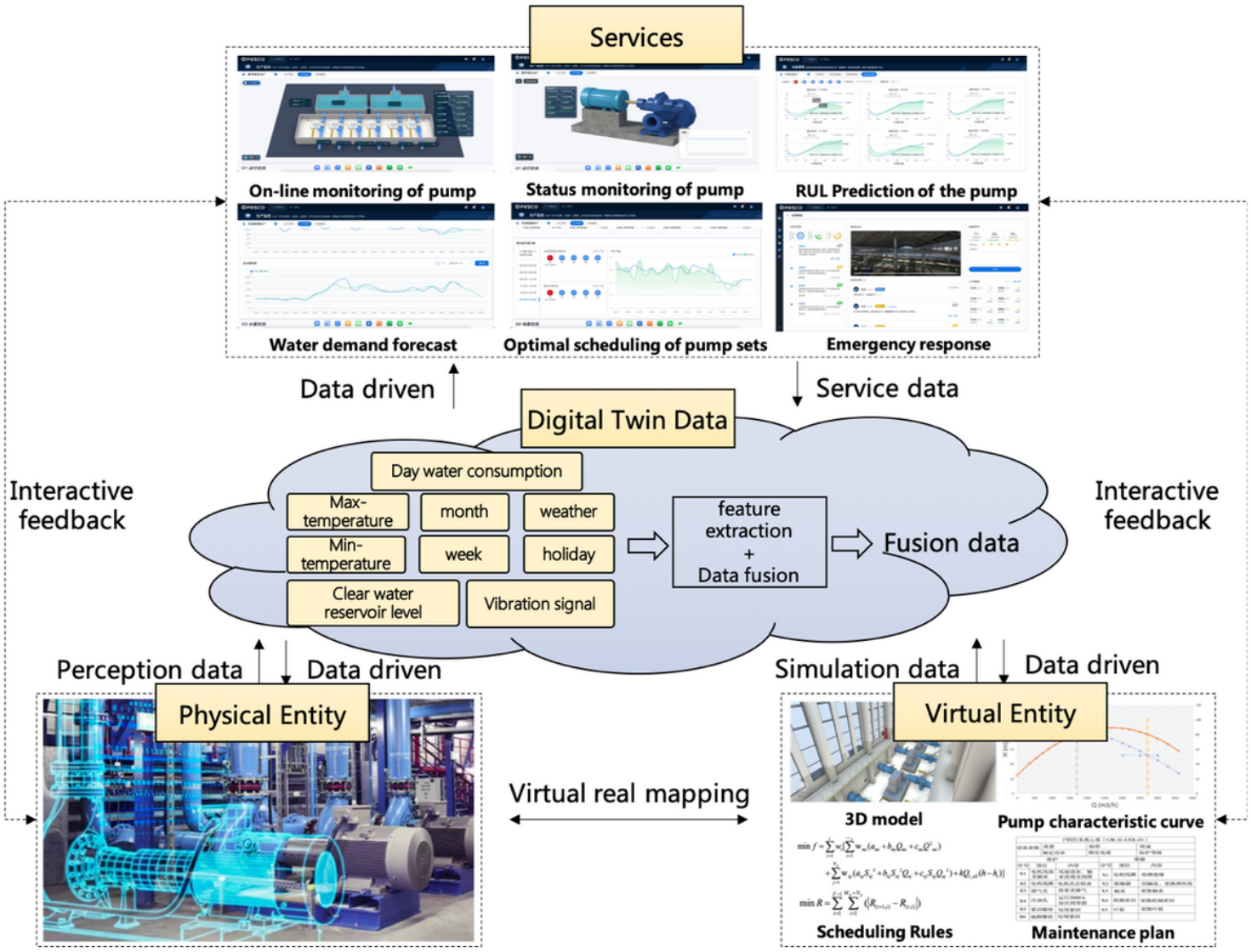


Figure 3

Five-dimensional DT model for pump stations in the water purification plants

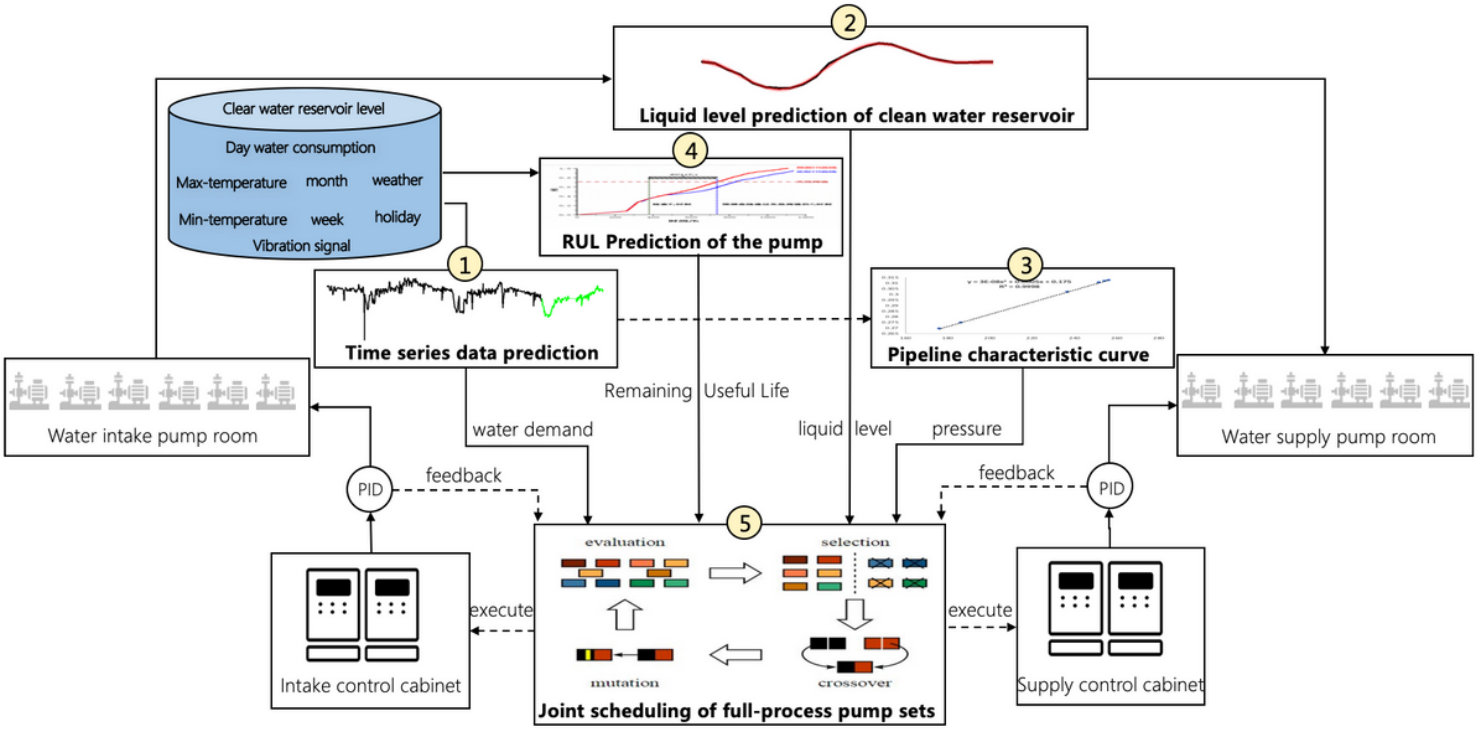


Figure 4

Operation mechanism of the full-process pump station joint scheduling in the water purification plant

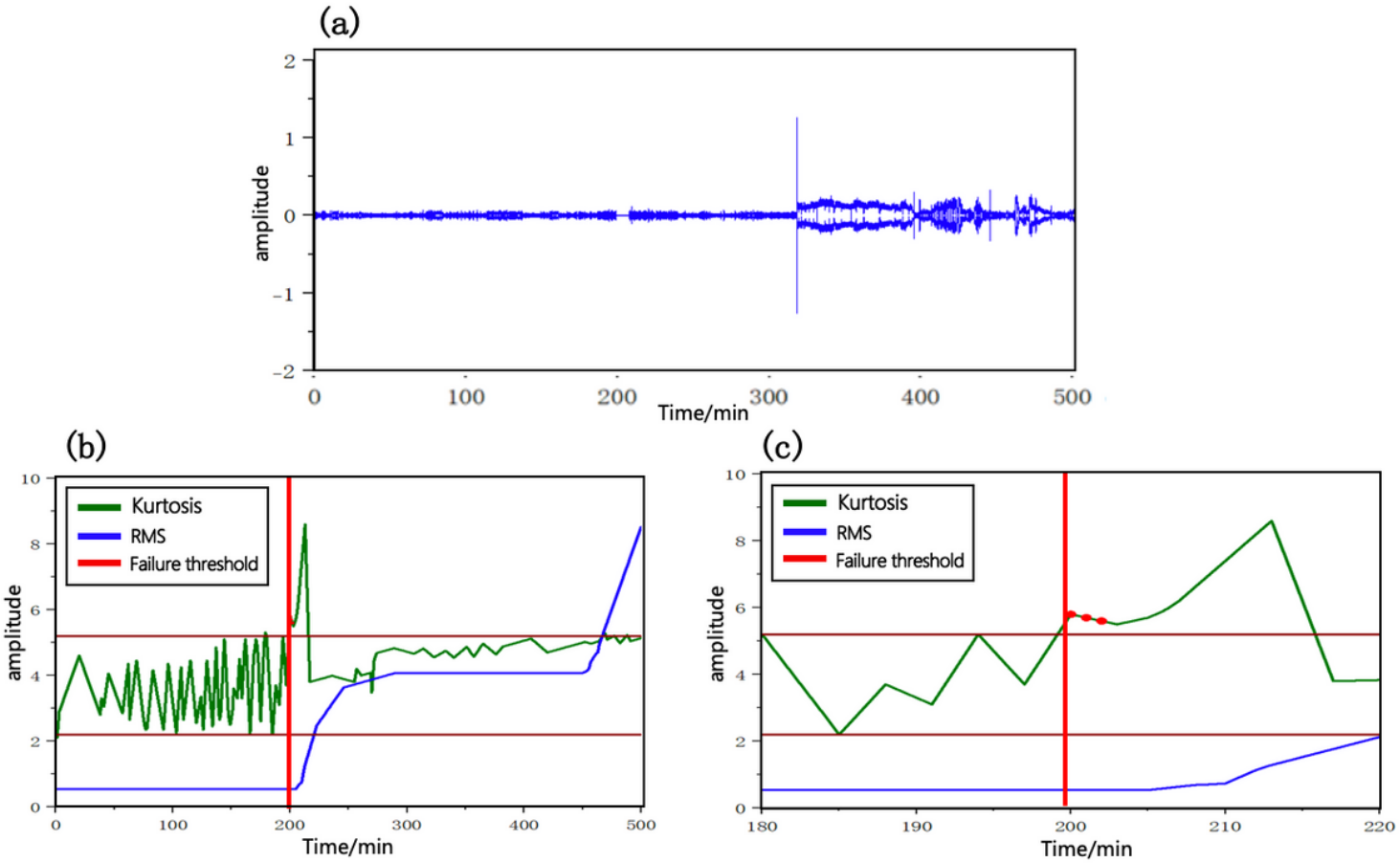


Figure 5

Comparison of opening and closing times (a) Original vibration signal diagram (b) Kurtosis and root mean square (c) local enlarged drawing of kurtosis and root mean square

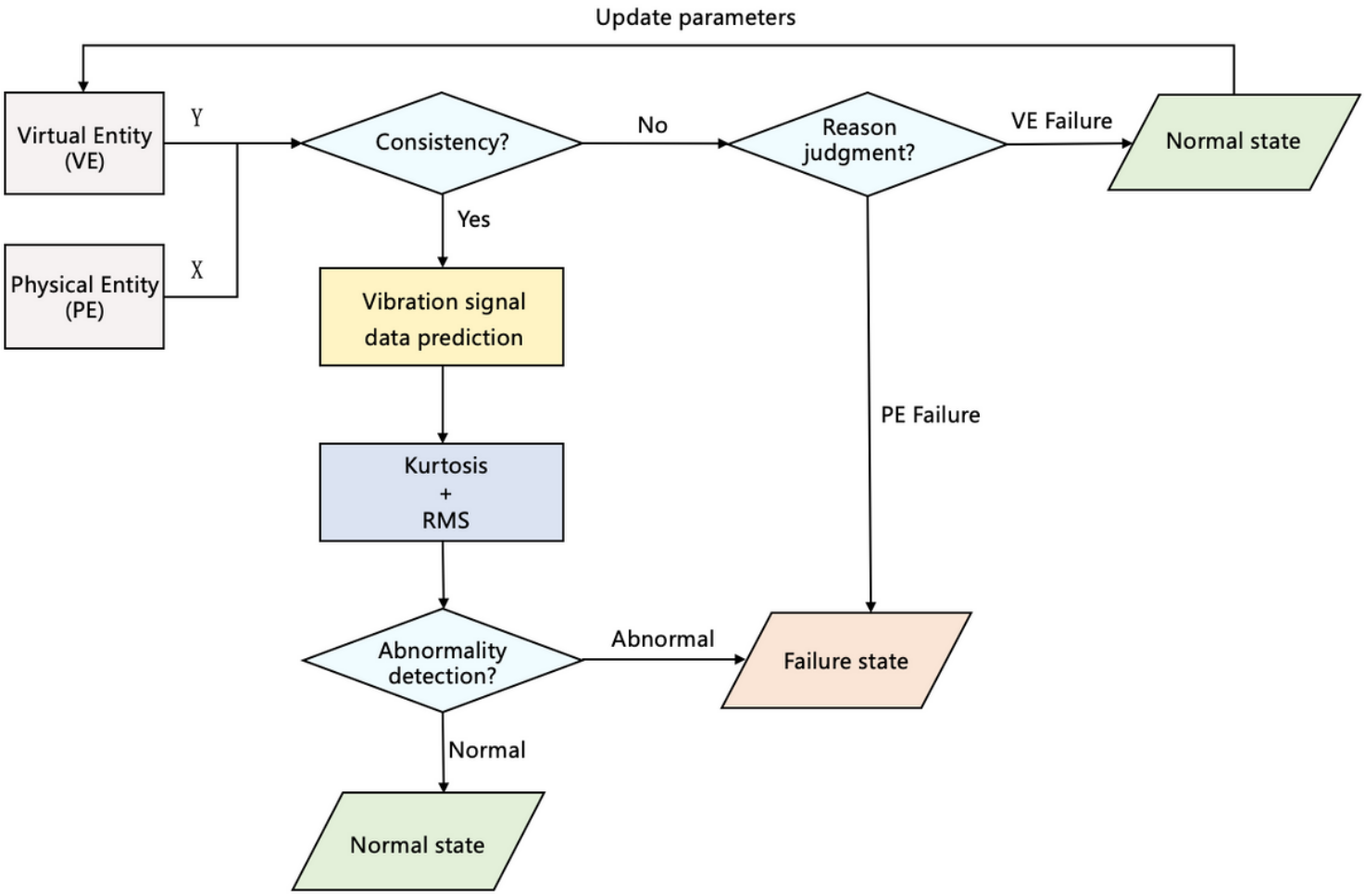


Figure 6

DT-based equipment availability prediction

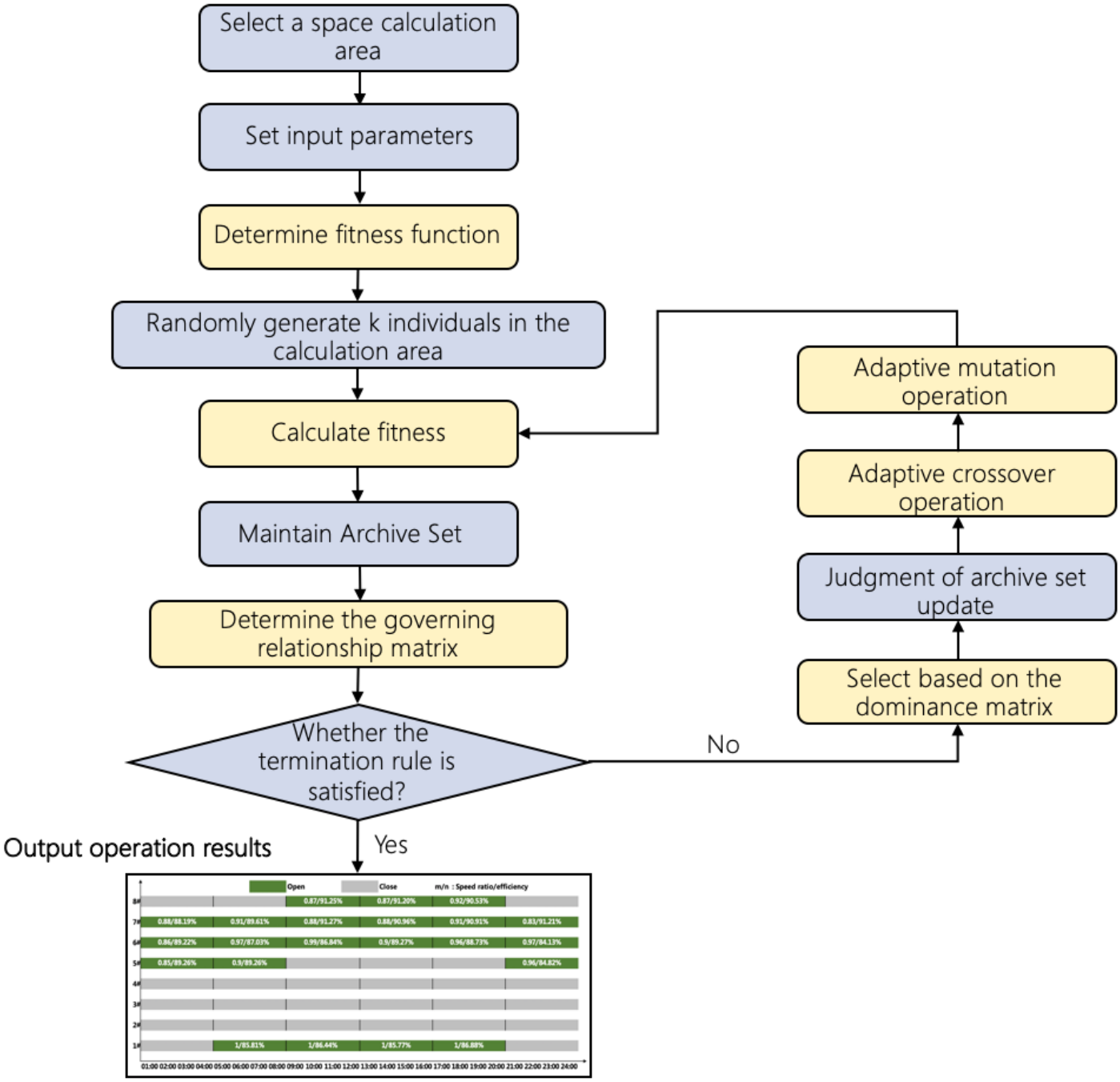


Figure 7

Flow of pump station scheduling optimization based on the IGA

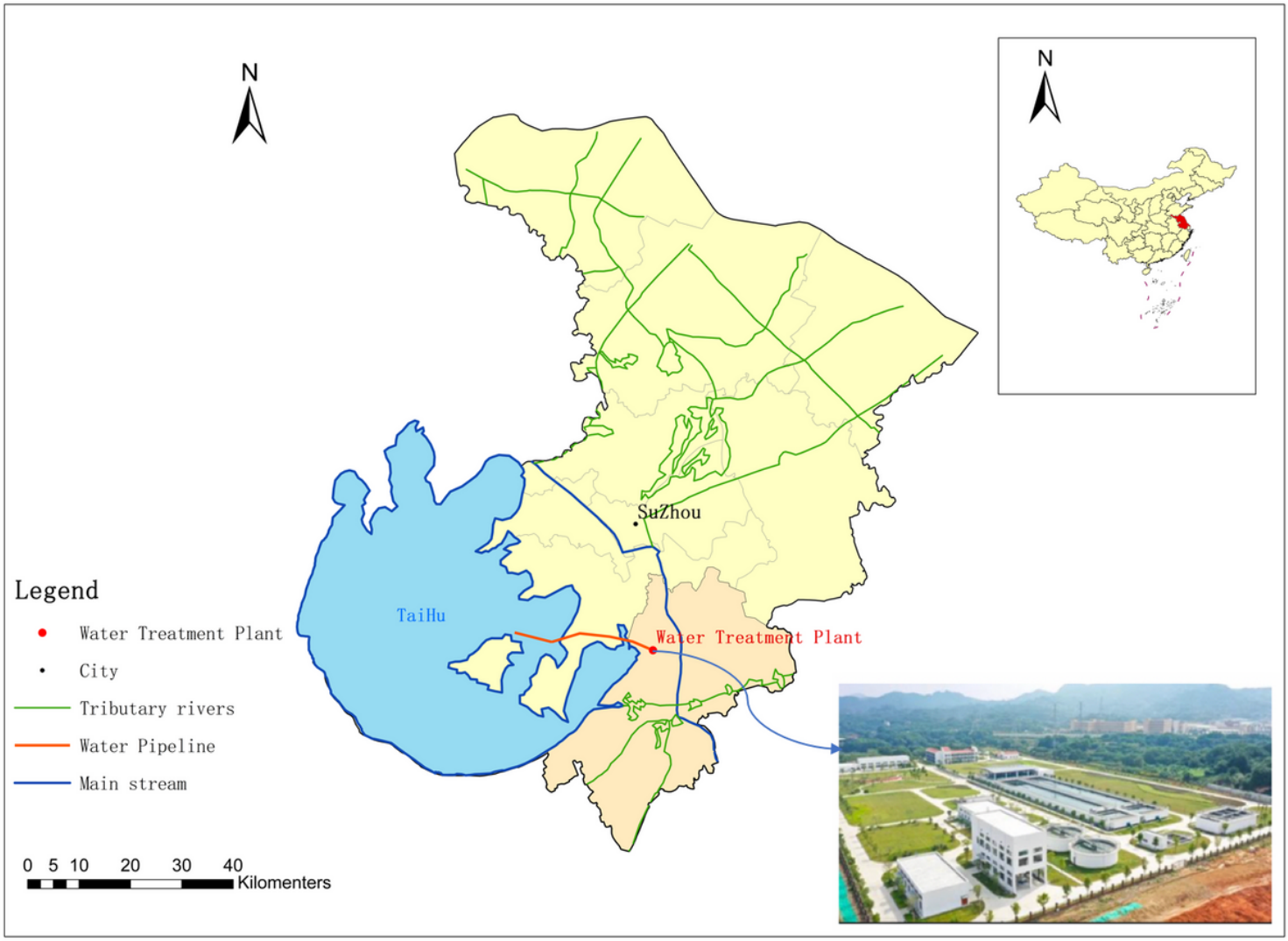


Figure 8

The water plant location map of the case study

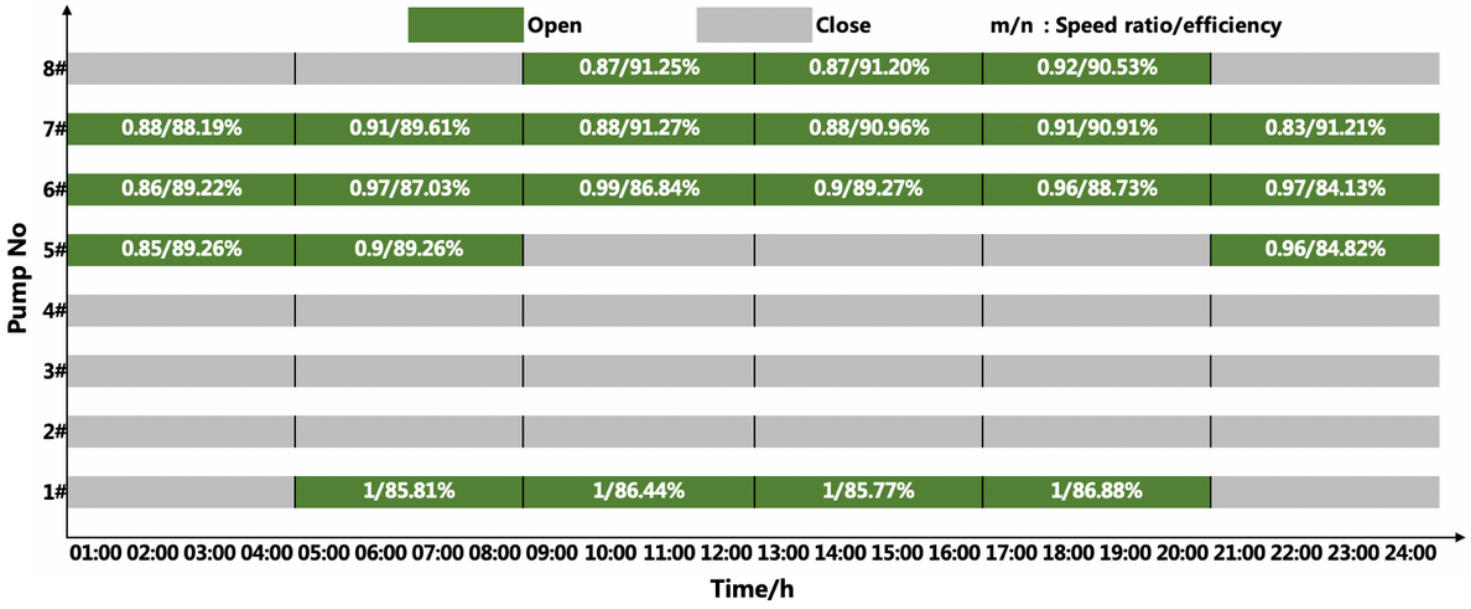


Figure 9

Pump opening solution after the pump station optimization under normal conditions

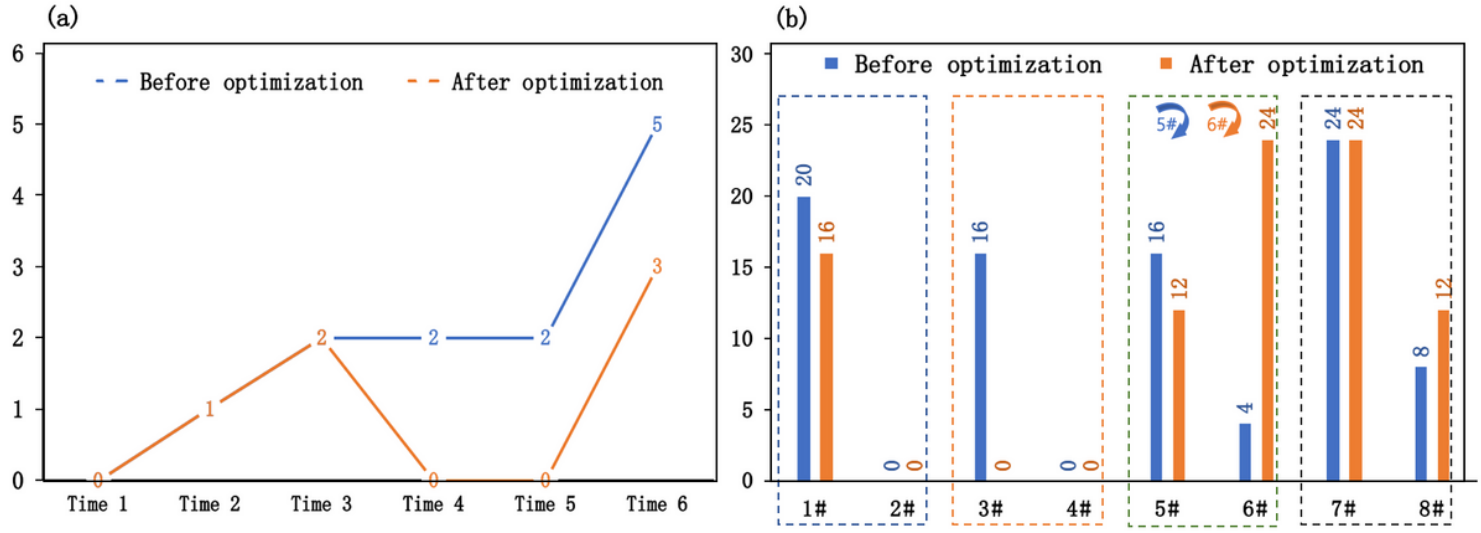


Figure 10

Comparison of opening and closing times (a) and operation duration (b) before and after pump station optimization under normal conditions

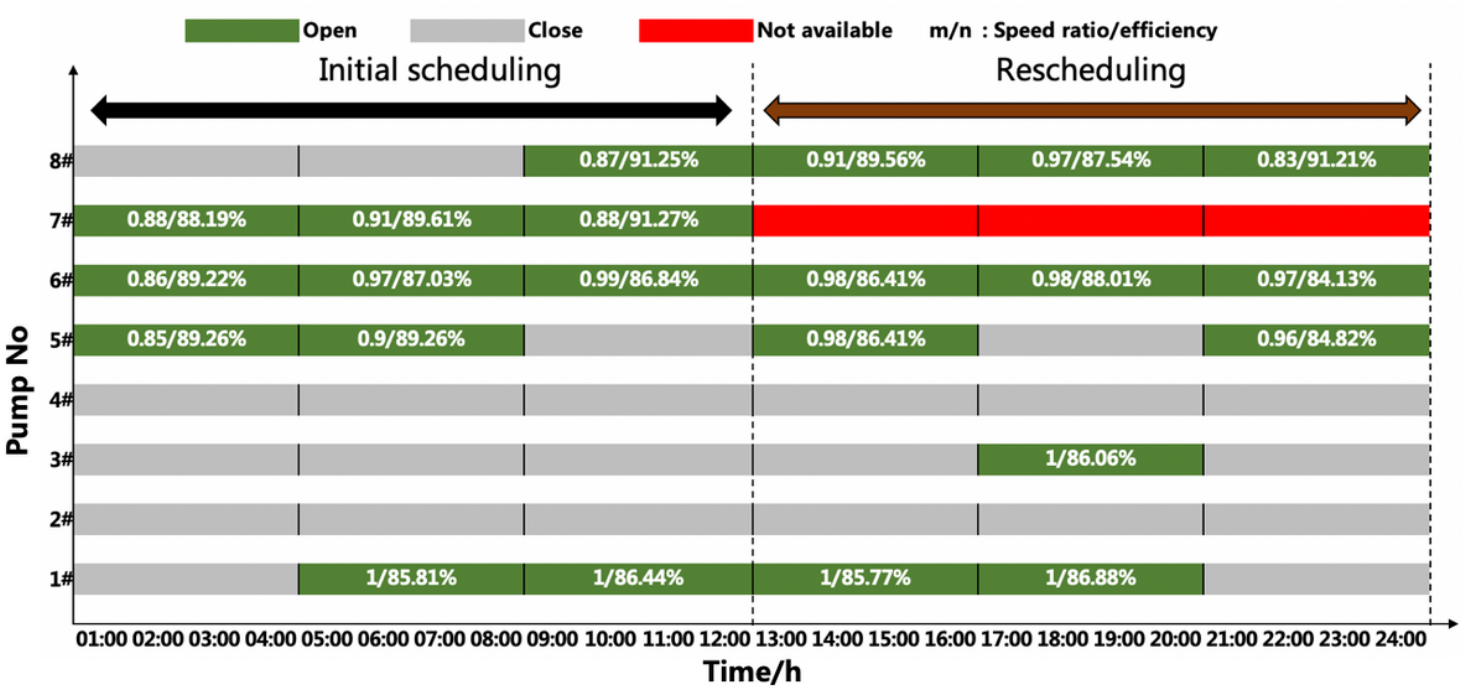


Figure 11

Pump opening solution of the pump station under disturbance

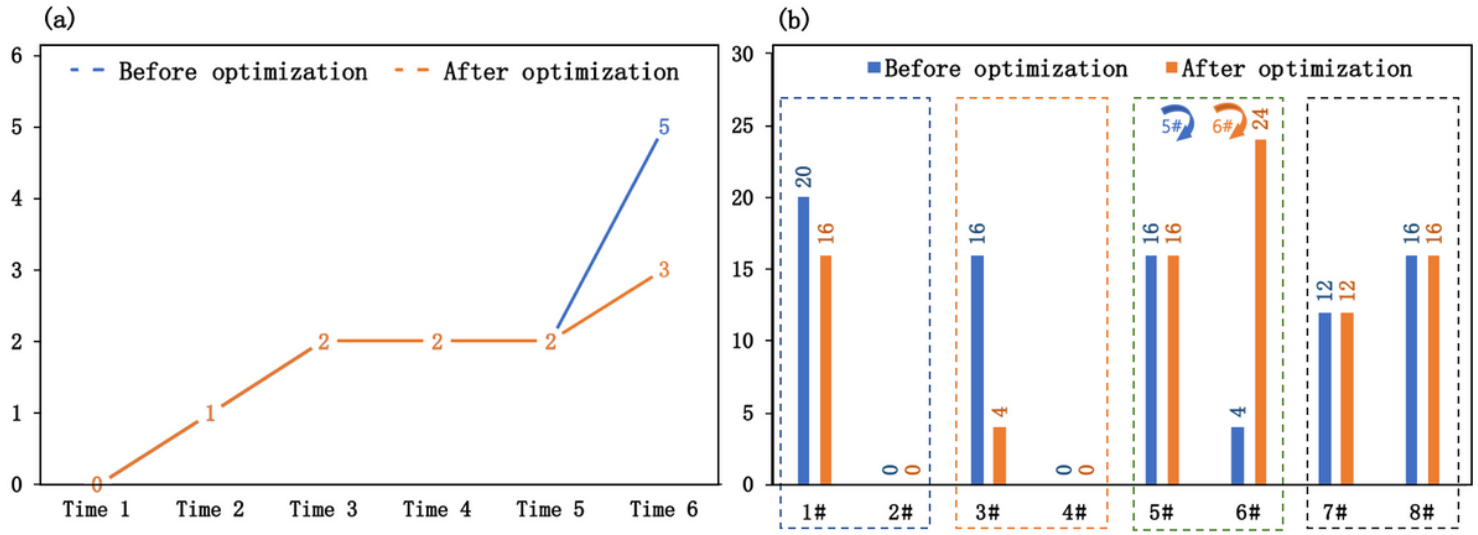


Figure 12

Comparison of rescheduling opening and closing times (a) and the operation duration (b) of the pump stations under disturbance

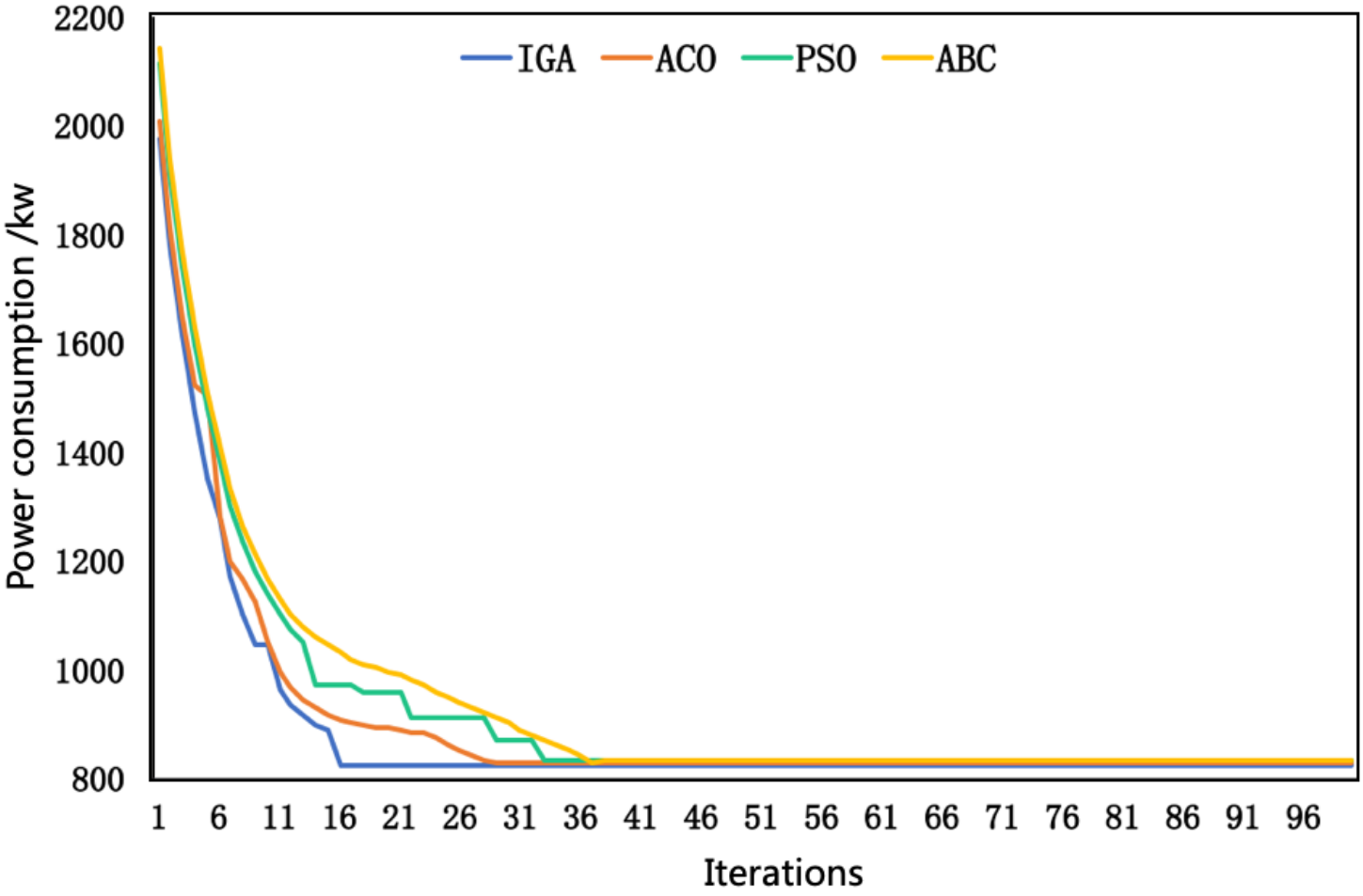


Figure 13

Convergence curve of the IGA and other meta-heuristic algorithms

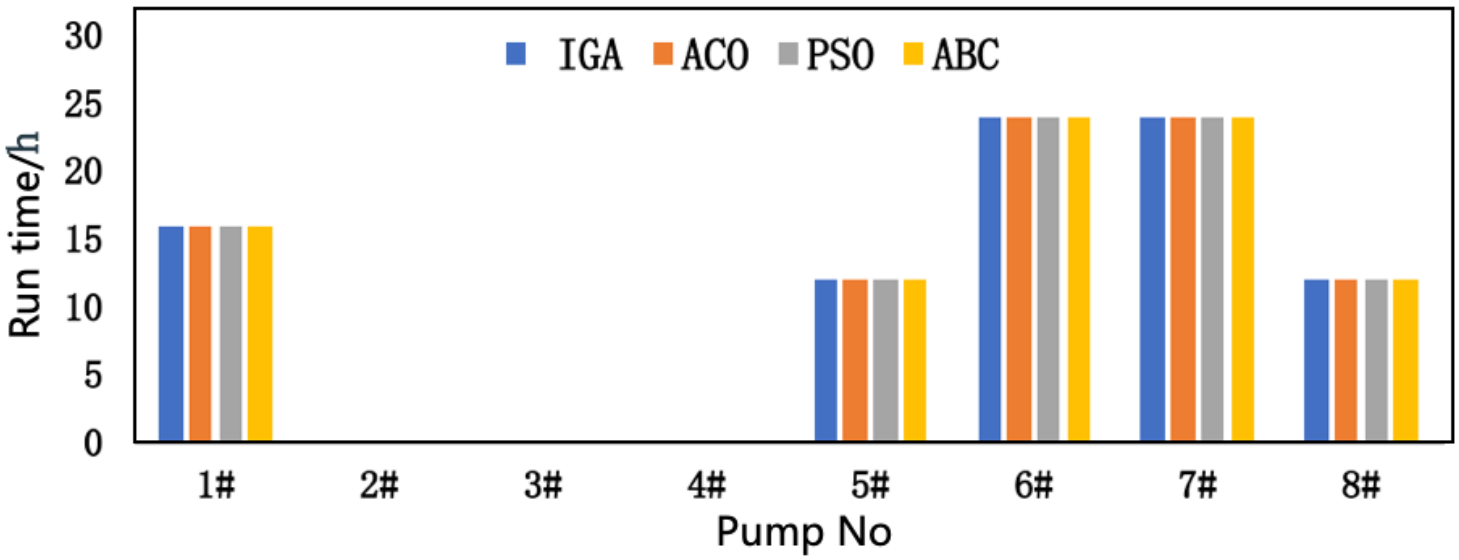


Figure 14

Comparison of equipment operation durations based on the IGA and other meta-heuristic algorithms

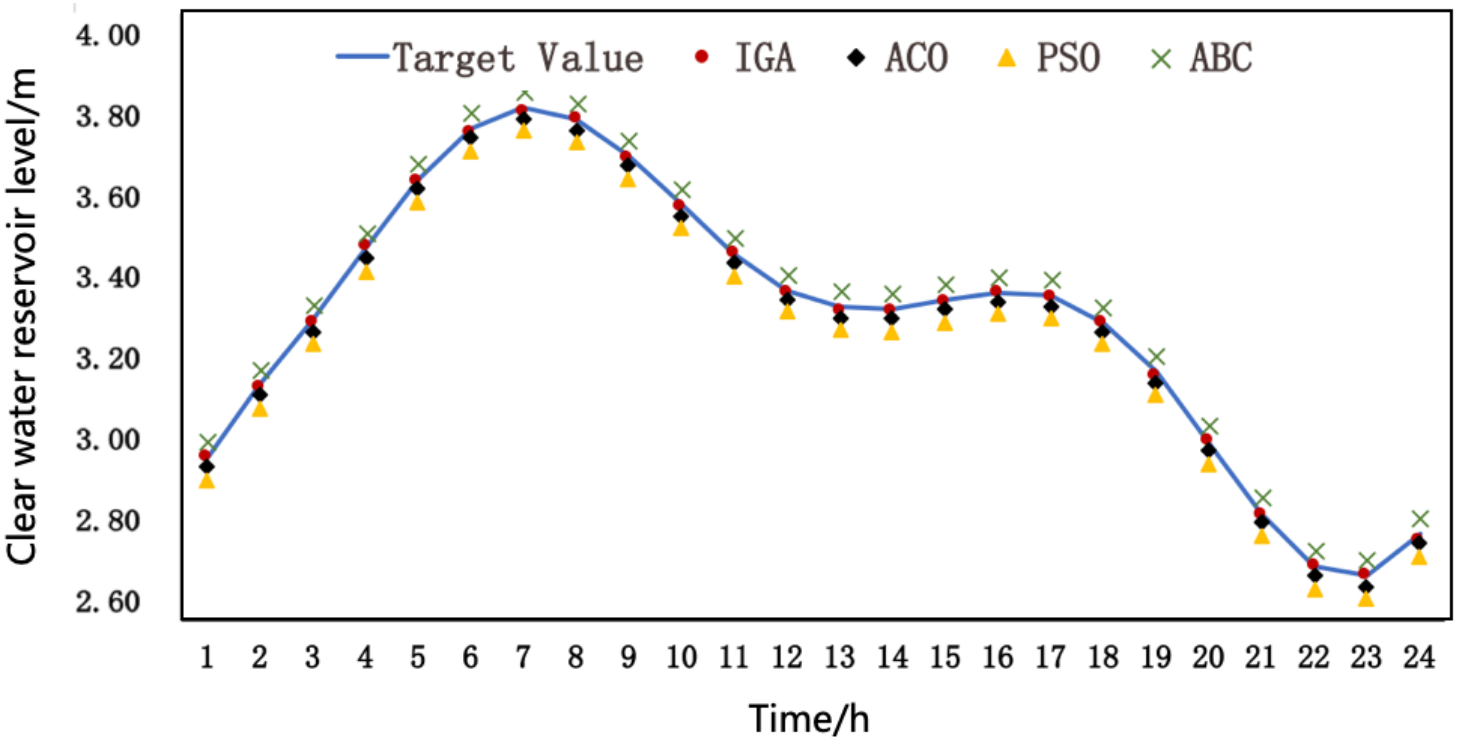


Figure 15

Comparison of the liquid level fluctuations of the clean water reservoir based on the IGA and other meta-heuristic algorithms